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Vehicle obstacle avoidance path planning method based on deep data mining

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Abstract

Aiming at the problems of low planning accuracy and long time-consuming in vehicle obstacle avoidance path planning method, a vehicle obstacle avoidance path planning method based on deep data mining is proposed. Firstly, the steering angle of obstacle vehicle is determined, the motion state is determined, and the obstacle data extraction is completed; Then, the obstacle operation data is placed in Cartesian coordinates to obtain a new state value and complete the preprocessing; Finally, determine the straight-line distance between the obstacle vehicle and the vehicle, build the vehicle obstacle avoidance path planning model with the help of deep data mining, input the obstacle data after training, output the path planning results, and introduce the error correction function to modify the output planning results to realize the vehicle obstacle avoidance path planning. The results show that the proposed method has high accuracy in obstacle avoidance path planning.

Keywords - deep data mining, obstacle, path planning, straight line distance, planning model, error correction

1. Introduction

In recent years, China's industrial technology and socio-economic level have been continuously improved. People's living standards have also improved, and their travel mode has also undergone great changes [1]. In order to save time, quickly reach the destination and travel, many travelers choose to drive a car [11]. China's per capita household vehicle ownership is also increasing, and the number of vehicle trips is increasing, resulting in increasing traffic pressure. Especially during the morning and evening rush hours on weekdays, the road traffic jams are serious and the driving speed of vehicles is slow, which reduces the speed of vehicles [2]. Accidents often occur on traffic roads, and if the obstacles in the road cannot be removed quickly, it will seriously affect the driving speed of vehicles [14]. Vehicle obstacle avoidance path planning refers to the formal route planned to effectively avoid obstacles according to the real-time situation of the road, which can improve the safety of vehicle driving and shorten the travel time by avoiding obstacles. Therefore, how to improve the speed of vehicles and avoid obstacles in the road is the key to improve the safety and speed of vehicles. Therefore, researchers in this field plan the obstacle avoidance path during vehicle driving, and have achieved some research results.

Deng et al. [4] proposed a path planning and trajectory tracking control method for emergency obstacle avoidance of driving vehicles. Firstly, the dynamic model of the vehicle is analyzed, and the tracker of the vehicle running route is designed according to the model structure of the vehicle. Then, according to the running track data extracted by the track tracker, the obstacle avoidance function is designed to determine the distance between the vehicle and the obstacles, comprehensively consider the feasibility of the planned path, and determine the error of the track running, Complete the obstacle avoidance research through planning. This method can effectively measure the distance between vehicles and obstacles, but the final planned obstacle avoidance path belongs to a completely ideal state, without too much consideration of other sudden problems, there are some shortcomings, which need to be continuously optimized and improved. Dong et al. [6] proposed an unmanned vehicle path planning method based on improved RRT algorithm. This method first analyzes the constraints in the process of vehicle Ackerman angle driving, removes the planning results of the path that does not meet the set constraints, and then searches the optimal driving path with the help of fast search random tree. On this basis, the obtained data are processed smoothly to realize the driving path selection of vehicle obstacle avoidance. The path obstacles determined by this method are less, and the selected path can be used as the choice of vehicle travel, but the planning speed of this method is slow, and there are still some limitations. Han et al. [10] proposed an obstacle avoidance principle and vehicle path planning model prediction method based on convex approximation. This method designs a new vehicle obstacle avoidance path planning method, and sets the corresponding simulation environment according to the. By analyzing the obstacle avoidance principle of vehicle driving, selecting the obstacle coordinate points, searching the range of obstacles, and determining the safe distance of vehicles and the weight value in obstacle path planning through the control model. Finally, the obstacles in the planned path are predicted according to the vehicle path planning model to complete the vehicle obstacle avoidance. The accuracy of obstacle prediction in the planned path is high, but the data interference in the planning model is not processed in detail, resulting in a certain deviation in the prediction results.

In order to solve the shortcomings of the above methods, a new vehicle obstacle avoidance path planning method based on deep data mining is designed in this paper. The main technical route of this paper is as follows:

Firstly, the steering angle in the running track of obstacle vehicle is determined, and the motion state of obstacle vehicle is determined through the calculation of the maximum boundary physical quantity of obstacle, so as to complete the extraction of obstacle data;

Then, put the obstacle operation data in Cartesian coordinates, obtain a new obstacle vehicle state value, correct the deviation data in the obstacle data, and complete the data preprocessing;

Finally, the linear distance relationship between obstacle vehicles and vehicles is determined, Taylor processing is carried out, the distance between semi-circular tracks running between obstacle vehicles and vehicles is set, the vehicle driving obstacle avoidance path planning model is constructed with the help of deep data mining, the trained obstacle data is input, and the path planning results are output, The error correction function is introduced to modify the output planning results to realize the obstacle avoidance path planning.

