# Short-Term Traffic Flow Prediction Postprint Based on Outlier Detection Kalman Filter

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**Date:** 2020-09-28T00:00:00+00:00

## Abstract

To address the demands of intelligent transportation, we propose a novel and effective short-term traffic flow prediction method that extends the Kalman filter through outlier identification, enabling it to identify and filter noise—an Outlier Identification Kalman Filter. While the Kalman filter can effectively filter traffic flow fluctuations that cause system uncertainty, this may result in the loss of subtle clues indicating sudden changes in traffic flow. To improve prediction accuracy, discrete wavelet transform is applied to identify and process the original signal, removing outliers while preserving the original signal source information effective for prediction. Additionally, historical reference values are used to correct the predictions. Finally, extensive experiments on four benchmark datasets demonstrate that, compared with commonly used and state-of-the-art prediction models, the results achieve an average reduction of 2.919% in MAPE and an average reduction of 79.582 in RMSE.

## Full Text

## Preamble

**Vol. 38 No. 3**
**Application Research of Computers**
**ChinaXiv Cooperative Journal**

### Outlier-Identified Kalman Filter for Short-Term Traffic Flow Forecasting

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## Abstract

In response to the demands of intelligent transportation, this paper proposes a novel and effective short-term traffic flow forecasting method that extends the Kalman filter through outlier identification, enabling it to recognize and filter noise—an approach termed the Outlier-Identified Kalman Filter (OiKF). While traditional Kalman filtering can effectively filter traffic flow fluctuations that cause system uncertainty, this may cause the loss of subtle clues indicating sudden changes in traffic flow. To improve forecasting accuracy, discrete wavelet transform is applied to process the original signal, preserving effective signal source information for prediction while removing outliers. Additionally, historical reference values are used to correct the predicted values.

Extensive experiments on four benchmark datasets demonstrate that, compared with commonly used and state-of-the-art prediction models, the proposed method achieves an average reduction of 2.919% in MAPE and 79.582 in RMSE.


**Keywords:** Kalman filter; active noise control; short-term traffic flow forecasting; state vector

## 0 Introduction

Accurate and timely traffic flow information is crucial for the successful deployment of Intelligent Transportation Systems (ITS), which integrate Internet of Things, vehicle networking, and smart transportation applications. It provides reliable traffic information for logistics departments, commercial institutions, tourism service agencies, and government management organizations to optimize route planning, improve efficiency, and save time; alleviate traffic congestion and reduce transportation costs; decrease vehicle exhaust emissions and save energy; and reduce traffic accidents while improving operational efficiency.

To enhance the intelligence level of transportation systems through the deep integration of big data and mobile internet technologies, traffic volume has become a key factor in determining road traffic conditions. Short-term traffic flow forecasting operates at a microscopic level, fundamentally different from mesoscopic and macroscopic strategic predictions based on traffic planning that calculate in hours, days, or even years. Its primary objective is to use appropriate methods to recursively predict traffic conditions from seconds to half an hour into the future based on current and historical traffic data. However, due to the inherent randomness of traffic flow and the presence of external noise [1–3], such as accidents or manual traffic control [4,5], developing algorithms that are both robust and accurate remains a challenging task.

Traffic flow prediction models and methods mainly include four categories: linear theory models, nonlinear theory models, dynamic assignment models, and knowledge discovery-based models. The Kalman filter (KF) and its variants are widely used powerful tools in traffic flow forecasting tasks [6–8], offering high computational efficiency, low memory requirements, suitability for static and non-stationary data analysis, dynamic updating of state variables using real-time data, and better adaptation to traffic flow changes. To address the high uncertainty in traffic flow (climate, traffic accidents, emergencies, etc.) and the distortion of subtle clues indicating traffic flow mutations caused by simple noise filtering preprocessing, this paper proposes a Kalman filter capable of accurately distinguishing between valid signals and noise, named the Outlier-Identified Kalman Filter (OiKF). This paper applies OiKF to short-term traffic flow prediction, experimentally evaluates it on four benchmark datasets, and compares its performance with classical Kalman filters and other commonly used parametric and non-parametric techniques. Extensive experiments demonstrate that this technique improves prediction accuracy and precision, proving the superiority of the outlier-identified Kalman filter for short-term traffic flow forecasting.

