Traffic Operation Status Research Based on Multi-source Data Fusion

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Abstract. At present, modern technologies such as big data, cloud computing and vehicle-road collaboration are developing rapidly, and the existing traffic detection data based on a single detector cannot meet the demand for high-precision data in the vehicle-road cloud environment. Facing the massive, heterogeneous and complex traffic data, this paper selects the data collected by LiDAR, HD camera and V2X communication unit as the data sources for this research, establishing the multi-source traffic data fusion model with wavelet neural network and genetic algorithm optimized BP neural network respectively, and builds the traffic status classification model based on fuzzy C-mean clustering algorithm. The fusion model and the traffic status classification model are verified for the single intersection road section in the vehicle-road cloud cooperative environment. The results show that the fusion accuracy of genetic algorithm optimized BP neural network reaches 93% and the status classification model has high feasibility, which can provide data support for intersection signal control and traffic guidance optimization.

Keywords: Data fusion · V2X communication unit · Traffic detection · Neural network · Fuzzy clustering

1 Introduction

With the increasingly serious phenomenon of urban road traffic congestion, traffic detection using big data and vehicle-road collaboration technologies have become one of the important means to alleviate traffic congestion nowadays. The detection data from a single source will produce errors due to the interference of various factors such as signal loss, bad weather and the limitation of detection equipment coverage. In the vehicle-road cooperation environment, the problems of poor stability and small coverage of single detection equipment in traditional traffic scenarios can be effectively solved by

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vehicle-vehicle communication and vehicle-road communication. Multi-source detection data can compensate for the consequences of missing information from a single data source that cannot be accurately described, improve detection accuracy, and enhance the performance of model estimation and prediction.

Data fusion using neural networks is highly implementable in terms of multi-sensor real-time processing of collected dynamic traffic data requirements, which can improve the accuracy of fusion results and timeliness of traffic status classification. Dia [1] et al. fused the basic data collected from floating vehicles, induction coils and used a neural network algorithm based on multilayer forward, modular processing for detecting traffic events. Jibrin [2] et al. proposed an application to fuse millimeter wave radar and camera sensor data to classify detected vehicles using convolutional neural networks. Kashinath [3] et al. proposed a generalized multi-coordinated data fusion framework for real-time heterogeneous data sources which used Kalman filtering and fuzzy logic to fuse the data. Cubero [4] et al. used artificial neural networks to fuse data from traditional 2D sensors and other sensors to generate a 2D occupancy raster map considering information from all sensors. Kasra [5] et al. proposed a fusion of multiple datasets from imaging sensors using a multi-sensor sparse-based clustering algorithm to obtain spatial and contextual information. Current traffic data fusion often uses multiple devices to extract traffic parameters, but the above studies do not incorporate the growing V2X technology, and the data are not sufficiently real-time and comprehensive. Therefore, this paper fuses multi-source data based on neural network algorithm, and establishes multi-angle and multi-level traffic data set, investigating urban vehicle-road cooperative status, which can provide theoretical basis for intersection signal optimization and effectively improve road capacity.

The rest of this paper is arranged as follows: in the second part, the principles of wavelet neural network and genetic algorithm to optimize BP neural network for data fusion are introduced; the third part details the experimental design and experimental results, which prove the superiority of the algorithm in this paper; the fourth part is the conclusion part of this paper.

2 GA-BP Model

Among fixed traffic detection devices, LiDAR detectors can be accurate to the centimeter level and HD camera detectors are easy to install. Every vehicle within the coverage area of V2X technology can be regarded as a mobile detector to achieve comprehensive, massive and fast information transmission and provide exponentially growing data [6]. Therefore, this paper combines the advantages of three devices, LiDAR, HD camera and V2X communication unit, to fuse multi-source heterogeneous traffic flow data. The average speed of a single motor vehicle is first derived from the data of the three detectors separately, and then the interval average speed of all vehicles passing through the experimental road section in every 5s is derived.

The data fusion method based on BP neural network can automatically learn to improve its own structure, processing large amount of data quickly, which can well meet the demand of real-time fusion processing of multi-source traffic data, so this paper selects BP neural network as the underlying framework of the fusion algorithm.