2. Vehicle obstacle avoidance path planning method based on deep data mining

2.1. Extraction of obstacle data during vehicle driving

In the path planning of vehicle obstacle avoidance, obstacles are the key to the safe path planning of vehicles. Considering the safety performance of vehicle driving, this paper first extracts the obstacle data during vehicle driving, so as to lay the foundation for subsequent vehicle driving armband path planning. It is difficult to directly extract the obstacle data during vehicle driving. The obstacles affecting the safe driving of vehicles in the traffic road mainly include: driving vehicles, walking pedestrians, other non motor vehicles and poor road traffic caused by traffic accidents [3]. Therefore, the state estimation of obstacles is the key to extract obstacle data. It is assumed that the current running speed and heading angle of the vehicle regarded as an obstacle can be obtained through the on-board sensor, but because the trajectory of the obstacle vehicle changes a lot, it is necessary to obtain the running speed and steering angle of the obstacle vehicle and extract the trajectory data of the obstacle vehicle. At this time, the determination of steering angle in the running track of obstacle vehicle is as follows:

$$z_i = v(x)\sum u(x) \tag{1}$$

where $v(x)$ represents the state change value of the obstacle vehicle, and $u(x)$ represents the amount of angle change in the movement of the obstacle.

The maximum boundary physical quantity of the obstacle is determined based on its steering angle in the determined running track of the obstacle vehicle, and its variation range in a short time is set to a fixed value [5]. At this time, the motion state of the obstacle vehicle can be expressed as:

$$\mathrm{r(i)} = \mathrm{maxr}\int_{\mathrm{j}}^{\mathrm{i}}[\mathrm{v(x)u(x)}]\mathrm{dt} \tag{2}$$

where maxr represents the maximum value of the boundary physical quantity, t represents the obstacle change time, and $\mathrm{r(i)}$ represents the short-term state value in the short-term operation.

Since the trajectory of obstacle vehicles in traffic can be regarded as a curve similar to a sector, and one trajectory represents its motion state, generally, the probability of obstacle driving along the middle of the road is large [9], and its operation diagram is shown in Figure 1.

After analyzing the possible trajectory of the obstacle, the obstacle data is extracted from the obstacle vehicle based on its relative control ideal displacement. In this data extraction, the whole obstacle is not considered, and the trajectory of obstacle movement cannot be regarded as unchanged. There are still problems such as speed change and side slip [8], so the determined coordinates of obstacle vehicle operation are:

$$o_i = \begin{bmatrix} cos\theta & 0 \\ sin\theta & 0 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} v_i \\ \\ e_i \end{bmatrix} \tag{3}$$

where o_i represents the coordinate point change of the obstacle vehicle, θ represents the direction corner of the obstacle vehicle, v_i represents the linear speed of the operation of the obstacle vehicle, and e_i represents the angular speed.

On this basis, the extraction of obstacle data during vehicle driving is completed with the help of discretization. The obtained obstacle data results are as follows:

$$\mathrm{Q(k+1)} = \Delta\mathrm{sin\theta}v_i + \delta_x \tag{4}$$

where $\mathrm{Q(k+1)}$ represents the results of obstacle data extraction, and k represents the extracted interval sampling and δ_x is the discrecrete coefficient.

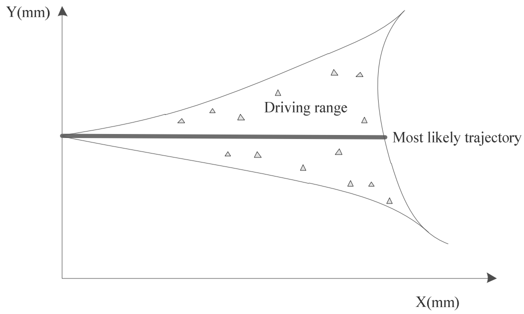

Fig. 1 - Schematic diagram of obstacle moving state

In the extraction of obstacle data during vehicle driving, determine the steering angle in the running track of obstacle vehicles, determine the motion state of obstacle vehicles through the calculation of the maximum boundary physical quantity of obstacles, calculate the driving probability of obstacles along the middle of the road, and complete the extraction of obstacle data.

2.2. Preprocessing of obstacle data during vehicle driving

Due to its changeable characteristics, it is necessary to preprocess the deviation extracted from the obstacle data in order to facilitate the effective planning and research of the follow-up path. In the deviation preprocessing of obstacle data extraction, the obstacle running data is placed in Cartesian coordinates, and the running vehicle state value is input to obtain a new vehicle state value [12]. Set the obstacle vehicle operation status data as c_x, c_y , and decompose it into the Cartesian coordinate system, and its processed obstacle data feature point reference point coordinate system is shown in Figure 2.

According to the converted coordinate system in Figure 2, the corresponding points of the obstacle vehicle in the running track are:

$$\mathrm{c} = [c_x, c_y, \varphi_\mathrm{i}] \tag{5}$$

where c represents the pretreatment obstacle coordinate point.