## 1 Related Research

Traditional Kalman filtering and its variants provide clear and powerful fundamental tools for analyzing and solving a wide range of estimation problems, with broad applications in many engineering fields, particularly for discrete-time system state estimation, including signal processing, optimal control, navigation, and more. Practical applications encompass parameter estimation, system identification, target tracking, and simultaneous localization. Many of these processes can be described using state-space systems—if a mathematical model can be established for a process, mathematical tools can be used to control the process and obtain information about it. Numerous studies have utilized state-space systems to model short-term traffic flow prediction problems. Okutani and Stephanedes [9] first introduced state-space models to predict traffic diversion in highway entrance ramp areas, demonstrating that the model outperformed the traffic volume prediction model used in the second-generation Urban Traffic Control System (UTCS-2). Stathopoulos and Karlaftis [10] also proposed a model based on optimal state estimation theory, showing that multivariate state-space models improved the prediction accuracy of ARIMA models. Hu et al. [11] proposed a Hybrid Particle Swarm Optimization Support Vector Regression model (Hybrid PSO-SVR) for short-term traffic flow prediction, using particle swarm optimization to reduce model learning time by optimizing support vector regression parameters. Guo et al. [12] proposed using a first-order grey model GM for short-term urban road traffic flow prediction, which introduced road load and delay factors, significantly improving prediction accuracy compared to the original grey model. The Least Squares Boosting (LSBOOST) model is an ensemble framework for multiple learning algorithms [13] that has shown good results in short-term electricity demand forecasting and could be attempted for short-term prediction in other domains.

However, as previously mentioned, short-term traffic flow data is frequently corrupted by local noise, which can significantly affect prediction accuracy. Previous studies have focused on the role of Kalman filtering in noise filtering for short-term traffic flow prediction while neglecting the fact that noise filtering can compromise signal quality. For example, Xie et al. [14] studied the application of Kalman filters in discrete wavelet analysis, concluding that noise pollution seriously affects traffic flow prediction performance. Wang et al. [15] used an adaptive traffic flow prediction algorithm based on Kalman filters that considered both state and observation Gaussian noise. To further improve prediction accuracy, Zhou et al. [7] proposed a novel hybrid Kalman filter for traffic flow prediction by compensating for preliminary prediction errors. However, as noise filtering capability gradually improved, prediction accuracy tended to plateau and even begin to decline. The main reason is that while filtering noise, useful signals—particularly subtle clues indicating traffic flow mutations—were also filtered out.

Unlike existing work, this paper reconstructs the Kalman filter using a new cost function and proposes a novel and effective noise-identified Kalman filter, OiKF. This technique achieves high-quality effective signals while efficiently filtering noise and applies it to short-term traffic flow prediction, proposing a robust traffic flow forecasting algorithm. Specifically, this paper uses Discrete Wavelet Transform (DWT) to decompose and reconstruct raw traffic flow data into approximate and detail components. Compared with the work of Zhou et al. [7], which only discarded detail components, this method considers multi-level detail components. Different levels of detail components are treated as either noise affecting prediction performance or clues improving prediction performance. Together with the approximate component that maintains the basic pattern of the original traffic flow data, they serve as model inputs to solve for the optimal solution at the next moment, while historical reference points are used to correct predicted values, thereby improving prediction accuracy.

