Original Research Article

Research on urban road traffic flow prediction based on wavelet denoising and multi-layer perceptron

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ABSTRACT

Aims: Develop a new type of traffic flow prediction model to improve the accuracy of traffic flow prediction, better assist intelligent traffic management, improve traffic efficiency, reduce traffic congestion, and thus better improve sanitation and quality of life.
Study design: Develop an urban road traffic flow prediction model with strong predictive power and excellent stability.
Place and Duration of Study: Southwest University of Science and Technology, between July 2021 and March 2022.
Methodology: Adopting wavelet threshold to denoise, first decompose the original data, then perform noise filtering on the subsequences obtained after decomposing, and finally reconstruct the denoised data. Use denoised data to train a multilayer perceptron and make predictions on future data. At the same time, several representative models are selected to compare with the proposed model to verify the competitiveness of the proposed model.
Results: The proposed model has the smallest prediction error in the two training sets with different temporal granularity. In addition, using the data after wavelet denoising for training and prediction results in a smaller prediction error than using the data without denoising.
Conclusion: The proposed prediction model has strong prediction ability and generalization performance in the field of traffic flow prediction. The wavelet denoising method can effectively improve the prediction accuracy of traffic flow prediction.

Keywords: {Traffic flow, wavelet threshold denoising, multi-layer perceptron, multi-step forecasting}

1. INTRODUCTION

With the development of social economy, people's living standards are improving day by day, and the number of private cars is becoming more and more. The increase in the number of traveling vehicles has made the situation of road congestion more and more serious. On the one hand, traffic congestion will cause serious pollution to the environment, and on the other hand, it will greatly increase the incidence of traffic accidents and threaten people's lives and health. Traffic flow forecasting plays a fundamental role in the planning and development of traffic management and control systems, and in recent years, traffic forecasting has become an important task in the field of intelligent transportation[1]. Improving the accuracy of traffic flow prediction is conducive to intelligent traffic management to improve traffic efficiency and reduce congestion. However, traffic flow data is often highly volatile, and there is a lot of data noise. So far, traffic flow prediction is still a classic but challenging problem[2].

For a long time, a large number of researchers have been pouring into the field of traffic flow prediction, and achieved a large number of satisfactory results. Xiaomo Jiang applies dynamic wavelet neural network model to traffic flow prediction[3]. Bidisha Ghosh in 2007 using Bayesian time series models to predict short-term traffic flow[4]. Yanru Zhan, Yunlong

Zhang and Ali Haghani proposed a novel hybrid model: A hybrid model based on spectral analysis and statistical volatility. And applied to the field of short-term traffic flow prediction[5]. What's more, deep learning algorithm is one of the most common and most effective methods in the field of traffic flow prediction. Many researchers have applied deep learning algorithm to traffic flow prediction and achieved very good results[6-9].

From the literature review results, it can be seen that in recent years, most scholars have devoted themselves to proposing a model with strong predictive ability, but only a small number of scholars have improved the accuracy of prediction by correlating the data. Improving the prediction accuracy of the model through data preprocessing is the core part of the data mining task, which can extremely effectively increase the accuracy of the prediction results. Therefore, in this study, we use wavelet threshold denoising to preprocess the data, and apply the denoised data to traffic flow prediction.

2. METHODOLOGY

2.1 Wavelet domain denoising

The wavelet domain denoising (WD) method was first proposed by Professor Johnstone and Donoho in 1992[10]. It is a nonlinear denoising method, which can achieve approximate optimality in the sense of minimum mean square error, and has the characteristics of the simplest implementation and the smallest amount of calculation.

The basic principle is: Orthogonal wavelet decomposition has the ability of time-frequency local decomposition. During signal processing, the amplitude of wavelet components is relatively large, which is in obvious contrast with the uniform realization of noise in high frequency parts. After wavelet decomposition, most of the wavelet coefficients with larger amplitudes are useful signals, while the coefficients with smaller amplitudes are generally noise, that is to say, the wavelet transform coefficients of useful signals are larger than those of noise. The threshold denoising method is to find a suitable threshold, keep the wavelet coefficients larger than the threshold, and process the wavelet coefficients smaller than the threshold accordingly, and then restore the useful signal according to the processed wavelet coefficients.

