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Short-term vessel traffic flow forecasting by using an improved Kalman model

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Abstract

Vessel traffic flow forecasting is of significant importance for the water transport safety, especially in the multi-bridge water areas. An improved Kalman model combining regression analysis and Kalman filtering is proposed for short-term vessel traffic flow forecasting between Wuhan Yangtze River Bridge (hereafter WYRB) and the Second Wuhan Yangtze River Bridge (hereafter SWYRB). Given the vessel traffic flow of WYRB is positively correlated with that of SWYRB, its regression coefficient is obtained as well as the regression predictions. The predictions are further used to replace the state transition equation of Kalman filtering. The prediction results of the improved Kalman model demonstrate better agreements with field observations, and hence, illustrate good capability of the proposed method in the short-term traffic flow forecasting. The discrepancy between the model predictions and field observations is generally attributed to the inherent deficiency of Kalman filtering method and the errors resulted from automatic identification system (AIS) data (e.g. missed AIS data). The proposed method can provide a support for the real-time and accurate basis for the ship traffic planning management.

Keywords Vessel traffic flow forecasting · Regression analysis · Improved Kalman model · Multi-bridge water area

1 Introduction

The prime objective of traffic management strategies is to handle road traffic operations up to the highest level of service and provide more reliable, safer, and greener transportation. In past decades, traffic management has been limited to responsive schemes which react to prevailing traffic conditions. However, with the advancement in technology and the wide development of intelligent transportation systems, traffic operators are deploying active traffic management strategies which can dynamically apply alternative strategies proactively in response to predicted traffic conditions [1,2]. Therefore, the ability to timely, reliably, and accurately forecasting the dynamics of traffic over short-term horizons attracts much more attentions of researchers [3]. Short-term traffic forecasting models, therefore, are an integral element of the toolset needed for real-time traffic control and management. Moreover, such tools are important in providing travelers with reliable travel time information, optimizing traffic signals, and deployment of emergency management systems.

Ship traffic volume is a reflection scale of ship traffic flow. To a certain extent, the size of ship traffic flow can reflect whether traffic is orderly and congested. Investigation on the

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ship traffic flow is an important part of marine traffic planning, only to grasp the traffic flow information in real time, in order to more accurately predict the future traffic flow, provide real-time and accurate basis for the ship traffic planning management.

Since the early 1980s, short-term traffic forecasting has been an integral part of most intelligent transportation systems (ITS) research and applications; most effort has been paid to develop methodologies that can be used to model traffic characteristics and produce anticipated traffic conditions. A large number of literatures have used single point data from motorways and employed univariate mathematical models to predict traffic volumes or travel times.

In the literature, short-term traffic forecasting covers predictions over the time period of a few seconds to few hours in the future using current and historic measurements of traffic variables [4]. The approaches used in short-term traffic forecasting can be broadly classified into four categories [5]: primitive, linear, nonlinear and combined methods. Naive approaches refer to models that provide simple estimate of traffic in the future, e.g. historic averages [6]. Parametric approaches refer to models-based techniques which require a set of fixed parameter values as part of the mathematical or statistical equations they utilize, e.g. analytical models, macroscopic models and models based on time series analysis [7]. The majority of these approaches suffer from the assumptions that the model parameterization was proven to perform relatively poorly under unstable traffic conditions and complex road settings [8]. On the other hand, non-parametric approaches are mostly data-driven and apply empirical algorithms for the predictions, e.g. approaches based on data analysis and neural network techniques. Such approaches are advantageous as they are free of any assumptions regarding the underlying model formulation and the uncertainty involved in estimating the model parameters. Other short-term traffic models have implemented a hybrid of the aforementioned approaches [9].

The majority of the studies on short-term traffic forecasting were conducted using standard statistical techniques such as simple smoothing, complex time series analysis and filtering methods. Applications of smoothing for traffic forecasting include kernel smoothing, simple exponential smoothing, and neural networks. Others used time series analysis such as autoregressive integrated moving average (ARIMA) models [10–12]. A variation of the ARIMA model, which is Seasonal ARIMA (SARIMA) models, has also been implemented in many studies [13] applied a combination of cell transmission and SARIMA models. Filtering models (e.g., Kalman filtering [14]) have also been applied in short-term traffic forecasting. Recently, Chen et al. [15] proposed an algorithm based on particle swarm optimization and Chen and Rakha [16] developed a particle filter for traffic prediction.

The Kalman filter (KF) updating method has been widely used as an efficient measure to assimilate real-time hydrological variables for reducing forecasting uncertainty and providing improved forecasting. However, the accuracy of the KF relies much on the estimation of the state transition matrix and is limited due to the errors inheriting from parameters and variables of the traffic flow models. Especially in an inland multi-bridge water area, it is of significant importance to monitor the traffic flow patterns as well as forecasting vessel traffic flow density variations, which provides a framework of maritime risk prevention and control. An improved Kalman model has thus been proposed for short-term vessel traffic flow forecasting and its applicability in the multi-bridge water area is verified. The comparison between model predictions and field data illustrates the accuracy of the improved Kalman model.