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## 2 OiKF Short-Term Traffic Forecasting Theory Model and Implementation

In the theoretical model, discrete wavelet transform is first used to filter outliers, followed by analysis of the general method for traffic flow prediction using the Kalman filter (KF). Finally, the Outlier-Identified Kalman Filter (OiKF) and its theoretical model are proposed, and the process of implementing short-term traffic flow prediction using this theoretical model is described.

### 2.1 Discrete Wavelet Transform for Outlier Processing

Wavelet Transform (WT) is a tool for detailed signal analysis through scaling and translation, providing a variable "time-frequency" window [16]. The mother wavelet function is a square-integrable function, i.e., satisfying the admissibility condition:

Scaling and translation transformations of the mother wavelet function yield:

where $a$ is the scale parameter and $b$ is the translation parameter. If the signal is a square-integrable function, i.e., , then the continuous wavelet transform is defined as:

where is the complex conjugate of . Discretizing the scale parameter $a$ and translation parameter $b$ with and yields the discrete wavelet function:

The discrete wavelet transform of is:

If forms an orthonormal basis in , then can be reconstructed as:

For discrete-time signals, discrete wavelet transform can be simply implemented through multiple passes of high-pass and low-pass filtering, where the high-pass filter captures high-frequency information representing signal details, and the low-pass filter captures low-frequency information representing signal approximations. The low-frequency and high-frequency information pass through corresponding synthesis filters to obtain the low-frequency and high-frequency components of the original signal. By synthesizing the required components based on actual conditions, signal decomposition and reconstruction can be achieved for purposes such as denoising and outlier filtering.

### 2.2 KF Short-Term Traffic Prediction Model

Let represent a set of raw traffic flow data from time *t-n* to *t-1*. In short-term traffic prediction, the target prediction value is , i.e., the traffic volume at the next time *t*. In previous work by Zhou et al. [7], the traffic flow to be predicted was expressed as a combination of past traffic flow and corresponding weights:

where is the state transition matrix, and are measurement noise and process noise, respectively, both being zero-mean, uncorrelated Gaussian white noises with known process noise covariance matrix and measurement noise covariance matrix .

Once is obtained, the traffic flow prediction value for the next time *t+1* is the optimal estimate at time *t* combined from equations (1) and (2). The same assumption was made in the work of Lan et al. [17], Xie et al. [14], and Zhou et al. [7].

### 2.3 OiKF Short-Term Traffic Prediction Model

In the OiKF short-term traffic prediction model, discrete wavelet transform is used to decompose and reconstruct traffic flow, ultimately consisting of two parts: the approximate component and the detail component . The basic principle is: due to the presence of outliers (high uncertainty caused by climate, traffic accidents, emergencies, etc., generating outliers in the raw data stream), raw traffic flow data is severely corrupted by locally existing outliers/noise. To solve this problem, discrete wavelet transform is used to replace the raw data with the low-frequency approximate component obtained through decomposition and reconstruction as partial system input for traffic flow prediction, achieving filtering of outliers caused by uncertainty while maintaining the basic pattern of the original traffic flow. To avoid losing subtle clues in the raw data that indicate traffic flow mutations, the other part—the high-frequency detail component —is used as a control input variable corrupted by outliers to capture subtle clues hidden in rapidly changing traffic conditions.

Based on the decomposition and reconstruction of raw traffic flow data using discrete wavelet transform, an extended Kalman filter is implemented. Its dynamic linear system can be expressed as:

where is the control matrix, similar in function to . To distinguish it from the traffic flow weights in equation (2), it is re-denoted as . The detail component can be re-expressed as Gaussian white noise with covariance . Through this extension, the technique inherits all the advantages of traditional Kalman filtering for noise removal while ensuring raw data quality.

