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A Spatio-temporal Traffic Flow Forecasting Method Based on WAC-GCN

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Abstract: *Traffic flow prediction plays an important role in smart city construction. Aiming at the problem that it is difficult to extract the spatio-temporal dynamic correlation of traffic flow, a traffic flow prediction model based on wavelet analysis, 2D convolutional neural network and graph convolutional neural network (WAC-GCN) was proposed. Firstly, the spatial correlation heat map was constructed by nodes to find the spatial correlation characteristics between different nodes. Secondly, the control variable method is used to adjust the parameters of the model, and the Early Stopping technique is introduced to improve the generalization performance of the model and reduce the waste of time and resources. Finally, the test set was used and different modules were eliminated to obtain the prediction results of the corresponding traffic flow prediction model. The experimental results on the real highway data set show that the proposed network model has better accuracy than the baseline model with some modules removed.*

Keywords: *Traffic flow prediction; Wavelet transform; Graph convolutional neural network; 2D convolutional neural network; Spatial characteristics*

1. Introduction

In the field of intellgent transportation systems(ITS), traffic congestion has attracted much attention [1]. Accurate prediction of traffic flow is the key to solving traffic congestion problem and realizing traffic control and guidance. By mining the potential rules of massive traffic flow data and predicting traffic flow information in real time, it can provide better travel experience for traffic participants, while improving traffic efficiency and safety. Considering the complex temporal and spatial characteristics of short-term traffic flow data, scholars are focusing on the problem of traffic flow prediction considering temporal and spatial characteristics.

The method based on machine learning can achieve a good traffic flow prediction effect, but there are still performance bottlenecks in the case of large amounts of data and high feature dimensions. In order to make up for the shortcomings of relevant methods, the academic community has introduced deep learning methods to capture the temporal and spatial dependence of traffic flow information by designing and perfecting neural networks. For example, the long and short term memory network LSTM [2] improves the learning efficiency of the spatio-temporal dependent features of traffic flow.Zhang et al. [3] proposed to transform the spatio-temporal gridded traffic flow data into multi-channel image data, so as to simply use convolutional neural networks for spatiotemporal correlation feature learning. The above methods are generally applicable to data with regular Euclidean structure [4], such as images, grids, etc. However, the distribution of detectors used by traffic control departments to collect traffic flow information usually belongs to non-Euclidean structure, so the prediction accuracy of these methods on some traffic flow data is limited.To this end, Zhang et al. [5] proposed that the spatialtemporal convolutional graph attention network (STCGN) takes into account the global inter-regional correlation based on the local spatial correlation of the road network, and realizes the comprehensive traffic flow prediction from local to global.Li et al. proposed the Temporal Graph Convolutional Network (T-GCN) model [6], which simultaneously integrated the GCN and GRU, where the graph convolutional network learns complex topologies to capture spatial dependencies between traffic flow graph nodes, while the gated recursive unit learns dynamic changes in traffic data to capture temporal dependencies.To capture the temporal and spatial dependencies of traffic data,The academic circle combined the time graph Convolutional network (T-GCN)[7], the graph Convolutional network (GCN)[8] and the gated cycle unit (GRU)[9], and used the graph convolution to learn the topological structure to capture the spatial

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dependence and the gated recursive unit to learn the change of traffic data to capture the time dependence of traffic flow data.

Compared with the previous methods without GCN network, although these methods have improved the prediction accuracy of the model to a certain extent, there are still can not capture the spatio-temporal dependence of traffic flow data effectively at the same time, thus affecting its long-period prediction accuracy. Since the existing methods can not effectively solve this problem, this paper designs a traffic flow prediction method (WAC-GCN) which can effectively extract the spatio-temporal dynamic characteristics of traffic flow.

2. Method

2.1 Wavelet Analysis

Wavelet analysis(WA)[10] is a signal analysis method used to analyze signals at different time and frequency scales. The core of WA is the wavelet transform, which is a time-frequency analysis method for signals according to scale and resolution.

For a signal f(x), its wavelet transform is defined as follows.

$$T_f(\varphi_{a,b}(x)) = \left\langle f(x), \varphi_{a,b}(x) \right\rangle = \frac{1}{\sqrt{|a|}} \int_R f(x) \varphi^*(\frac{x-b}{a}) dx \tag{1}$$

In Equation (1): $\varphi_{a,b}(x)$ is the wavelet basis function;a is the extension factor and b is the translation factor. By changing the size of a and b, the shape and position of the wavelet basis function are changed. $T_f(\varphi_{a,b}(x))$ Represents that the signal f (x) is transformed by wavelet basis function. $\varphi_{a,b}(x)$;R is all real numbers.