At this time, the preprocessed obstacle data result is:

$$\mathrm{c}' = \alpha \frac{[(c_x, c_y)^2 + (c_y, \varphi_\mathrm{i})^2]\sigma}{|(c_x, c_y)^2 - (c_y, \varphi_\mathrm{i})^2|'} \tag{6}$$

where σ representing the radius of curvature of the road in the trajectory of the obstacle operation, $|(c_x, c_y)^2 - (c_y, \varphi_\mathrm{i})^2|'$ represents the real coordinates of the tracking point and α is the trend of change in the exercise path.

After the obstacle data coordinate points obtained after preprocessing, the displacement deviation of the obstacle vehicle needs to be further processed [7], and the following results are obtained:

$$\omega_i = \sqrt{(s - s_i)^2 + (l - l_i)^2} \tag{7}$$

where s represents the displacement in the obstacle operation, l represents the deviation of the coordinate point in the displacement.

In the preprocessing of obstacle data during vehicle driving, place the obstacle operation data in Cartesian coordinates [13], obtain a new obstacle vehicle state value, correct the deviation data in the obstacle data, and complete the preprocessing of obstacle data during vehicle driving.

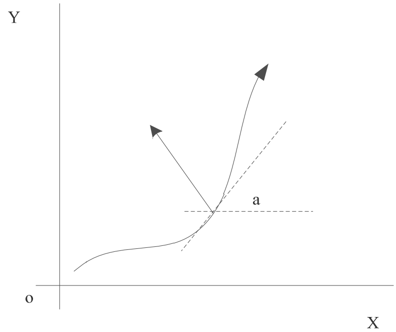

Fig. 2 - Schematic diagram of obstacle data feature point reference point coordinate system

2.3. Implementation of vehicle obstacle avoidance path planning method based on deep data mining

Based on the obstacle data extraction and preprocessing obtained above, when the vehicle is driving in a highly dynamic environment, it needs to meet certain constraints to realize the planning of vehicle obstacle avoidance path. In the setting of this paper, the distance between obstacles should be considered and the distance between them should be limited.

When the vehicle travels in a straight line, it travels in the middle of the road with a relatively stable track. At this time, the distance between the obstacle vehicle and the vehicle is a linear relationship, that is:

$$p_i = \frac{1}{\gamma_i}(-gsin\vartheta + \sqrt{g^2 sin\vartheta + 2\gamma_i y}) \tag{8}$$

where γ_i represents the straight line distance between the obstacle vehicles, g represents the speed value of the horizontal operation of the vehicle.

In order to set the effective distance between the vehicle and the obstacle, Taylor process formula (8) to determine the value around the obstacle. At this time, the function of the transverse acceleration of the obstacle expands the series at zero to obtain:

$$\tau = p_i(1 - \frac{y}{2gsin\vartheta\varphi})T \tag{9}$$

where φ represents the lateral acceleration values of the obstacle data and T represents the Taylor processing coefficient.

The vehicle cannot always run in a straight line during driving, and there is a running mode of curve track during its movement. Therefore, it is necessary to set the distance between it and the obstacle in this case. When the vehicle runs along the curve track, the rotation angle of the vehicle is the key to control its curve operation. Therefore, the running track is regarded as a semi-circular track, that is, its running track can be expressed as:

$$W_i = \frac{H_v}{tan\beta} - \frac{\tau}{3} \tag{10}$$

where H_v represents the vehicle curve trajectory running track path, β represents the semicircular radius value.

At this time, the distance between the obstacle and the track when the vehicle is running on a curve is set as:

$$D_r = \rho_i \sum B'_i \tag{11}$$

where ρ_i represents the obstacle limit distance, B'_i represents the probability value of overlap with the obstacle in the operation of the vehicle curve.

On the basis of the above-mentioned constraint conditions for vehicle driving obstacle avoidance path planning, the vehicle driving obstacle avoidance path planning is carried out. In this paper, the deep data mining method is used to realize the effective planning of vehicle obstacle avoidance path. Deep data mining is an artificial intelligence algorithm for deep analysis of data. It can quickly process data and mine the deep attributes of data. Therefore, this paper realizes vehicle obstacle avoidance path planning with the help of deep data mining algorithm.

In the obstacle avoidance path planning, the state space of the vehicle is determined through the deep data mining algorithm.The lateral displacement of the vehicle in the geodesid is expressed as Q_y , depending on the system change of the vehicle, the vehicle speed change state is:

$$Q_y = M_y cosa + M_x sina \tag{12}$$

where M represents the amount of lateral displacement in the vehicle driving.

When the change of vehicle speed is determined, its running direction is also a key spatial state affecting obstacle avoidance path planning. At this time, the change of steering angle in vehicle direction control is:

$$°\mathrm{F}_i = I_i \mu_f \sum Q_y \tag{13}$$

where $°\mathrm{F}_i$ represents the steering drive angle change value, and μ_f represents the steering state space change.