Section 2 provides a brief description of the data source and model establishment. Section 3 presents model results and model-data comparisons, followed by a discussion in Sect. 4. Final conclusions are drawn in Sect. 5.

2 Proposed model

2.1 Model description

The regression model predictions of traffic flow are applied to replace state transit equation of Kalman model. The corresponding error is estimated with a prior knowledge. Therefore, the short-term forecasting of vessel traffic flow in the multi-bridge water area is achieved by using an improved Kalman model (Fig. 1).

2.2 Data source

The primary automatic identification systems (AIS) data contain vessel information, such as vessel position, speed, course, etc. In the present study, the multi-bridge water area between WYRB and SWYRB (as shown in Fig. 2) has been selected for verifying the combined model. AIS data are provided by the Wuhan Maritime Bureau, from which the vessel traffic flow information is extracted as an input of the model. An example of typical AIS data is shown as below (Table 1).

In Table 1, mmsi is the abbreviation of "Maritime Mobile Service Identify", UTC represents data transmission time, lon stands for longitude, lat represents latitude, speed represents ship speed, cargo type represents the type of ship, course represents the direction of the course. Due to the nonlinear nature of the vessel traffic flow time sequence, the vessels cross WYRB and SWYRB are counted hourly from 8:00am to 15:00pm (see Table 2 for example). The total vessel traffic flow data cover Feb. 1st– 21st, 2016.

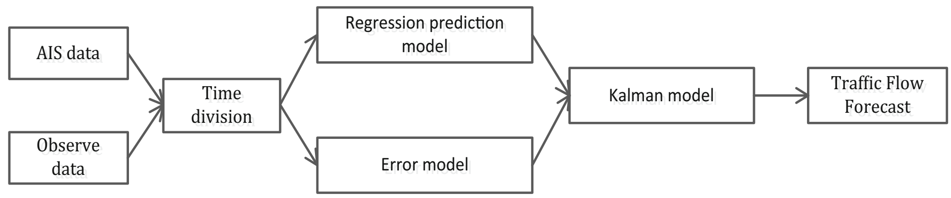


Fig. 1 Outline diagram of the improved Kalman model

Fig. 2 Multi-bridge water area between WYRB and SWYRB (by Google Map)

The extraction of traffic flow data is completed by AIS data. After the AIS signal is parsed, by dividing the area by section, the relevant cross-section coordinates are obtained, the cross-section A is defined as (ax1, ay1-ax2, ay2), and the latitude and longitude of the section B is (bx1, by1-bx2, by2). The AB curve is determined by two points f(a) and f(b). Set the ship AIS signal to the current latitude and longitude (sx, sy), if (sx, sy) ⟨f (a), and (sx, sy)⟩ f (b), the ship is in the designated area. The number of traffic flows N divided by the designated area S, the traffic density of the obtained area can be obtained M = N/S (Fig. 3).

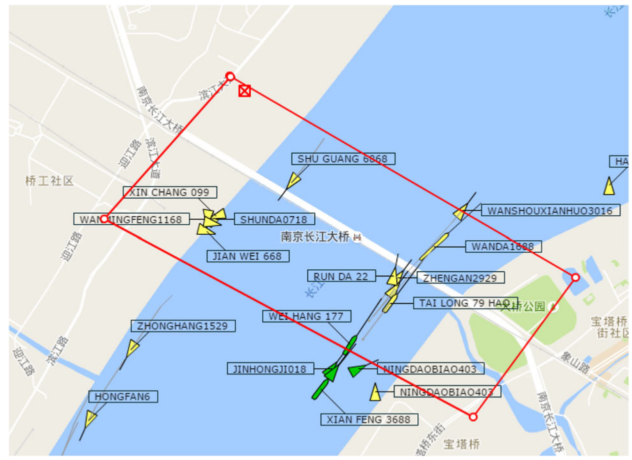


Fig. 3 Schematic diagram of vessel traffic flow data acquisition

2.3 Regression prediction model

Regression model is a mathematical model for quantitative description of statistical relations. Suppose that the ship's mooring law does not change greatly in the two target locations. Then there is a certain relationship between the numbers of ships. The correlation can be simulated by regression model.