In the prediction model, the objective cost function is:

The problem is solved using the cost function shown in equation (7) to obtain the optimal solution. represents the optimization objective obtained at time *t*, the operation represents the covariance matrix composed of the squared estimation errors at each moment, and is the Kalman gain matrix. Due to space limitations, detailed derivation of the optimization formula (7) can be found in the related work of Zhang et al. [8] and Ma et al. [18]. This paper presents the basic algorithmic process:

First, based on the weights and error covariance matrix at time *t-1*, a priori estimate and corresponding error covariance matrix are obtained. Then, the Kalman gain matrix and measurement value are used to update the estimate and corresponding covariance matrix to obtain the posterior estimate (the optimal estimate) and corresponding covariance matrix . After obtaining the optimal estimate, the traffic flow prediction value can be calculated through equation (3). Finally, and are used as inputs for the next moment (prior estimate) to calculate the next optimal estimate, forming a dynamic rolling continuous prediction process.

Furthermore, through analysis of actual data waveforms, traffic flow data exhibits certain periodic characteristics. Therefore, historical data provides valuable reference information. During prediction, the predicted value at time is first obtained through equation (3), then corrected using historical reference values. In the approximate component, a period of data from time points before time is selected as the current actual traffic flow data sequence . From the already predicted historical data sequence, the most similar historical sequence is searched, and the observed value at time is selected as the reference value. The prediction correction process is shown in Figure 1 [Figure 1: see original paper].

The final predicted value is obtained through weighted averaging of and . Let the reference value be , and its calculation formula is defined as:

The basic process of short-term traffic prediction using the Outlier-Identified Kalman Filter is presented as Algorithm 1.

**Algorithm 1: Outlier-Identified Kalman Filter Algorithm Steps**

1. **Initialization Phase**: Set the state transition matrix , control matrix , process noise covariance matrix , measurement noise covariance matrix , and detail component noise variance .
2. **Prediction Phase**: Based on the state estimate and error covariance at time *t-1*, calculate the prior estimate and error covariance at time *t*.
3. **Update Phase**: Calculate the Kalman gain matrix, then update the state estimate and error covariance using the measurement value to obtain the posterior estimate and corresponding covariance matrix.
4. **Correction Phase**: Search for the most similar historical sequence to obtain the historical reference value , and perform weighted averaging with the predicted value obtained in Phase 3 according to equation (8) to obtain the final predicted value.

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## 3 Experiments and Analysis

### 3.1 Datasets

The experiments use benchmark test data—traffic flow data from four highways in Amsterdam, Netherlands (denoted as A1, A2, A4, and A8) [4,5,7,8,15,19]—to conduct validation experiments on the proposed OiKF. These four highways terminate at Amsterdam' s ring road, the A10 highway, with their distribution shown in Figure 2 [Figure 2: see original paper]. The data were collected from four detection points using MONICA sensors located at a certain distance near the ring road convergence points. The data sequence spans from May 20, 2010, to June 24, 2010, with statistics compiled every minute (counting vehicles passing during that minute and converting to hourly flow rate).

These four highways are representative: - **A1** is a border highway and Europe' s first high-occupancy 3+ separated lane, with instantaneous and large lane occupancy changes, making prediction difficult. - **A2** is one of the busiest highways in the Netherlands, with significant congestion variations, used to validate prediction model effectiveness under traffic jams. - **A4** is a standard national highway with relatively moderate and normal traffic conditions. - **A8** is a connecting highway approximately 10 kilometers long, used to validate prediction effectiveness for traffic emergencies.

### 3.2 Experimental Setup

In the experiments, the state transition matrix is initialized as an identity matrix with size $n$ set to 8. The measurement outlier covariance matrix is set as a zero matrix, while the initial state covariance matrix and process outlier covariance matrix are set to . The control matrix is initially set to . The initial weights are set to . For discrete wavelet transform operations, Daubechies 1 and Haar wavelets are selected as mother wavelets. When searching for historical reference values, experimental validation shows that data sequences segmented by one-day intervals have the highest correlation, so the sequence length is set to 144, and the historical reference point weight is set to 0.2.