According to the driving state of the main vehicle determined above, the distance between the main vehicle and the obstacle is determined by using the depth data mining algorithm, and the distance between the main vehicle and the obstacle is determined as follows by setting the measurement function through the random tree in the depth data mining algorithm:

$$\varepsilon(\mathrm{a},\mathrm{b}) = ב\sqrt[2]{\mathrm{n_k}(\mathrm{a}-\mathrm{b})^2 + (\mathrm{a}+\mathrm{b})^2} \tag{14}$$

where ב represents the newly generated obstacle node, (a,b) represents the coordinates of the obstacle distance from the main vehicle, and $\mathrm{n_k}$ represents the angle between the obstacle and the main vehicle in the K th node.

After determining the shortest distance between the vehicle and the obstacle during driving, the vehicle obstacle avoidance path planning model is constructed, that is:

$$\nexists_i = \sum \frac{N}{sin\alpha_{max}} \tag{15}$$

where the α_{max} represents the distance between the vehicle wheel and the obstacle, and N represents the number of obstacles in the path.

According to the above constructed vehicle obstacle avoidance path planning model, the extracted obstacle data is input into the model, and the output result is the planned result. However, due to some errors in the output results, the error correction function is introduced to correct the planned results. The results are as follows:

$$P = E \lim_{n\to\infty} \left(1+\frac{1}{n}\right)^n d \sum \frac{N}{sin\alpha_{max}} \tag{16}$$

where P represents the revised planned path result, d represents the correction proportion of the vehicle driving path. The planning process of vehicle obstacle avoidance path based on deep data mining is shown in Figure 3.

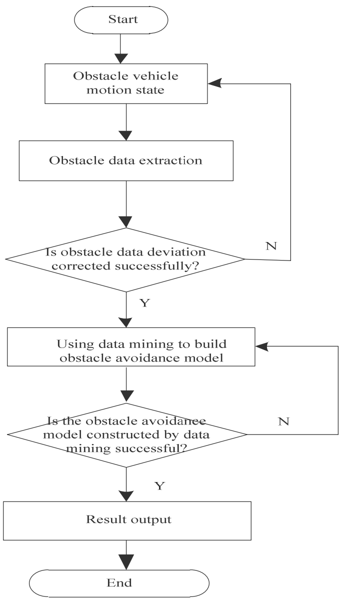

Fig. 3 - Planning process of vehicle obstacle avoidance path based on deep data mining

In the vehicle driving obstacle avoidance path planning, the linear distance relationship between obstacle vehicles and vehicles is determined, Taylor processing is performed, the distance between semi-circular tracks running between obstacle vehicles and vehicles is set, the vehicle driving obstacle avoidance path planning is constructed with the help of deep data mining, the trained obstacle data is input, and the path planning results are output, The error correction function is introduced to modify the output planning results to realize the obstacle avoidance path planning.

3. Experimental analysis

3.1. Experimental scheme design

In order to verify the effectiveness of the proposed method, experimental analysis is carried out. In the experiment, a traffic section in a certain place is selected as the target section of the study, and corresponding obstacles are set in the section. The sample study section includes two main roads with a length of 500 meters and multiple branch sections. Multiple obstacles are set in the study section. Through the prediction of obstacles and the calculation of distance, Analyze the effectiveness of the path planned by the design method. The schematic diagram of road state in the experiment is shown in Figure 4.

3.2. Experimental index design

According to the experimental scheme designed above, the proposed method, the method of Dong et al. [6] and Han et al. [10] are compared. In the experiment, the selected experimental indicators are the planning accuracy of vehicle obstacle avoidance path and the time cost of planning.

(1) The accuracy of obstacle avoidance path planning refers to the accuracy of path planning to avoid obstacles and reach the destination smoothly; The calculation formula is:

$$Right_i = \frac{\varsigma_i}{ALL} \times 100\% \tag{17}$$

where $Right_i$ represents the planned accuracy values, ς_i representing the paths with obstacles, and ALL representing all travel paths.