Define the time series of vessel traffic flow at one specified cross-section as

$$Q_t = (q_1, q_2, \ldots, q_i) \tag{1}$$

Table 1 Information of typical AIS data obtained in the Yangtze River, China

Mmsi	Utc	Lon	Lat	Speed	Cargo type	Course	Tru
0	21/02/2016 05:24:31	114.3022	30.585853	3.5	70	206.7	− 0.1
0	21/02/2016 05:25:31	114.301693	30.58497	3.5	70	208	− 0.1
0	21/02/2016 05:27:36	114.300467	30.583213	3.5	70	220.5	− 0.1

Table 2 Vessel traffic flow data extracted from AIS (Feb 21st, 2016)

Time	9:00–10:00	10:00–11:00	11:00–12:00	12:00–13:00	13:00–14:00	14:00–15:00
WYRB	16	15	15	18	19	17
SWYRB	15	17	17	16	18	19

In which q_i represents vessel traffic flow at the time $t = i$. For the sake of simplicity, the vessel traffic flow at WYRB and SWYRB is defined as Q_{1t} and Q_{2t} respectively. In Fig. 2, it is noted that Q_{1t} is positively correlated with Q_{2t}. Therefore, the following relationship is derived according to the classic regression theory.

$$Q_{1t} = f\left(Q_{2(t-1)}\right) \tag{2}$$

The regression expression f is obtained by the least square method. The sampling frequency of data is limited by the distance between two points. Assume the distance between WYRB and SWYRB is L and the average vessel speed is V, the time interval Δt of the data sequence is therefore determined. By Formula 3, the best correlation time interval is half an hour.

$$\Delta t = t_n - t_{n-1} = L/V \tag{3}$$

In which, L represents the distance between WYRB and SWYRB, V represents the average speed of the ship in this section. The average velocity is calculated by the statistical sample, and its value is 6 Knots.

2.4 Error model

Due to the fact that many ships in the inland waterway of the Yangtze River are to open the AIS system, there is a certain loss of signal in the AIS signal transmission, which results in the fact that the actual data do not match the AIS data. In addition to the vessel traffic flow extracted from AIS data, field data collection (M_t) has been obtained by in situ counting manually and video recording system (Fig. 4). The error of Kalman filtering can be determined by subtracting M_t by Q_t (Fig. 5).

$$M_t = (m_1, m_2, \ldots, m_i) \tag{4}$$

$$E_t = (e_1, e_2, \ldots, e_i) \tag{5}$$

The average value and variance of Kalman filtering error is written as μ and σ, which form the Gaussian distribution function.

$$w(k) = \left(\mu, \sigma^2\right) \tag{6}$$

2.5 Improved Kalman model

In the present study, an improved Kalman Model is proposed to predict the traffic flow. The general idea of using Kalman filtering is to deal with the interferences in the original traffic dataset, on basis of which the regression model is to initial the equation. The accuracy of the hybrid algorithm in the short term forecasting of traffic flow is evaluated and influencing factors are explored. The present results indicated that the latter (i.e. Improved Kalman filtering) could be more promising

Fig. 5 Snapshot of video recording system of vessel traffic flow at SWYRB

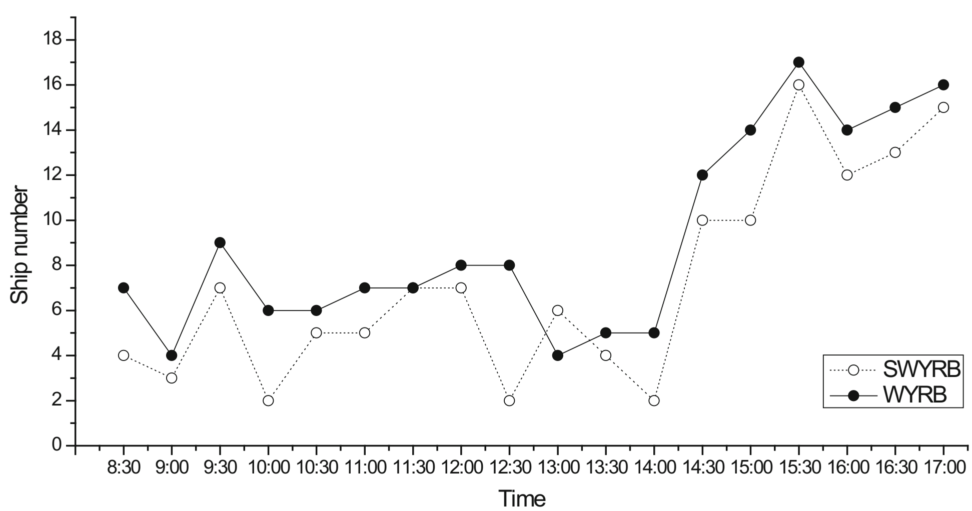


Fig. 4 Vessel traffic flow correlation between Q_{1t} and Q_{2t}

for the hybrid model. Kalman method of repairing the dataset follows its basic five formulas. The determination of state transition equation is a prerequisite for applying Kalman filtering in vessel traffic flow forecasting. Traditionally it is written as:

$$X_{k|k+1} = AX_k + BU_k + w(k) \tag{7}$$

Considering the instability of vessel traffic flow, the state equation U_k of auto-regression analysis is hard to obtain. Thus the predicted Q_t is used and the simplified state equation is obtained. In Eq. (7), X_k is the traffic flow number of time k, A and B are the system control parameters, in which A can be set to 1 in this example. U_k is the state transition matrix, which is determined according to the autocorrelation of traffic flow. It is assumed that the temporal variation of the water level is linear. w_k is the error matrix, therefore, Eq. (1) is rewritten as:

$$X_k = Q_t + w(k) \tag{8}$$

where $w(k)$ is the predicted noise function. The measurements are made up of AIS observations and errors.

$$Y_k = O_k + v(k) \tag{9}$$

In Eq. (9), Y_k is the measurement data, v (k) is the error matrix, H is the state parameter and set to 1. The Kalman gain and error variance are calculated as follows.

$$K_g = P_{k|k-1}\left[P_{k|k-1} + \mathrm{cov}(w)\right]^{-1} \tag{10}$$

$$P_{k|k-1} = P_{k-1} + \mathrm{cov}(v) \tag{11}$$

$$P_k = \left(1 - K_g\right) P_{k|k-1} \tag{12}$$

where Q_t is the predicted value of the regression model, O_k is the vessel traffic flow information extracted from AIS data, K_g represents Kalman Gain, and $P_{k|k-1}$ is the error variance at the time $t = i$. Here, we use the regression model instead of the original transfer equation in the Kalman filter. In addition, the error matrix is replaced by the difference between the measured and the observed values.

3 Experimental results

Take Wuhan section as the research area. Wuhan section, the Hankou Wuhan Department is a busy area of inland waterways, more vessels. Tian Xingzhou, the port of commerce was a large bend, navigation environment is complex. Especially in the dry season, the vessel cannot be on the left side of the Tian Xingzhou, the right side of the channel can only pass the width of 1 km, prone to ship - standard collision accident. At the experimental site, there is a wharf between WYRB and SWYRB, and there is a strong linear relationship between two points (Fig. 6).

The vessel traffic flow information is extracted from the AIS data (Fig. 4) and used as an input of the regression model. The regression coefficients for a number of model orders are computed (Table 3).

Table 3 Computed regression coefficients for different model orders

Order	Coefficients				
	0	1	2	3	4
1	− 1.4295	0.9496	–	–	–
2	3.8960	− 0.3104	0.0610	–	–
3	− 0.00297	0.1509	− 1.1285	6.1175	–
4	0.0023	− 0.0979	1.5302	− 9.2759	22.5133

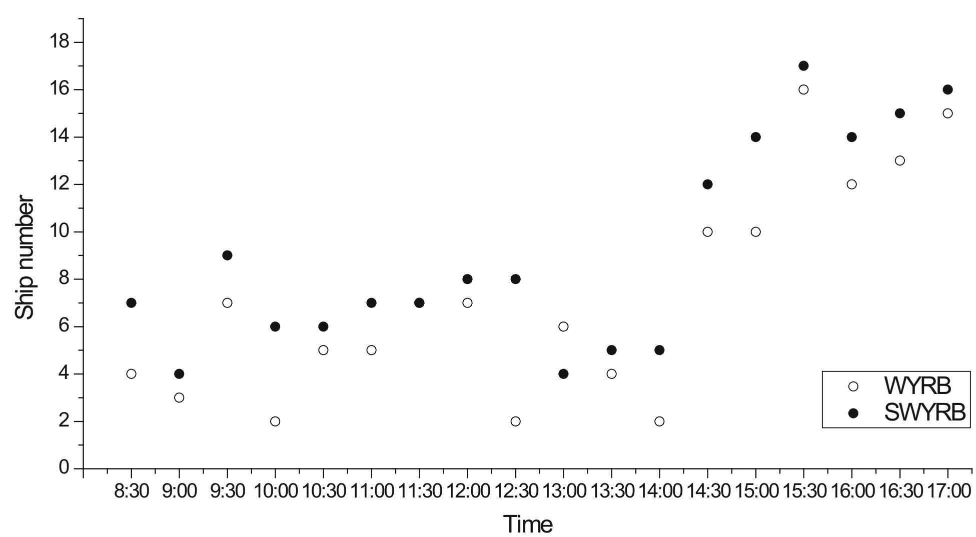


Fig. 6 Vessel traffic flow extracted from AIS data (date: 2016/2/21)