Define:

$$F(t) = s(t) + e(t) \tag{1}$$

Among them, $s(t)$ represents the valuable signal, and $e(t)$ is the noise part. Do wavelet transform on both sides of Equation 1 at the same time:

$$WT_f(a,b) = WT_s(a,b) + WT_e(a,b) \tag{2}$$

Equation 2 shows that the wavelet transform of the actual measurement signal is equal to the sum of the wavelet transforms of multiple signals.

For Equation 1, after orthogonal wavelet transform, the correlation of the signal $F(t)$ can be removed to the greatest extent, and most of the energy is concentrated on a few wavelet coefficients with relatively large amplitudes. And the noise $e(t)$ will be distributed on all time axes under each scale after wavelet transformation, and the amplitude is not very large. In each scale of wavelet transform, the wavelet coefficients of the noise are reduced to the greatest extent, and then the processed wavelet coefficients are used to reconstruct the signal, so that the noise can be suppressed.

2.2 Multi-Layer Perceptron

The multilayer perceptron (MLP) is the improvement and perfection of the feedforward neural network[11]. It mainly consists of three parts: input layer, output layer and hidden layer. Figure 3 shows a schematic diagram of a three-layer multilayer perceptron. Each layer in MLP has its fixed task, and the input layer is mainly responsible for receiving input samples. The hidden layer is the core part of the entire MLP, mainly processing and processing the input data. The output layer mainly performs activation processing and performs operations according to the required tasks such as prediction and classification

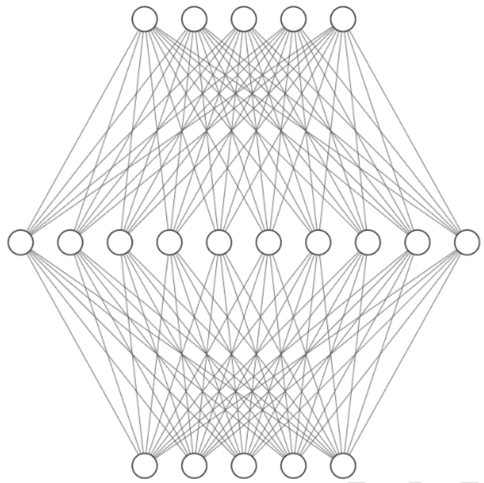


Figure 1 Schematic diagram of three-layer neural network

The following computations are performed on each neuron in the output and hidden layers:

$$O(x) = G(b(2) + W(x)h(x)) \tag{3}$$

$$h(x) = \Phi(x) = s(b(1) + W(1)x) \tag{4}$$

Where $b(1)$, $b(2)$ represent bias vectors, $W(1)$ and $W(2)$ represent weight matrices, and G and S are activation functions. It is worth mentioning that $W(1)$, $b(1)$, $W(2)$, $b(2)$ are parameters that need to be optimized. There are many choices of activation functions, as shown in Table 1:

Table 1 Several common activation functions

Function	Formula	Derivative
ReLU (Rectified linear unit)	$f(x) = \max(x, 0)$	$f(x)' = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$
sigmoide	$sigmoid(x) = \frac{1}{1 + e^{-x}}$	$sigmoid(x)' = \frac{e^{-x}}{(1 + e^{-x})^2}$
tanh	$tanh(x) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$tanh'(x) = 1 - \left(\frac{e^z - e^{-z}}{e^z + e^{-z}}\right)^2$

2.3 Experiment

2.3.1 Data description

This study uses data derived from the OpenITS platform[12]. Whitemud Drive is an urban highway that runs through Edmonton, Alberta, Canada, with a total length of 28 kilometers. This study is based on the traffic flow of Whitemud Drive.

Through data preprocessing, the original data is sorted into two granularities of 10 minutes and 30 minutes, and some statistical properties of the data set are analyzed. The results are shown in Table 2.