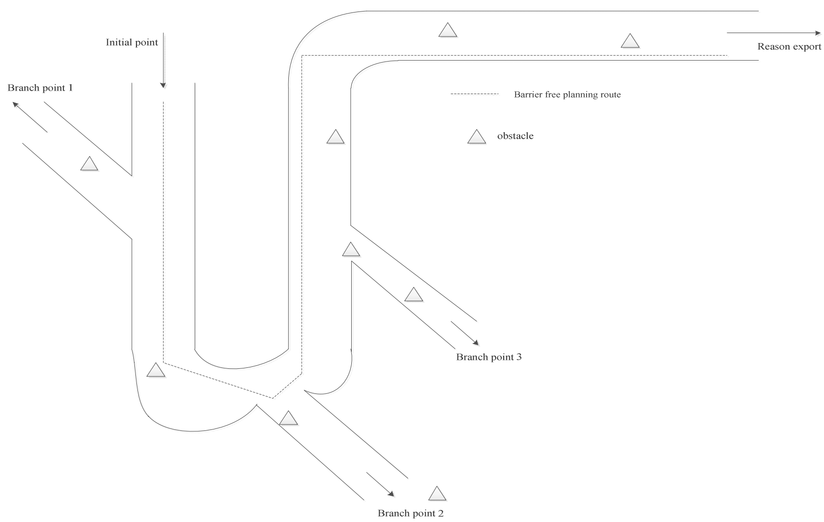

Fig. 4 - Experimental sample State Road

(2) The time cost of planning refers to the time cost of route planning on the basis of ensuring the planning accuracy. The experimental index reflects the efficiency of obstacle avoidance path planning, and is the key measurement index.

3.3. Analysis of experimental results

3.3.1. Analysis and research on accuracy of obstacle avoidance path planning with different methods

Avoiding obstacles in road selection can improve the efficiency and safety of vehicle operation. Therefore, the proposed method, the method of Dong et al. [6] and Han et al. [10] are experimentally analyzed to plan the obstacle avoidance path of the sample experimental road. The planning accuracy is shown in Figure 5.

By analyzing the experimental results in Fig. 5, it can be seen that there are some differences in the accuracy of obstacle avoidance path planning of sample experimental roads by using the proposed method, Dong et al. [6] and Han et al. [10] method. Among them, the accuracy of obstacle avoidance path planning for sample experimental roads using this method is high, and the highest is about 97%; The accuracy of the other two methods is always lower than that of this method, which verifies the effectiveness of this method.

3.3.2. Time consuming analysis of obstacle avoidance path planning with different methods

On the basis of ensuring the accuracy of obstacle avoidance path planning, the proposed method, Dong et al. [6] and Han et al. [10] method are used to analyze the time-consuming of obstacle avoidance path planning of sample experimental roads. The results are shown in Figure 6.

By analyzing the experimental result data in Figure 6, it can be seen that there are some differences in the planning time of obstacle avoidance path of sample experimental road by using the proposed method, Dong et al. [6] and Han et al. [10] method. Among them, the proposed method can effectively avoid obstacles for planning, which takes a short time and always shows a downward trend; The minimum is about 0.8s; The planning time of obstacle avoidance path of sample experimental road by the methods of Dong et al. [6] and Han et al. [10] is always high, and it is always higher than that of this method. In contrast, the proposed method, l Dong et al. [6] and Han et al. [10] method take less time to plan the obstacle avoidance path of the sample experimental road, which verifies the effectiveness of the proposed method.

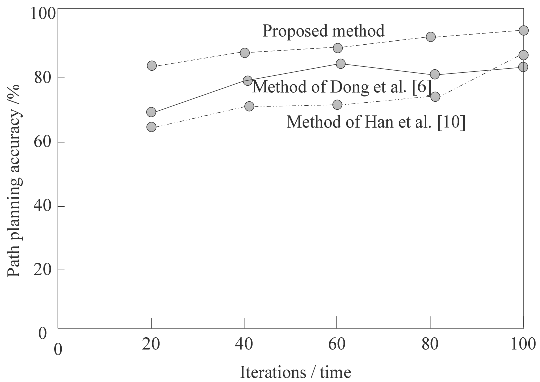

Fig. 5 - Analysis of comparison results of obstacle avoidance path planning accuracy of different methods

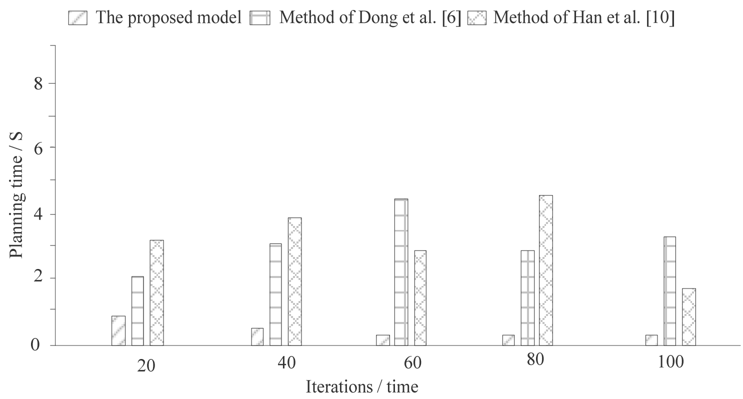

Fig. 6 - Comparison of time-consuming of obstacle avoidance path planning with different methods