2.2 GCN

The convolutional neural network(CNN) firstly filters the input two-dimensional matrix based on the convolution of shared parameters, and then extracts the relevant features after nonlinear activation function and pooling. However, the graph structure with correlation between nodes has strong non-Euclidean features in spatial distribution and loses translation invariance features. The traditional CNN convolution method is not applicable to this kind of graph structure data. The researchers proposed the graph convolutional neural network(GCN), as shown in Figure 1.

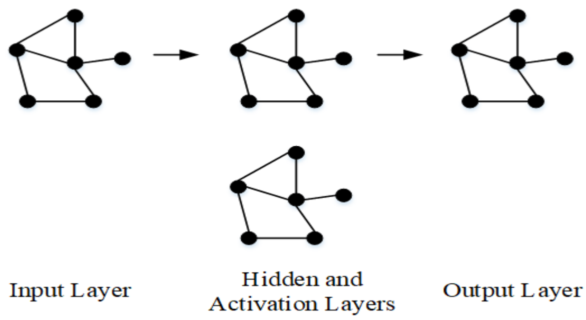

Figure 1: Schematic diagram of convolutional neural network structure

The function of GCN is defined as:

$$H^{l+1} = f(H^l, A) = \sigma(\hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^l W^l) \tag{2}$$

$$H^{l'} = \hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^l \tag{3}$$

$$\hat{A} = A + I \tag{4}$$

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Where: A∈Rn×n is the adjacency matrix, I is the identity matrix, D is the diagonal node degree matrix of A, W is the weight matrix of the L-th layer, H∈Rn×m is the feature matrix, where m is the number of features of each node in n nodes, H∈Rn×m is the feature matrix with topological information, σ(·) is the activation function.

2.3 2D CNN

2D Convolutional Neural Network (2D CNN) is a kind of neural network model widely used in traffic flow prediction.The core idea of 2D CNN is convolution operation, which uses convolution check to filter input images and extract image information of different scales, different directions and different features. The process of convolution operation can be expressed as the sliding and multiplying accumulation of convolution kernel on the input image, and finally generate a new feature map. This feature graph can be processed by activation functions, such as ReLU functions, to enhance its nonlinear representation. As shown in Figure 2.

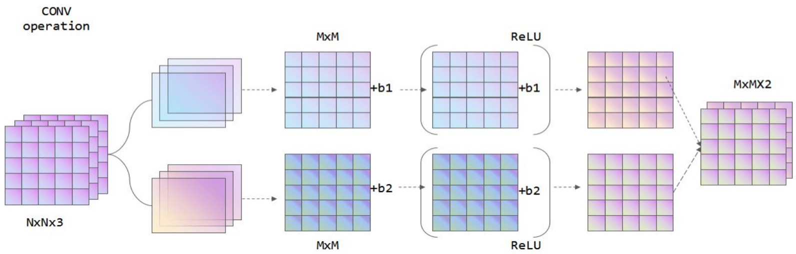

Figure 2: Schematic diagram of convolution operation

The fully connected layer, also known as the dense layer, is a type of layer used to reduce data dimensions, as well as to capture nonlinear correlations between high-level features and outputs. The whole process can be expressed as follows:

$$Y = f\left(\sum_{i=0}^{\infty} W_i X_i - \theta\right) \tag{5}$$

Where Xi represents the input neuron, and the parameter Wi is adjusted by error so that the output of the network gradually approaches the expectation:

$$W_i^{t+1} = W_i^t + \eta(y - \hat{y})X_i \tag{6}$$

The visualization is shown in Figure 3. The fully connected layer is often added after the convolution, in which each neuron is weighted to sum all the neurons in the previous layer, followed by a bias term, and finally a nonlinear transformation via the Softmax activation function.

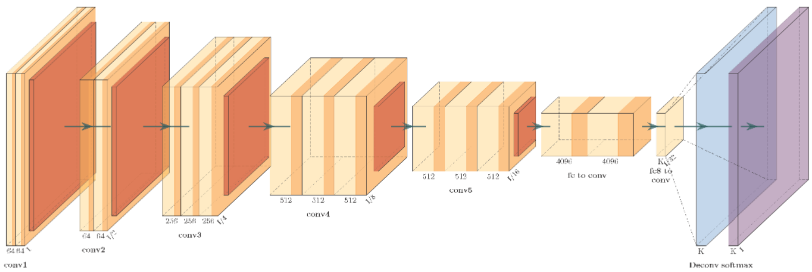

Figure 3: Structure of the fully connected layer

The fully connected layer is often used for feature extraction and classification tasks in neural networks. In the feature extraction task, the full-connection layer can map the high-dimensional features of the previous layer to the low-dimensional space and extract the most important features of the data. In the classification task, the fully connected layer can transform the extracted features into class probabilities or class labels by linear and nonlinear transformations.