In the BP neural network training process, the convergence speed and the accuracy of the training results are closely related to the initial values of its weights and thresholds, but these parameters are more random and the algorithm tends to fall into local minima, so the genetic algorithm is used to optimize the BP neural network so as to enhance the network accuracy. The error between the predicted average speed and the true average speed is designed as an individual fitness function:

$$F = \sum_{i=1}^{n} abs(y_i - y_i') \tag{1}$$

where, y_i is the average speed of the predicted output of the i^{th} node in the neural network structure; y_i' is the actual average speed of the output of the i^{th} node.

Each individual can get its respective fitness value after the calculation of Formula (1), and the roulette wheel method is used for selection. Then the individual is selected according to the relative ratio of individual fitness value to the sum of fitness values of the whole population [7]. If the fitness value satisfies the set conditions, the parameters obtained by decoding this individual are the optimal weights and threshold values. If the set condition is not satisfied, it is judged whether the set number of evolutionary generations is reached, and if it is reached, the genetic algorithm is exited, a more reasonable network structure is redesigned, and the next round of coding is continued for the next round of selection, crossover, and mutation. The structure diagram of the genetic algorithm optimized BP neural network is shown in Fig. 1.

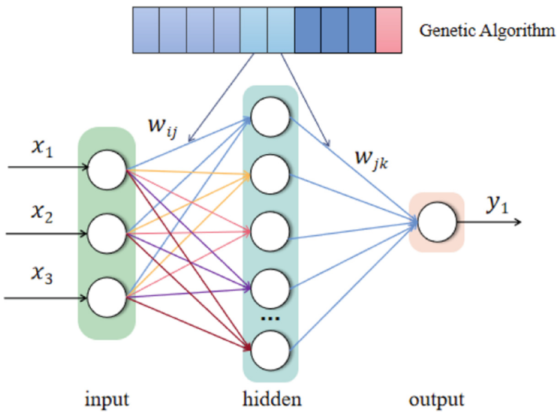

Fig. 1. GA-BP network structure diagram

In Fig. 1, x_1, x_2, x_3 is the input value, which is the average travel speed acquired by the roadside device and V2X device in the same time interval; W_{ij} is the weight from the input layer to the hidden layer; W_{jk} is the weight from the hidden layer to the output layer; y_1 is the fused output value obtained by neural network learning.

After extracting traffic parameters and performing multi-source data fusion, this paper uses the fuzzy C-mean clustering algorithm to classify traffic status, and the algorithm flow is shown in Fig. 2.

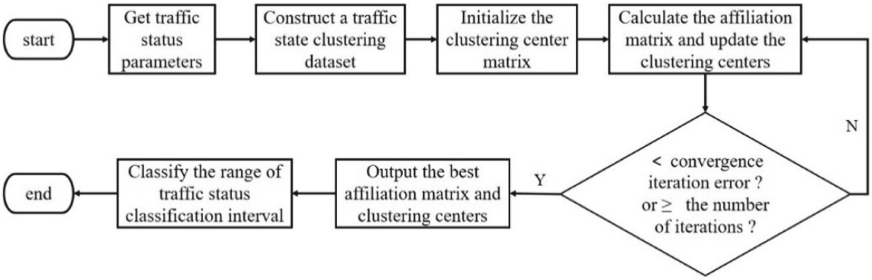

Fig. 2. The FCM-based traffic status classification algorithm flowchart

3 Experiment

3.1 Experimental Design

The data source of this paper is one-way traffic flow data from a typical intersection in Shijingshan District. The roadside sensing platform includes LIDAR detectors, HD cameras, intelligent RSUs and MEC servers. The experimental acquisition time is 10 min within 5:00 pm on weekdays. In this paper, about 20,000 vehicle data are obtained after preliminary screening, and the average travel speeds obtained from different detectors are extracted after pre-processing of offset and missing data.

Both the wavelet neural network and the BP neural network optimized by genetic algorithm in the fusion model are 3 layers, consisting of input layer, hidden layer and output layer, and dropout of the neuron is set to 0.2 in order to prevent training overfitting. After several comparison experiments, the best combination of hyper parameters is obtained as follows: the number of nodes in the implicit layer is 5, and the learning rate is 0.001. The number of iterations is 1000, and the ratio of training set, test set and validation set is 7:2:1.