4. Conclusion

In order to improve vehicle road operation safety and reduce the time-consuming of obstacle avoidance path planning, a vehicle obstacle avoidance path planning method based on deep data mining is designed in this paper. By determining the steering angle in the running track of the obstacle vehicle, and through the calculation of the maximum boundary physical quantity of the obstacle, the motion state of the obstacle vehicle is determined, and the driving probability of the obstacle along the middle of the road is calculated to complete the extraction of the obstacle data; Put the obstacle operation data in Cartesian coordinates, obtain a new obstacle vehicle state value, and complete the obstacle data preprocessing during vehicle driving; Determine the linear distance relationship between the obstacle vehicle and the vehicle, deal with it, set the distance between the semi-circular track between the obstacle vehicle and the vehicle, build the vehicle obstacle avoidance path planning model with the help of deep data mining, output the path planning results, and introduce the error correction function to correct the output planning results, Realize vehicle obstacle avoidance path planning. Experiments show that the proposed method has the following advantages:

(1) The highest accuracy of obstacle avoidance path planning using the proposed method is about 97%, which has a certain accuracy;

(2) The obstacle avoidance path planning using the proposed method is time-consuming and efficient.

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An evaluation method of urban public transport restriction policy based on genetic algorithm

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Abstract

Under the background of the gradually deteriorating relationship between traffic supply and demand, in order to solve the problems of low accuracy and long time-consuming of traditional methods for evaluating the effect of urban public transportation restriction policy, an evaluation algorithm of urban public transportation restriction policy based on genetic algorithm is proposed. Firstly, the characteristics of the public transport network are analyzed from the three aspects of traffic demand, traffic flow and the capacity of public transport sections, and the evaluation indicators are selected according to the results of the analysis. The knowledge rule theory is introduced to optimize the evaluation weight of the model, thereby improving the evaluation accuracy. Analysis of the experimental results shows that this method has the characteristics of high accuracy of evaluation results and low evaluation time.

Keywords - genetic algorithm, traffic restriction, traffic network characteristics, principal component analysis, traffic index, knowledge rules

1. Introduction

With the continuous acceleration of my country's urbanization development process, the continuous improvement of the social and economic level, the rapid increase in the number of motor vehicles, and the gradual increase in the demand for traffic, but the urban space has certain limitations, so there are contradictions, often traffic jams, vehicles scratching and so on [6]. In order to further ease the traffic pressure and avoid causing widespread congestion, many cities have adopted a traffic restriction policy. Each city has different traffic restriction policies. In order to scientifically evaluate the impact of various traffic restriction policies on urban public transportation, many experts and scholars have actively carried out research, using various advanced algorithms to evaluate the implementation of urban public transportation traffic restriction policies to assist transportation. The department adjusted the policy details and carried out traffic control in a more orderly manner [13].

In recent years, with the attention and active research of scholars on the evaluation of urban public transport restriction policies, certain results have been achieved. Chen et al. [7] took Beijing as an example to study the traffic congestion problem under the implementation of the traffic restriction policy in Chinese cities. The model conducts dynamic analysis, and explores the impact of the current urban restriction policies and measures on the ecological carrying capacity of the urban environment and the ecological carrying capacity of roads from economic, social, environmental and other methods. Evaluate road policies, etc., and propose relevant policies to control congestion. Although this method can evaluate the traffic restriction policy implemented by the city, it takes a long time and cannot fully reflect the traffic control situation of the city, and the evaluation lacks certain authenticity. In the same year, Chen and Zan [8] further studied the above-mentioned system, using system dynamics and grey prediction theory to construct a system dynamics model under the influence of urban transportation policy, taking Zhengzhou as an example, using Vensim software to conduct simulation research on governance policy, which proves that the traffic restriction policy has a significant control effect on vehicle exhaust in the short term, and the parking fee policy can reduce the number of motor vehicle trips. Although this method can evaluate the transportation policy implemented by the city, its time-consuming problem is still not improved. Xi et al. [16] evaluated the fairness of urban traffic based on mobile phone signaling data, taking Kunshan City as an example, to study the local public transport restriction policy and public transport infrastructure, Policies are evaluated, and measures such as optimizing public transportation infrastructure and increasing bus speed are proposed to optimize local transportation. Although this method can evaluate the traffic conditions under the local traffic restriction policy and propose strategies to improve traffic fairness, it does not explain the improvement of local traffic by increasing the speed of public transportation, and the method is complicated in operation, takes a long time to evaluate, and does not It is good for promotion.

Based on this, through the analysis of the above research status, it is known that in the evaluation of the implementation effect of the traffic restriction policy, scholars mainly conduct qualitative analysis on the implementation effect. Many problems need to be solved, and related theories and methods need to be improved. In order to realize the effective evaluation of the implementation effect of the public transportation restriction policy, this paper proposes an evaluation algorithm of the urban public transportation restriction policy based on the genetic algorithm. First, analyze the characteristics of the public transport network after the implementation of the traffic restriction policy from three aspects: traffic demand, traffic flow and the traffic capacity of public transport sections, and select scientific and reasonable evaluation indicators to establish an evaluation system for the implementation of urban public transport traffic restriction policies. The component analysis method completes the establishment of the evaluation model. In order to improve the scientific evaluation ability of the evaluation model, the genetic algorithm is used to optimize its evaluation weight and improve its overall performance, hoping to provide help for the analysis of urban public transportation restriction policies.