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2.4 WAC-GCN

Considering that traffic flow data is a nonlinear time series with some noise interference, and in order to fully explore the spatio-temporal characteristics of the road network and explore the spatial heterogeneity, a WAC-GCN model is proposed to predict traffic flow.

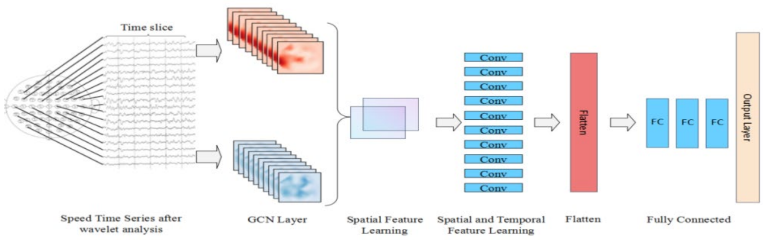

Figure 4: WAC-GCN model structure

Firstly, wavelet analysis is used to process the data. Secondly, the processed time series data is input to multi-layer GCN for processing, and the spatial characteristics of the road network are mined. Then, after the feature superposition, 2D CNN is used to extract the spatio-temporal features again. Finally, the full connection layer is used for dimensionality reduction to output the results. The model structure is shown in Figure 4.

3. Case Analysis

3.1 Spatial characteristics analysis

Since the goal of the research is to model the regional road network data, it is necessary to analyze the spatial correlation of each node in the road network space. In the real road network, based on the connectivity of the road, the traffic between the nodes in each neighborhood affects each other. In the prediction modeling, the interaction relationship between nodes, that is, the spatial correlation between nodes, is generally expressed and quantified by the correlation coefficient. The following is a preliminary definition of the spatial correlation of the road network through Pearson correlation coefficient (PCC):

$$\rho_{X,Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)}\sqrt{E(Y^2) - E^2(Y)}} \tag{7}$$

Where, $\rho_{X,Y}$ is the correlation coefficient, X and Y are the data of two different detectors, and E is the average function.

The heat map of spatial correlation between nodes of the selected network data is shown in Figure 5. It can be seen from the figure that there is a correlation relationship between any two nodes in the network, indicating that affected by the spatial connectivity characteristics of the road, when the flow of a single node is high, other nodes will also have corresponding peak flow phenomenon, and vice versa. The data of different detector nodes have similar timing rules and data distribution.

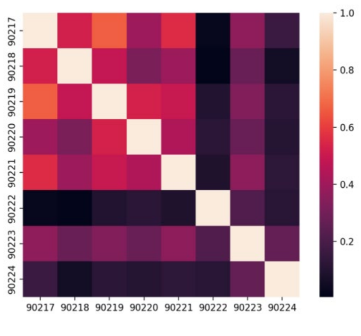

Figure 5: Heat map of correlation between nodes of the road network

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3.2 Evaluate metrics and loss functions

The mean square error (MSE) was selected as the loss function. Two indexes including mean absolute error (MAE) and R^2 are used to evaluate model performance, as shown in (8) - (10):

$$Loss = MSE = \frac{1}{N}\sum_{i=1}^{N}(\tilde{X}_i - X_i)^2 \tag{8}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\tilde{X}_i - X_i\right| \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}(X_i - \tilde{X}_i)^2}{\sum_{i=1}(X_i - \bar{X}_i)^2} \tag{10}$$

$\tilde{X}_i$ is the predicted value, X_i is the actual value, N represents the total number of values that the model needs to predict.

3.3 Model parameter Settings

In order to select the most suitable parameters, the parameters are carefully adjusted, in the process of parameter adjustment, the control variable method is used. The final specific parameter Settings are shown in Table 1:

Table 1: Model parameter Settings

Parameter	Description
Batch size	4
Optimizer	Adam
Initial learning rate	0.001
Default epochs	5000
Validation ration	0.1
Time_interval	15
Time_lag	10
Tg_in_one_day	96
Forecast_day_number	5
Is_train	True
Is_val	False
Pre_len	1

The Early Stopping technology is used in the stopping part of the model, which has two main functions: On the one hand, it can save the optimal model up to the present with the help of verification set loss, which can avoid overfitting of the model and ensure the generalization performance of the model; On the other hand, if the model is trained to a certain standard, the performance of the model may be degraded if the training continues. In this case, the Early Stopping technology can stop the model training to avoid wasting time and resources. The Early Stopping parameter is set to 100, that is, when the verification set loses more than 100 times and stops falling, the training process will be stopped[11].