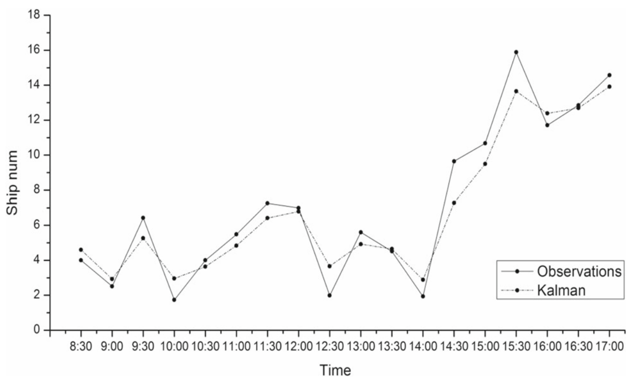


Fig. 7 Time series of vessel traffic flow comparison between field observations and improved Kalman model forecasting (date: 2016/2/21)

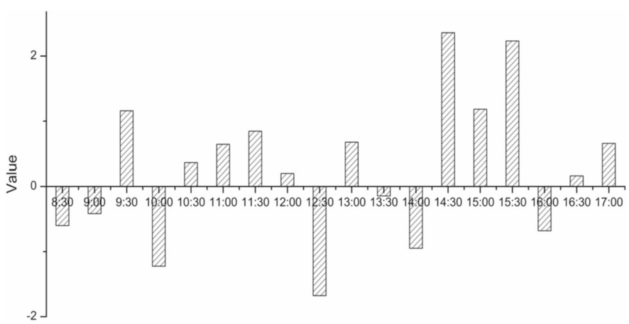


Fig. 8 Bar graph of the absolute residual variations by the improved Kalman model

By replacing the state transition equation with the regression model results, the improved traffic flow forecasting could be obtained by superimposing field observations with the error model. The comparison between model predictions and field observations of vessel traffic flow is generally favorable (Fig. 7). The RMSE error of the improved Calman filter is shown in Fig. 8, with a maximum value of 2.475.

4 Discussion

4.1 Role of the regression model degrees

The accuracy of the regression model will directly determine the accuracy of the Kalman prediction result. The accuracy of the regression model is expressed by the coefficient of the regression model. To determine correct model degree, the regression model has been tested (Fig. 8). It is noted that the root mean square (RMS) error decreases quickly when the model degree increases to 3. For 1st order regression model, the coefficient (a_1) is close to unity (Table 3). In other words, the vessel traffic flow of WYRB and SWYRB is linearly correlated, consistent with the practical observations (Table 4).

Table 4 Prediction errors of the regression model with different degrees

Degree	Sum of absolute error	Sum of average error
1	22.3398	1.2411
2	21.0263	1.1681
3	20.9230	1.1624
4	20.9230	1.1624

4.2 Applicability of regression and improved Kalman model

The vessel traffic flow data (Feb. 1st–21st, 2016) in the multi-bridge water area are applied in the regression and improved Kalman model. Their performance in the vessel traffic flow forecasting is thus evaluated (Figs. 9, 10). Both two models provide reasonable predictions of vessel traffic flow when the input conditions fall in the training dataset. However, the improved Kalman model is superior to the regression model and more suitable for the traffic flow forecasting (Fig. 11; Table 5).

It is found that the improved Kalman filter is not stable in one day data. In the February 6th prediction result, the Kalman filter method is worse than the regression model, while the February 25th day results are just the opposite. It is possible that the distance between the two places is too close, leading to a strong linear relationship. So the regression model presents a minor error. To verify the applicability of the algorithm, we do some experiments in other reaches. Shiye reach, as the middle reach of the Yangtze River. There is a branch on it, and the situation is more complicated. We take a section of each branch, and also before the branch after the branch, in total 4 sections (as shown in Fig. 12).

The data format is the same as the hourly ship data, and the sample time is from 1st to 31st, October, 2016. Section 4 is the prediction target, and the input contains 4 combinations, which are Sects. 1, 2, 3 and combine Sects. 2 and 3. In addition, the model performance is evaluated by three different indexes as the root mean square error (RMSE), r-square (R2) and mean absolute percentage error (MAPE). The determination coefficient (R2) falls in a range of 0 to 1, while larger values indicate more reliable predictions. MAPE is a measure of prediction accuracy of a forecasting method in statistics, e.g. trend estimation, and has an advantage of being scale independent. They are defined and calculated as follows.