2. Evaluation of the implementation effect of urban public transport restriction policy

In order to make a scientific evaluation of the travel restriction policy, it is necessary to first understand the current situation of urban public transportation after the implementation of the policy, and then clarify the relevant factors that affect the urban public transportation network, and select relevant indicators to establish a scientific and reasonable evaluation system. This paper analyzes the characteristics of the public transport network after the implementation of the traffic restriction policy from the traffic demand, traffic flow and traffic capacity of public transport sections, scientifically selects the evaluation indicators, establishes an evaluation system, and finally establishes the urban public transport traffic restriction policy through the principal component analysis method. Evaluation model.

2.1. Analysis of public transport network characteristics

After the implementation of the traffic restriction policy, the public transportation network has a certain complexity. This paper analyzes the traffic demand, the conservation of traffic flow and the capacity of public transportation sections.

2.1.1. Traffic demand

In the field of transportation, traffic travel demand is a very important parameter index, which is usually expressed by O-D demand, specifically refers to the traffic travel demand between the starting point and the end point in a transportation network [1]. O-D requirements are represented by a two-dimensional matrix:

$$\mathrm{W} = \begin{pmatrix} w_{11} & \cdots & w_{1b} \\ \cdots & \ddots & \cdots \\ w_{a1} & \cdots & w_{ab} \end{pmatrix} \tag{1}$$

where a represents the starting point; b represents the end point; and W represents the traffic travel demand for this section of the journey.

For formula (1), the following constraint expression exists:

$$\mathrm{V}(a,b) = \int_{a,b}^{+\infty} y_a\,(h)\varphi_a(h) \tag{2}$$

$$\mathrm{T}(a,b) = \frac{\sqrt{c}}{2\pi}\phi(a,b) \tag{3}$$

where $\mathrm{V}(a,b)$ represents the amount of traffic in the area[15]; $y_a(h)$ and $\varphi_a(h)$ represent the stay time of the vehicle at the starting point and the ending point, respectively; $\mathrm{T}(a,b)$ represents the travel limit time[11]; $\phi(a,b)$ Represents the requirements of the vehicle type with limited travel; c represents the vehicle route selection condition.

2.1.2. Conservation of traffic flow

In the field of public transportation research, traffic flow can be referred to as traffic volume, which specifically refers to the number of traffic entities in a certain distance within a period of time[1]. Entities can refer to vehicles or pedestrians. Divided into motor vehicles, non-motor vehicles and pedestrians, etc., this paper mainly takes the motor vehicles as the research object [3, 9]. Under normal conditions, the traffic volume of a certain area belongs to a random number. Since the traffic volume is related to the pedestrian traffic mode and road traffic conditions, the traffic volume needs to meet the following conservation conditions:

$$D_{ij} = \sum_{i,j=1}^{N} \left|E_{ij}\right|^2 \times \frac{(\omega_a-\omega_b)^2}{2} \tag{4}$$

where D_{ij} represents the overall traffic volume; E_{ij} represents the traffic volume of a certain route; N represents the number of routes; ω_a represents the traffic volume at the starting point; ω_b represents the traffic volume at the end point.

Considering that the traffic network is composed of different sections, which may be shared by the same path, the traffic volume always represents the sum of the path flows of the section [17]. Namely:

$$D_{ij} = \sum_i^N \sum_j^N \sum_k^N d_{ijk} \tag{5}$$

where k represents the number of intersections; d_{ijk} represents the traffic volume of different paths.

2.1.3. Capacity of public transport section

The capacity of public transport section refers to the maximum number of vehicles and pedestrians that can pass through the road in a certain period of time, that is, the maximum flow rate of the road [4]. This indicator will be affected by road conditions, control measures and real-time conditions of road operation, which is usually expressed in vehicle / h. Generally, the traffic capacity of public roads should be higher than the road traffic volume. When this condition is met, the road operation is good, the vehicle speed is fast, and the driving has a certain degree of freedom; When this condition is not met, or when the traffic volume is large, the road operation will deteriorate, and in serious cases, traffic jam will be formed [14, 12].

The capacity of public transport section is expressed by capacity coefficient, and the specific formula is:

$$\mathrm{Q}(x) = q_1(x) + q_2(x) + \cdots + q_3(x) \tag{6}$$

Convert formula (6) to obtain:

$$\mathrm{Q}(x) = V\big(T_0(x), T_1(x)\big) \tag{7}$$

where V represents the speed of the vehicle in unit time; $T_0(x)$ represents the headway; $T_1(x)$ represents the headway.