Table 2 Several features of the dataset

Time	Mean	Median	Std	Max	Min	Numsbers
10 minutes	835.86	924.00	552.89	1998.00	24.00	136
30 minutes	779.06	812.22	517.24	1924.00	42.00	141

What's more, in order to more intuitively understand the data characteristics and changing trends of the data set, the data trend graphs of the two data are displayed, as shown in Figure 2.

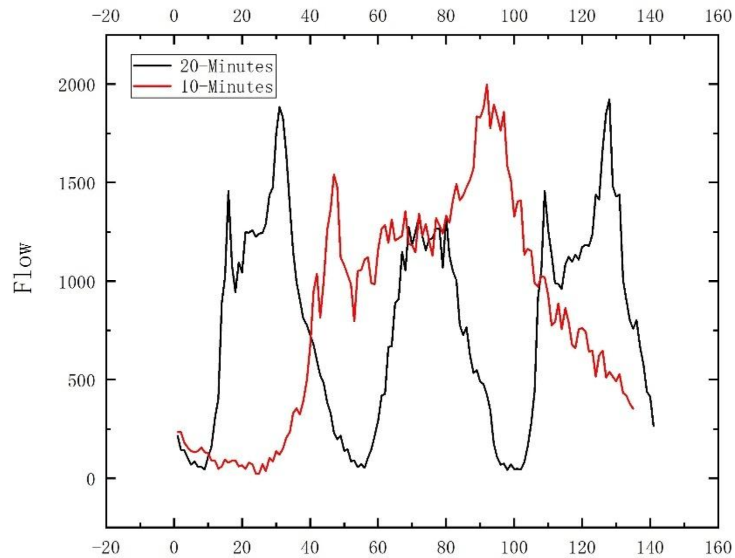


Figure 2 Data detailed trend graph

From the figure, we can observe that the traffic flow data of this expressway has several very prominent features: a) The data has strong volatility. b) The data has a certain periodicity. c) There is a lot of data noise in the data.

2.3.2 Establishment of WD-MLP Hybrid Model

In the previous section we learned that there is a lot of noise in the traffic flow data, and the data is very volatile. Therefore, in this study, we denoise the data through wavelet decomposition and reconstruction, and input the denoised data into the MLP.

The main idea is divided into the following four steps::
Step 1: Initialize the wavelet parameters, and determine the type of wavelet to be used.
Step 2: Perform wavelet decomposition on the original sequence, then perform noise filtering, and finally reconstruct the denoised data.
Step 3: Divide the denoising data and use the data to train MLP
Step 4: Compare and analyze the results of WD-MLP and other models