3.2 Experimental Results

The following experimental results compare the performance of the two fusion algorithm models, as shown in Table 1. The fusion accuracy results of the GA-BP network are also recorded in this paper, as shown in Fig. 3.

Table 1. Comparison of fusion results

	MAPE	MAE	RMSE	Time (s)
WNN	0.17	0.16	0.22	0.46
GA-BP	0.07	0.14	0.19	0.56

By analyzing the fusion results comparison table, it can be found that the GA-BP fusion model outperforms the WNN model in all kinds of evaluation indexes, and the

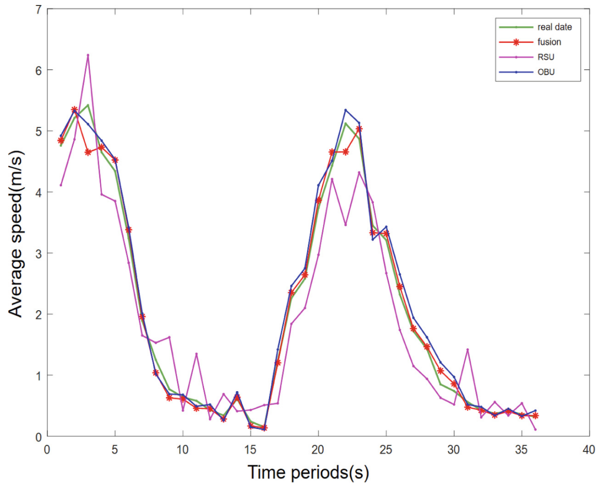

Fig. 3. The fusion accuracy of GA-BP model

fusion accuracy is higher up to 93%, while the training time of both is closer, so the GA-BP fusion model is selected for the fusion of traffic parameters. The multidimensional traffic status dataset obtained by combining the fusion results with other traffic-related parameters is shown in Table 2, including the traffic flow, average travel speed and other information related to traffic control signals of the road section.

Table 2. Traffic status dataset

Time period	Traffic flow	Average speed	Average queue length	Signal cycle	Signal light status	Signal state remaining time
174180	4	1.43	4.1	100	Green	45
174181	5	2.17	2.2	100	Green	40
174182	5	3.45	0	100	Green	35
…	…	…	…	…	…	…
174189	4	2.08	1.22	100	yellow	5
174190	5	1.16	2.33	100	red	50

In order to qualitatively analyze the mean travel speed time characteristics and to verify the accuracy of the fusion results from another perspective, the mean travel speed of six consecutive signal cycles is selected in this paper, and each signal cycle is divided into 20 time periods according to the 5s time interval. The distribution characteristics are shown in Fig. 4, and it can be seen that the average travel speed trend is basically the same for each signal period.

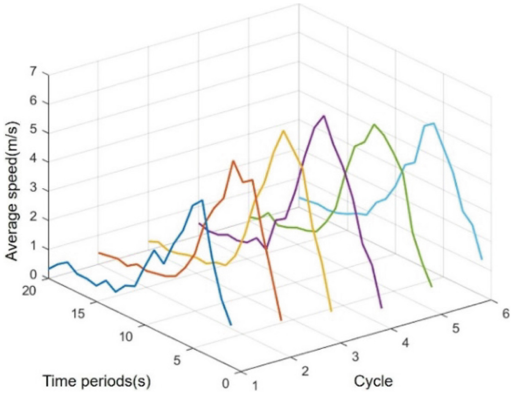

Fig. 4. Average travel speed time characteristics

In order to quantitatively analyze the closeness of the mean travel speed time characteristics, the Pearson correlation coefficient is used to calculate the time dependence of the mean travel speed for six consecutive signal periods [8]:

$$r = \frac{\mathrm{cov}(X, Y)}{\sigma X \sigma Y} = \frac{\sum_{i=1}^{m} (X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{m} (X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{m} (Y_i - \overline{Y})^2}} \tag{2}$$

where, X, Y are variables, m is the number of variables.