### 3.3 Evaluation Criteria

The prediction effectiveness evaluation criteria are defined as [4,5,7,8,14,19–23]: Root Mean Square Error (RMSE) measures the average error between a model' s predicted values and the system' s measured values; Mean Absolute Percentage Error (MAPE) is the percentage representation of this average error. They are defined as:

where $M$ represents the dataset size, and and are the predicted and actual values at time $t$, respectively.

### 3.4 Prediction Results and Analysis

The experiments test the datasets using OiKF. Figures 3(a)-(d) show the prediction results for 1,000 data points from the A1, A2, A4, and A8 highway traffic flow data, where the black solid line represents predicted values and the red dashed line represents actual observed values. Figures 4–7 show the correlation error frequency and CDF plots for 5,000 predicted points versus actual observed values for the four highways, obtained by taking the absolute difference between observed and predicted values divided by the observed values.

The experimental datasets consider traffic flow data under various influencing factors and environments. As shown in Figure 3 [Figure 3: see original paper], the prediction curves fit well with the actual observation curves, with relatively small errors even at data mutation points. This demonstrates that the proposed method overcomes the shortcomings of traditional Kalman filters, effectively captures subtle clues indicating traffic flow mutations, and can accurately predict short-term traffic flow.

In Figures 4–7, the x-axis represents error intervals, the left y-axis represents the number of predictions (frequency) among 5,000 points falling into corresponding intervals, and the right y-axis represents cumulative error. The bar charts show frequency, and the curves show CDF.

**Analysis of 5,000 data points'prediction error intervals and cumulative CDF curves:** - For A1 (Figure 4): Cumulative error reaches 90.36% in [0,0.2] and 96.39% for error $< 0.3$. - For A2 (Figure 5): Cumulative error reaches 92.03% in [0,0.2] and 96.55% for error $< 0.3$. - For A4 (Figure 6): Cumulative error reaches 88.56% in [0,0.2] and 95.95% for error $< 0.4$. - For A8 (Figure 7): Cumulative error reaches 89.10% in [0,0.2] and 95.45% for error $< 0.4$.

In all predictions, error $\leq 0.2$ exceeds 90%, proving that OiKF can accurately predict short-term traffic flow.

### 3.5 Comparative Analysis of Prediction Accuracy

To validate the overall effectiveness of the OiKF model, using the same dataset (traffic flow data from four highways in Amsterdam, Netherlands) as input, the prediction results of the proposed OiKF are compared with those of the traditional Kalman filter model [11] and several newly proposed traffic flow prediction models based on the evaluation criteria—MAPE/RMSE from equations (8) and (9).

Representative comparison algorithms include: - Particle Swarm Optimization Support Vector Regression (Hybrid PSO-SVR) [11] - Grey Model (GM) [12] - Standard baseline models [24]: Random Walk (RW), Historical Average (HA), Least Squares Boosting (LSBOOST) [13], and Exponential Smoothing (ES) - Recent research models: Autoregression (AR) [4], Hybrid Dual Kalman Filtering model (KF) [25], and hybrid learning-based models (SVRGSA and SVRPSO) [19]

The MAPE and RMSE experimental results for various algorithms are shown in Table 1 and Table 2 , respectively. Finally, the improvement rates of OiKF compared to other algorithms are analyzed.

**Table 1: MAPE Comparison with Various Prediction Models**

| Model | A1 | A2 | A4 | A8 |
|---|---|---|---|---|
| LSBOOST | | | | |
| SVRGSA | | | | |
| SVRPSO | | | | |

**Table 2: RMSE Comparison with Common Prediction Methods**

| Model | A1 | A2 | A4 | A8 |
|---|---|---|---|---|
| LSBOOST | | | | |
| SVRGSA | | | | |
| SVRPSO | | | | |

From Tables 1 and 2, the proposed method is more accurate than other comparison methods on the four benchmark datasets, with OiKF achieving the best results in both MAPE and RMSE experiments. The improvement in MAPE and RMSE compared to other model algorithms is shown in Figures 8 and 9.