$$RMSE = \sqrt{\frac{1}{N}(Xobs, i - Xpre, i)^2} \tag{13}$$

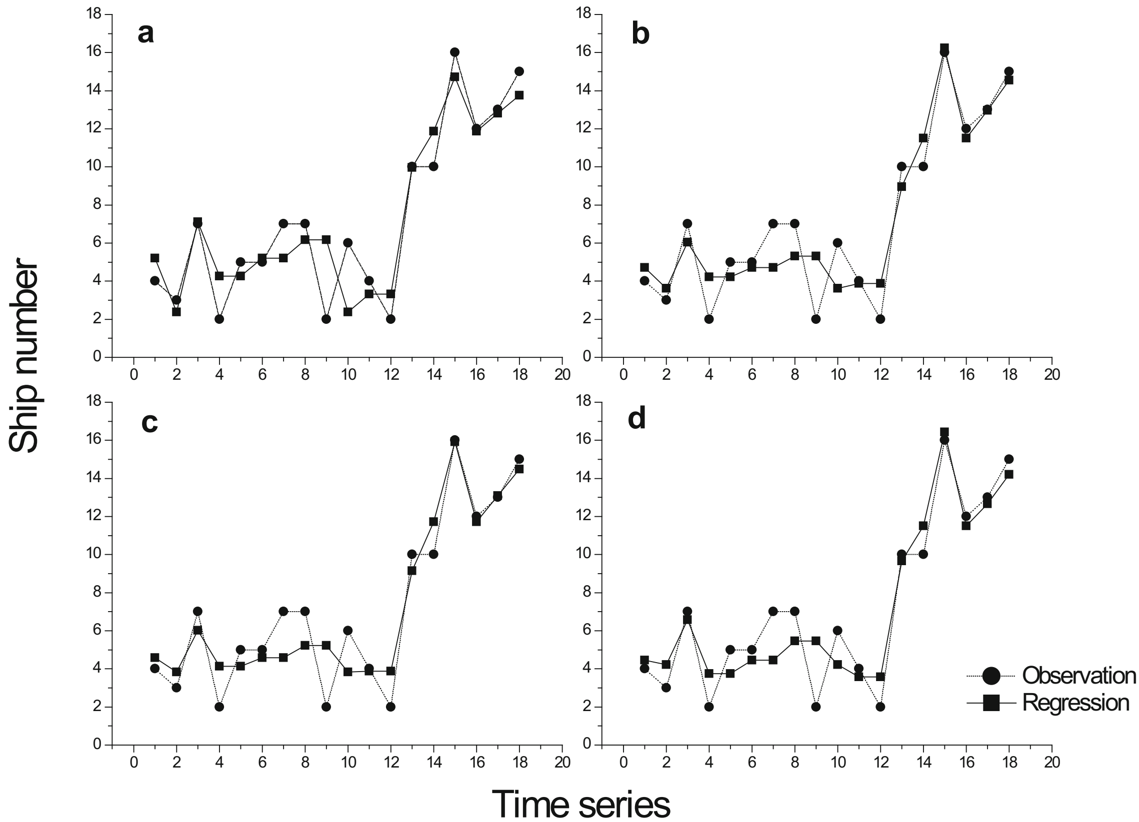
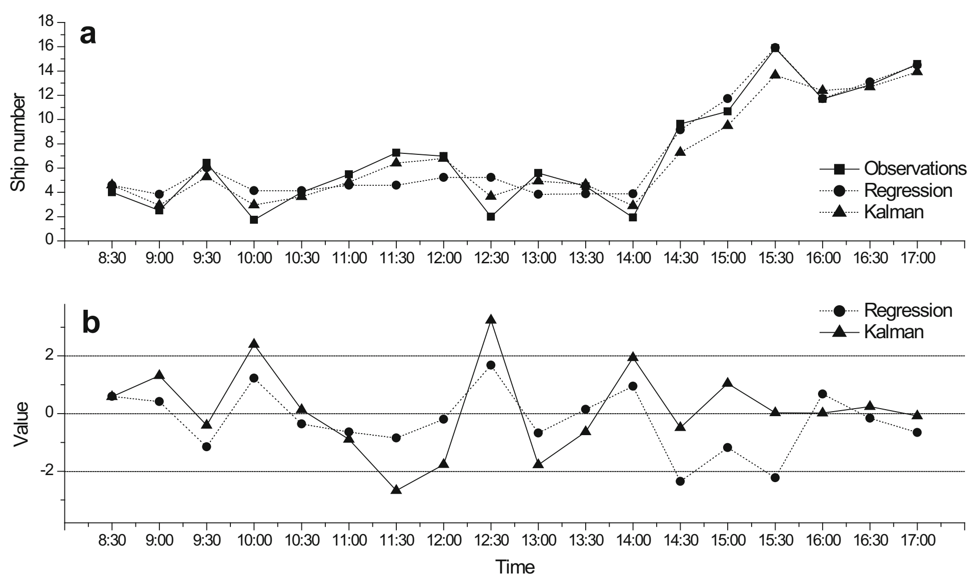


Fig. 9 Time series of vessel traffic flow comparison between field observations and combined model forecasting with different degrees. **a** degree=1; **b** degree=2; **c** degree=3; **d** degree=4