The Pearson thermal diagram is plotted as shown in Fig. 5, from which it can be seen that the correlation coefficients from cycle 1 to cycle 6 are all greater than 0.8, which is a very strong correlation. The change of traffic flow in the previous cycle time will have an impact on the traffic flow in the later cycle, indicating that the traffic flow parameters have temporal autocorrelation in the continuous change time. The strong correlation also proves from the other side that the average travel speed obtained by fusing the data from multiple sources does not show outlier values and has a higher accuracy.

After obtaining the multidimensional traffic status data set, the average travel speed and flow two-dimensional data are clustered using the fuzzy C-mean clustering related formula. The number of categories for traffic status classification is set as 4, corresponding to four traffic status of congested, smooth, slow and unobstructed respectively. The fuzzy index is set to 2, and the clustering results are shown in Fig. 6.

In Fig. 6, the red, yellow, blue and green dots indicate the four traffic operation status from unobstructed, smooth, slow to congested respectively. The categories are well separated from each other with obvious boundaries, which indicates an excellent clustering effect. The quantitative statistics of clustering centers and fuzzy classification intervals are shown in Table 3.

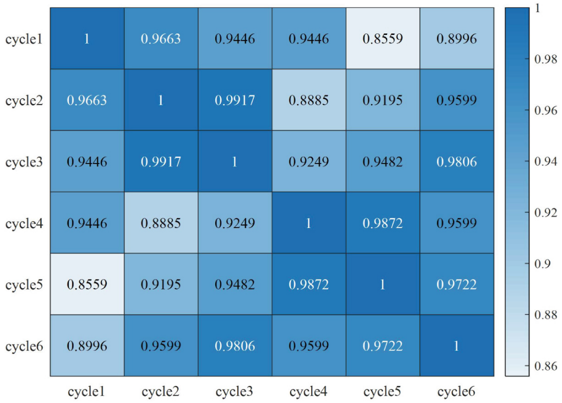

Fig. 5. Average travel speed Pearson correlation chart

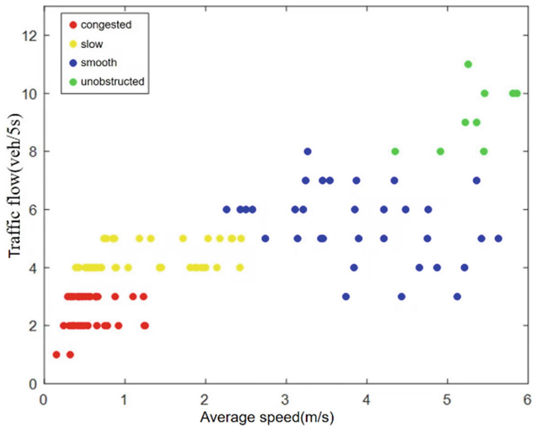

Fig. 6. Speed-flow clustering relationship diagram

Table 3. Traffic status clustering center and interval division based on FCM

	Average travel speed (m/s)		Traffic flow (veh/5s)	
	Clustering center	Range of interval	Clustering center	Range of interval
Unobstructed	5.59	[4.35, 15)	9.67	[0, 3)
Smooth	3.97	[2.26, 5.21)	5.53	[4, 5)
Slow	1.39	[0.74, 2.44)	4.33	[3, 8)
Congested	0.58	[0, 1.12)	2.61	[8, 11)

From the above table and result graph, we can find that when the intersection road section is in an unobstructed state, the average travel speed is higher; in a smooth state, the traffic flow increases and the speed decreases; when the number of vehicles continues to increase, it is easily disturbed by nearby vehicles and the speed decreases significantly; in a congested state, the vehicles are obviously obstructed and the travel speed is slow. The relationship between the average speed and the size change of the flow is consistent with the actual traffic flow change characteristics, indicating that the traffic state classification in this paper can accurately reflect the actual operation of the intersection section.

4 Conclusions

This paper collects traffic data with three devices: LiDAR, HD camera, and V2X communication unit, and extracts relevant parameters reflecting traffic flow characteristics. Then the multi-source heterogeneous traffic flow data are fused and the fusion results are used for traffic state analysis. The accuracy of GA-BP neural network fusion results reaches 93%, and the data reliability is much greater than that of single detection data, which improves the traffic data quality. In the traffic status classification of intersection sections based on fuzzy C-mean clustering algorithm, the boundaries between different categories are clear and the clustering effect is excellent.

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