**Figure 8** [Figure 8: see original paper] shows that the OiKF model achieves the best MAPE for measurement points on the A1, A2, A4, and A8 highways. The "Improve-Avg" item in Figure 8 statistics the average percentage reduction in MAPE of the OiKF model compared to other prediction models on each highway. The proposed prediction model reduces errors by an average of 4.524%, 3.775%, 2.002%, and 1.376% on the four highways compared to recent models (AR, SVRGSA, SVRPSO, etc.).

**Analysis of Figure 9** [Figure 9: see original paper] reveals that OiKF also achieves the best results in the 4$\times$12 groups of RMSE prediction result comparisons with common and state-of-the-art prediction models. The "Improve-Avg" data in Figure 9 shows that OiKF' s RMSE values are correspondingly reduced by an average of 120.339, 85.157, 64.889, and 47.943 compared to other models.

Box plots of the overall improvement in MAPE and RMSE for OiKF predictions on the four highways (distribution of MAPE reduction and RMSE decrease compared to other models) are shown in Figures 10 [Figure 10: see original paper] and 11 [Figure 11: see original paper].

The comparative analysis of experimental results demonstrates the superiority of the proposed prediction model over other common models and fully proves the effectiveness of the proposed method in solving short-term traffic flow prediction problems.

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## 4 Model Application Example

To address the widespread problems in bus enterprises of "dispatched scheduling,""static scheduling,"and "empirical scheduling"—which cause high investment, slow response, poor efficiency, and severe customer loss—the short-term traffic flow prediction model based on the Outlier-Identified Kalman Filter is embedded in the bus intelligent dispatching system. It performs short-term traffic flow prediction for special road sections to dynamically adjust bus dispatching requirements, improve the intelligence of bus operation dispatch management, and achieve efficient utilization of resources such as personnel, vehicles, and routes. Figure 12 [Figure 12: see original paper] shows the integration scenario of bus dispatching and GIS in the system, where OiKF is used to predict traffic flow for multiple main paths on the map and feed back to real-time bus dispatching.

The proposed OiKF model was tested and applied in the bus intelligent dispatching system of the "Guilin Travel Network—Transportation Services and

Tourism Integration Digital Economy Service Platform," a 2019 Ministry of Industry and Information Technology new information consumption demonstration project. One thousand prediction points were set on five main roads in Guilin City (North Ring Road 1, North Ring Road 2, Zhongshan North Road, East Second Ring Road, and Jiangang Road, as marked in Figure 12) to validate the effectiveness of OiKF, achieving good operational results. The early prediction feedback is provided to the dispatching system to effectively command, control, and regulate vehicle operation, maintain uniform and reasonable intervals, enable cross-line operation of vehicles, and support retrospective analysis, forming a closed-loop dispatching business management.

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## 5 Conclusion

This paper proposes a new short-term traffic flow forecasting method to improve prediction accuracy. The method enhances the traditional Kalman filter to enable outlier identification and filtering. Through experiments, comparison with models from current research, and testing in a bus intelligent dispatching system, the results demonstrate the method' s effectiveness and superiority. They also show that filtering outliers while ensuring raw data quality is necessary for short-term traffic flow prediction. Extensive experiments on four benchmark datasets indicate that compared with commonly used and state-of-the-art prediction models, the results achieve an average MAPE reduction of 2.919% and an average RMSE reduction of 79.582.

Future research will further extend this approach to other Kalman filter variants, such as the Extended Kalman Filter or Unscented Kalman Filter, and apply it to other prediction tasks, including server task sequence analysis and prediction, resource utilization prediction and analysis in cloud computing centers, and fine-grained task scheduling or task volume variation prediction over time. Combining neural network applications and achievements from new short-term traffic flow prediction models [26–28], the parameter settings of the OiKF model will be further optimized to improve prediction accuracy.

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