Fig. 10 **a** Time series of vessel traffic flow comparison between field observations and improved Kalman model forecasting (date: 2016/2/6); **b** Variations of the absolute residual variations by the regression and improved Kalman model



$$MAPE = \frac{1}{N}\left\{\sum_{i=1}^{n}\frac{|Xobs, i - Xpre, i|}{Xobs, i}\right\} \times 100\% \qquad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Xobs, i - Xpre, i)^2}{\sum_{i=1}^{n}(Xobs, i - \overline{Xpre, i})^2} \qquad (15)$$

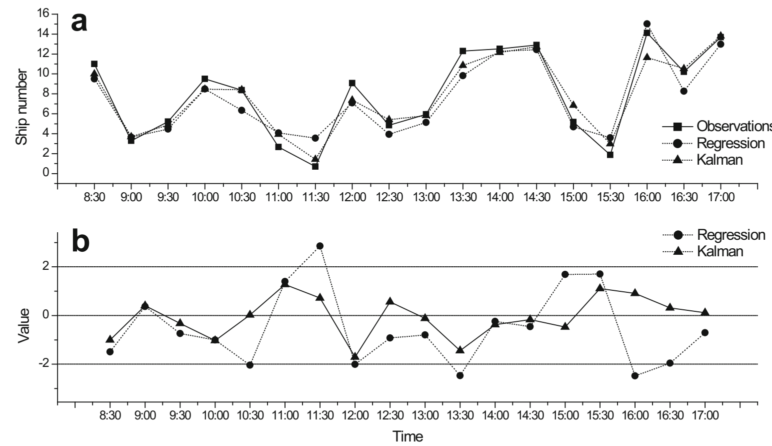


Fig. 11 **a** Time series of vessel traffic flow comparison between field observations and combined model forecasting (date: 2016/2/25); **b** Variations of the absolute residual variations by the regression and improved Kalman model

Table 5 Comparison between regression and combined models

Date	Absolute error		Average error	
	Regression model	Improved model	Regression model	Improved model
2016/2/6	16.1776	19.6712	0.8988	1.0928
2016/2/25	25.3148	12.0527	1.4064	0.6696

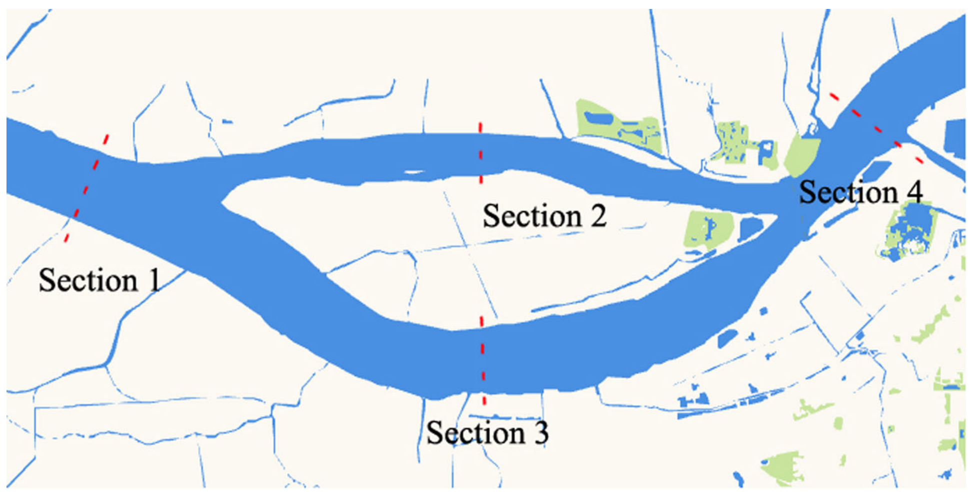


Fig. 12 Four sections in ShiYe water area

The degree of the regression coefficient is set to 4, as mentioned above. When the model input is Sects. 2 and 3, the unified modeling method is adopted. The inputs of cross Sect. 2 and 3 are regarded as two independent variables, and the regression model is constructed together. The results are shown in Table 6.

The experimental results show that the improved Kalman filtering method can improve the accuracy in 4 scenarios which proves that the model has certain applicability. Another point is that in the improvement of Kalman filtering results, the effect of Sect. 1 is not better than that of Sects. 2 and 3. This point is also reflected in the regression model. It shows that there is no absolute relationship between the results of the model and the distance between the two sections. The test result of Sect. 2 is the worst of the 4 results. The reason is that the number of ships passing through Sect. 2 is small and the regression relationship between the target sections is weak. Correspondingly, the regression relationship between Sect. 2 and target section is weak. The strength of regression relation will directly influence the model result. In addition, the two models have different results in the 4th dataset, Sects. 2 and 3. The result of multi-regression is between two independent regression results. The prediction result of Kalman filter is better than two independent results. This can reflect the advantage of the optimization method for linear methods.