The detailed establishment process of the hybrid model is shown in Figure 3

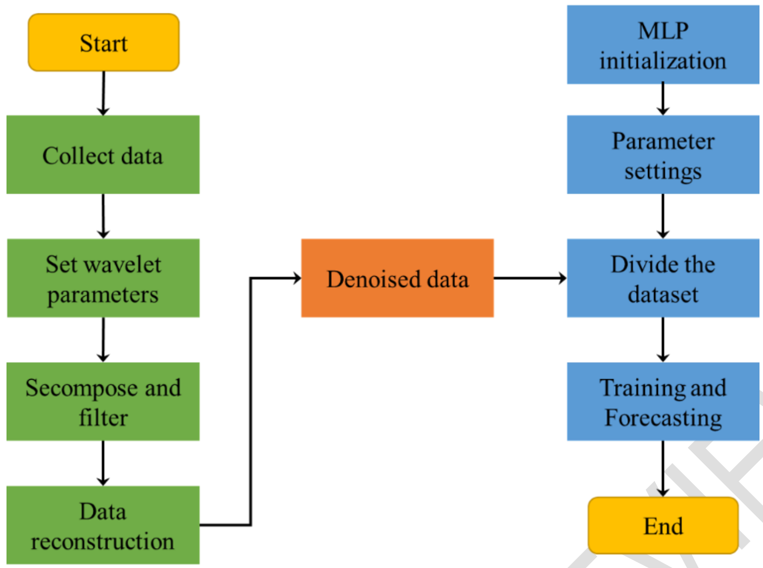


Figure 3 The construction process of the hybrid model

2.3.2 Evaluation metrics

In order to effectively test the predictive performance of the proposed model, in this study we introduce mean absolute percentage error (MAPE) to evaluate the prediction results of the model, and its calculation formula is shown in Equation 5. Where N is the number of samples, and $\hat{y}_i$ and y_i are the predicted and true values, respectively.. A MAPE less than 10% indicates an excellent model, a MAPE greater than 20% indicates an inferior model, and the smaller the MAPE, the better the prediction performance of the model.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{5}$$

More importantly, in order to verify the competitiveness of the model, we also introduced 5 other machine learning models to compare with the proposed model. All comparative models are listed in Table 3.

Table 3 Models for comparison

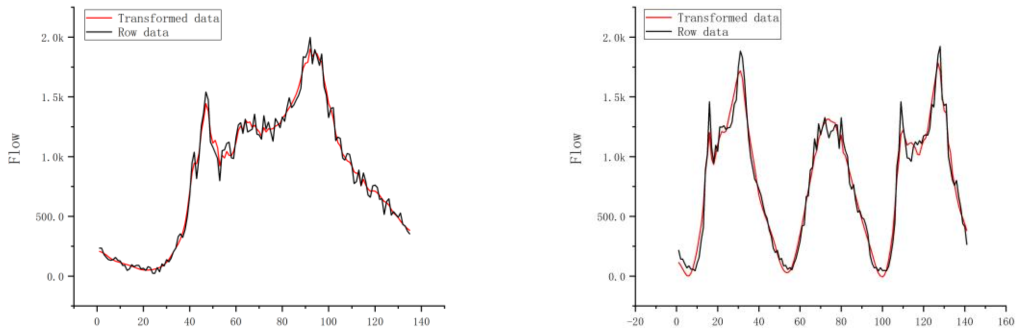
Model	Abbreviation	Literature	Invention time
Extreme gradient boosting	XGBoost	[13]	2016
Random forest	RF	[14]	2001
Light gradient oosting machine	LightGBM	[15]	2014
Least square support vector machine	LSSVM	[16]	1999
Linear regression	LR		1805

3. RESULTS AND DISCUSSION

3.1 Wavelet denoising result

In the above chapters, we have discussed the relevant principles of wavelet threshold denoising and the method if wavelet is used. Therefore, in this section, we analyze and display the results obtained by wavelet denoising.

On two datasets with different temporal granularity, we use wavelet threshold denoising method to denoise them. The Daubechies8 wavelet is used in the denoising operation, and the threshold is set to 0.5, and the denoised result is shown in Figure 4.



(a) 10 minutes (b) 30 minutes

Figure 4 Wavelet denoising result graph

It can be intuitively observed from the figure that after denoising, our dataset becomes significantly more stable and smooth. Compared with the original data, the periodicity of the data still exists but there is no very drastic fluctuation.

3.2 Forecasting result

In this section, we apply the proposed and comparative models to both datasets separately. One-step forecast on a dataset with a time granularity of 10 minutes, representing the forecast of road traffic flow 10 minutes into the future. On a dataset with a time granularity of 30 minutes, the prediction step represents the prediction of road traffic flow 30 minutes into the future. In this study, road traffic flow was predicted 50 and 150 minutes into the future, respectively. The detailed prediction results are shown in Table 4.