3.4 Analysis Results

After visualization, Figure 6 shows that the error between the results obtained by the traffic flow prediction model and the actual traffic flow data is relatively small, which reflects that the model has a strong ability to capture the change rule of traffic flow over time. The results with small error show that the model has high prediction accuracy and stability, which fully proves the feasibility and effectiveness of the model.

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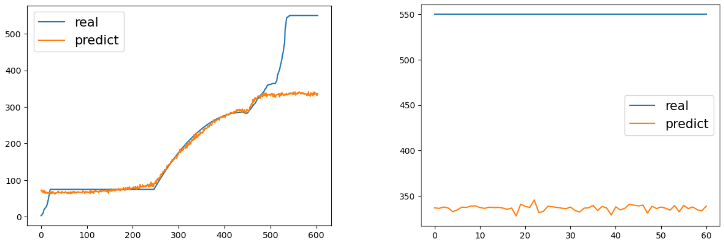

(b) Test set

Figure 6: Comparison of predicted and actual values

In this paper, MAE and R2 values of WAC-GCN, WAC-GCN without 2D CNN and WAC-GCN without wavelet analysis results are calculated using test sets. The evaluation index pairs of different forecasting methods are shown in the following figure.

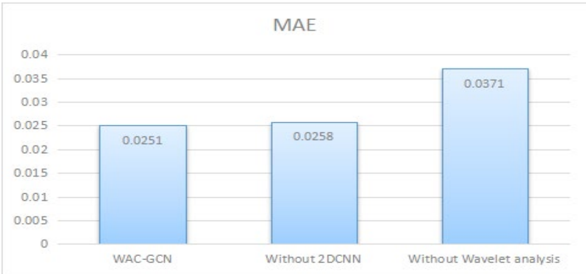

Figure 7: MAE comparison of different prediction methds

According to the results in Figure 7, MAE of the WAC-GCN model is smaller than that of both WAC-GCN without 2D CNN and WAC-GCN without wavelet analysis models. This shows that the use of wavelet analysis and 2DCNN to extract temporal and spatial features can significantly improve the prediction accuracy.

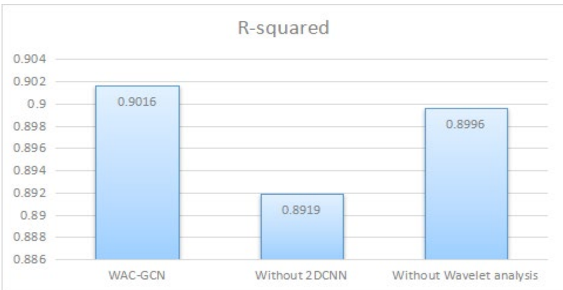

Figure 8: R^2 comparison of different prediction methods

Based on the results in Figure 8, it can be inferred that the R^2 of the WAC-GCN model is larger than both the WAC-GCN without 2D CNN and WAC-GCN without wavelet analysis models. The larger the R^2 value, the better the model fits the data. The R^2 of the WAC-GCN model is larger than both the WAC-GCN without 2D CNN and WAC-GCN without wavelet analysis models, that is, the WAC-GCN model has a higher degree of fitting to the data. The WAC-GCN model uses wavelet analysis and 2D CNN to extract temporal and spatial features, which further improves the prediction accuracy of the model. At the same time, the parameters of the WAC-GCN model have also been adjusted to better adapt to the characteristics of the data set, thus improving the fitting ability of the model.

4. Conclusion

In order to solve the problems of limited accuracy and low training efficiency of most existing spatiotemporal graph convolutional networks, this paper proposes a model based on wavelet transform, 2D convolutional neural network and graph convolutional neural network (WAC-GCN). The results of multiple rounds of validation on Caltrans Performance Evaluation System (PeMS), an open data set of American highway, show that the proposed model is significantly better than the benchmark model with some modules removed in each evaluation index. This shows that the combined graph convolutional

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neural network based on wavelet transform can better mine the spatial features of multi-dimensional high-order neighborhood in traffic flow data. The introduction of Early Stopping technology can ensure the generalization performance of the model and save time and resources. By comparing the real value and the predicted value on the training set and the test set, we know that the model has good performance of time series prediction.

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