Table 6 Prediction performance

Model input	Regression			Improved Kalman		
	RMSE	MAPE (%)	R^2	RMSE	MAPE (%)	R^2
Section 1	1.614	11.914	0.841	1.071	7.905	0.911
Section 2	2.431	17.944	0.679	1.974	14.571	0.713
Section 3	1.271	9.382	0.747	1.041	7.684	0.904
Section 2 and 3	1.644	12.135	0.794	0.932	6.879	0.947

5 Conclusions

Vessel traffic flow forecasting is of significant importance for the water transport safety, especially in the multi-bridge water areas. This paper proposes an improved Kalman model that uses the regression model to replace the transfer equation of the Kalman filter to predict the short-term vessel traffic flow. Its applicability is verified by performing predictions using field data (Manual Vessel Count). Experimental test results demonstrate better prediction performance of the proposed method than that of the traditional regression model. The discrepancy between model predictions and field observations could be attributed to the inherent deficiency of the Kalman filtering method. In addition, some small ships in the Yangtze River do not carry AIS, leading to the errors in the training dataset. In the experimental test in the SiYe water area, it can be seen that the prediction accuracy has no obvious relationship with the distance between two points. Meanwhile, the error of the Kalman filter is inclined to be the smaller one between the regression prediction error and the observation error. The present study indicates that the improved Kalman model is suitable and effective for the traffic flow forecasting with a smaller residual comparing with the regression model. Future work will investigate how to handle missing AIS data in the proposed method and develop a practical prediction system for vessel traffic flow forecasting.

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References

1. Tian, Z., Liu, F., Li, Z., Malekian, R., Xie, Y.: The development of key technologies in applications of vessels connected to the internet. Symmetry **9**(10), 211 (2017)
2. He, W., Li, Z., Malekian, R., Liu, X., Duan, Z.: An internet of things approach for extracting featured data using AIS database: an application based on the viewpoint of connected ships. Symmetry **9**(9), 186 (2017)
3. Li, Z., Zhang, Y., Yan, X., Peng, Z.: A novel prediction model for aircraft spare part intermittent demand in aviation transportation logistics using multi-components accumulation and high resolution analysis. Proc. Inst. Mech. Eng. G J. Aerosp. Eng. **229**(2), 384–395 (2015)
4. Hinsbergen, C., Lint, J., Sanders, F.: Short term traffic prediction models. In: Proceedings of World Congress on Intelligent Transport Systems, Beijing, China (2007)
5. Lint, J., Hinsbergen, C.: Short term traffic and travel time prediction models. Artif. Intell. Appl. Crit. Transp. Issues **22**, 22–41 (2012)
6. Xu, K., Shen, M., Ye, M.: A model approach to estimate Peer-to-Peer traffic matrices. Proc. IEEE INFOCOM **8**(1), 676–684 (2011)
7. Tselentis, D., Vlahogianni, E., Karlaftis, M.: Improving short term traffic forecastings: to combine models or not to combine? IET Intell. Transport Syst. **9**(2), 193–201 (2014)
8. Faouzi, N.: Nonparametric traffic flow prediction using kernel estimator. In: Proceedings of the 13th International Symposium on Transportation and Traffic Theory, Lyon, France (1996)
9. Bian, W., Chen, X.: Smoothing neural network for constrained non-lipschitz optimization with applications. IEEE Trans. Neural Netw. Learn. Syst. **23**(3), 399–411 (2012)
10. Cetin, M., Comert, G.: Short-term traffic flow prediction with regime switching models. J. Transp. Res. Board **1965**(1), 23–31 (2016)
11. Lee, S., Fambro, D.: Application of subset autoregressive integrated moving average model for short-term freeway traffic volume forecasting. J. Transp. Res. Board **1678**(1), 179–188 (1999)
12. Hamed, M., Al-Masaeid, H., Said, Z.: Short-term prediction of traffic volume in urban arterials. J. Transp. Eng. **121**(3), 249–254 (1995)
13. Guo, J., Williams, B., Smith, B.: Data collection time intervals for stochastic short-term traffic flow forecasting. J. Transp. Res. Board **2024**(1), 18–26 (2007)
14. Okutani, I., Stephanedes, Y.: Dynamic prediction of traffic volume through Kalman filtering theory. Transp. Res. B Methodol. **18**(1), 1–11 (1984)
15. Chan, K., Dillon, T., Chang, E.: An intelligent particle swarm optimization for short-term traffic flow forecasting using on-road sensor systems. IEEE Trans. Ind. Electron. **60**(10), 4714–25 (2013)
16. Chen, H., Rakha, H.: Real-time travel time prediction using particle filtering with a non-explicit state-transition model. Transp. Res. C Emerg. Technol. **43**, 112–26 (2014)

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