Table 4 **MAPE(%) of prediction results for both datasets**

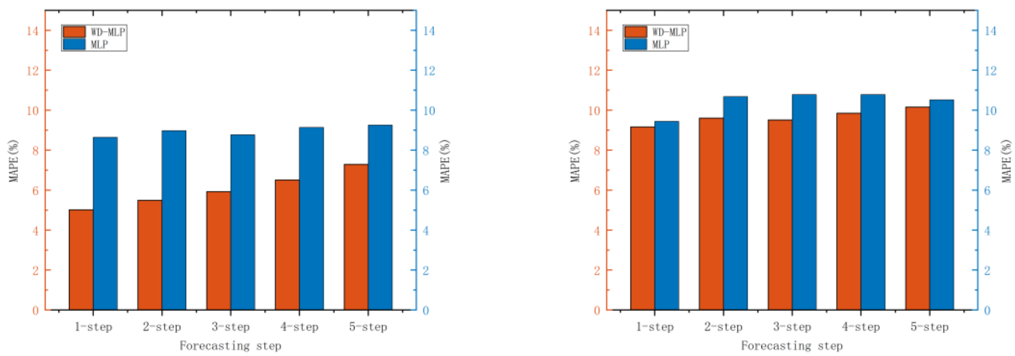
Dataset	Models / Step	WD-MLP	MLP	XGBoost	RF	LightGBM	LSSVM	LR
10 minutes	1-step	5.015	8.647	48.418	43.941	36.956	9.554	9.403
	2-step	5.487	8.977	49.899	46.434	44.248	8.393	12.575
	3-step	5.923	8.771	50.932	47.874	46.971	9.406	14.939
	4-step	6.504	9.139	52.098	49.144	49.094	13.679	17.866
	5-step	7.291	9.255	53.595	50.575	51.1381	15.926	20.658
30 minutes	1-step	9.166	9.442	15.893	13.438	14.814	9.873	17.108
	2-step	9.606	10.684	17.531	16.161	18.111	13.058	22.007
	3-step	9.508	10.784	20.832	19.166	23.894	17.142	27.327
	4-step	9.848	10.783	25.621	23.239	30.921	23.776	33.755
	5-step	10.156	10.522	33.626	29.071	40.594	30.155	39.338

From the table, we can see that in the dataset with the time granularity of 10 minutes, WD-MLP has a very absolute advantage, and the MAPE of WD-MLP is the smallest among all comparison models in one to five step prediction. These conclusions also hold for the dataset with a time granularity of 30 minutes.

It is worth mentioning that from Figure 2 and Table 2, we can see that datasets with different time granularities have different statistical characteristics and different data trends. But the proposed model has the best performance in both datasets, which is enough to show that the proposed model has excellent stability and generalization in addition to good prediction performance

3.3 Discussion

In this section, we mainly discuss the boosting effect of the wavelet threshold denoising ratio model. In all comparative experiments, we discuss the prediction results of both WD-MLP and MLP models separately. Figure 5 shows the prediction results of the WD-MLP and MLP models on the two datasets respectively.



(b) 10 minutes (b) 30 minutes

Figure 5 Comparison of prediction results of WD-MLP and MLP

From the figure, we can clearly see that the wavelet threshold denoising has a huge improvement on the model. In the data set with a time granularity of 10 minutes, WD-MLP is 2.29% smaller than the total average MAPE of MLP's five-step prediction. In the dataset with time granularity of 30 minutes, WD-MLP is 0.79% smaller than MLP. According to the summary of the results on the two datasets, we can conclude that the wavelet threshold denoising is very effective in improving the prediction performance of the model.

4. CONCLUSION

Improving the accuracy of traffic flow prediction is the most critical part of an intelligent transportation system. Accurate traffic flow prediction can effectively prevent traffic jams, reduce traffic accidents, and improve sanitation. In this study, we combine wavelet threshold denoising and MLP to propose a WD-MLP hybrid model and apply it to the field of AC traffic flow prediction, and achieve very satisfactory results.

From this study, we can draw the following conclusions: a) The prediction performance of WD-MLP is better than other competitors on all prediction steps, which shows that the hybrid model has strong prediction ability. b) On two datasets with different time granularities, the WD-MLP model has absolute advantages, which indicates that the hybrid model has better stability and generalization performance. c) Comparing the two models of WD-MLP and MLP, WD-MLP always has higher prediction accuracy, which shows that wavelet threshold denoising can effectively increase the accuracy of prediction results in the field of traffic flow prediction.

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