Through the above analysis, the basic characteristics of urban public transportation are understood, the corresponding influencing factors are extracted as evaluation indicators, and the evaluation index system of urban public transportation restriction policy is established.

2.2. Evaluation index system

According to the above analysis, the characteristics of the public transport network are mainly reflected in the traffic demand, the conservation of traffic flow and the capacity of the road section. Therefore, in the design of the evaluation algorithm for the implementation effect of the urban public transport restriction policy, the above factors are fully considered. Comprehensive performance of urban traffic in the context of the implementation of public transport restriction policies.

In order to make the evaluation results more specific, the above three aspects are expanded to form multiple specific evaluation indicators, so as to improve the comprehensiveness of the evaluation results. According to the above, the evaluation index system of urban public transportation restriction policy is established as the evaluation standard of policy implementation effect. Figure 1 shows the evaluation index system of urban public transport restriction policy.

In this evaluation system, the first-level indicators include traffic demand, traffic flow and the capacity of public transport sections under the restriction policy, while the second-level indicators mainly include restriction time, restricted vehicles, traffic occurrence, traffic congestion index, and effective road area. Table 1 shows the evaluation indicators of the implementation effect of the urban public transport restriction policy.

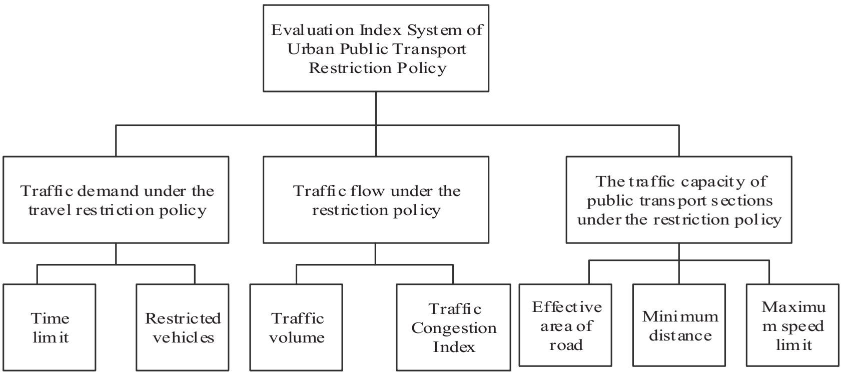

Fig. 1 - Evaluation system of urban public transport restriction policies

Tab. 1 - Evaluation indicators of urban public transport restriction policies

Index	Unit
Time limit	h
Restricted vehicles	/
Effective area of road	m^2
Minimum distance	m
Maximum speed limit	km/h
Traffic Congestion Index	/
Traffic volume	vehicle/h

Different from other evaluation methods, this paper also introduces the parameter of traffic congestion index in the evaluation process of urban traffic restriction policy. The traffic index is a conceptual index value, which is used to reflect the smoothness of traffic roads. The interval is 0.1-1.0. The higher the traffic index value, the more serious the congestion of public transport roads. Based on this, the establishment of the urban public transport restriction policy evaluation system is completed.

2.3. Evaluation model modeling

The principal component analysis method is used to establish the evaluation model of urban public transport restriction policy. In order to eliminate the interference of related factors, the data normalization process is performed on the observed values of the initial observation matrix M to obtain a standardized data matrix. Calculate the correlation coefficient matrix $R = P \times \left(r_{ij}\right)_n$ of the above evaluation indicators, where r_{ij} represents the correlation coefficient between the index mean factors M_i and M_j of the evaluation indicators i and j, and its expression is:

$$r_{ij} = \frac{1}{n}\sum_{k=1}^{n}(x_{ki} - \bar{x}_i)\left(x_{kj} - \bar{x}_j\right)\sigma_i\sigma_j \tag{8}$$

where $\bar{x}_i$ and $\bar{x}_j$ represent the mean of samples i and j, and σ_i and σ_j represent the standard deviation of samples i and j.

Calculate the eigenvalues and eigenvectors of R, calculate the eigenvalues λ according to the characteristic equation, obtain P eigenvalues, and then confirm the number of principal components. The number of principal components N is usually confirmed by the cumulative contribution rate E. When the cumulative contribution rate of the index is greater than 85%, it is the principal component. The cumulative contribution rate is expressed as

$$E_j = \frac{\sum_{j=1}^{N}\lambda_j}{\sum_{j=1}^{n}\lambda_j} \tag{9}$$

After confirming the number of principal components, confirm the principal component quantity, and obtain the principal component evaluation model of the urban public transportation restriction policy

$$F = \sum_{j=1}^{N}\eta_j a_j \qquad (j = 1,2,\dots,N) \tag{10}$$

where η_j represents the evaluation weight, and a_j represents the principal component index.

After establishing the principal component evaluation model of the urban public transport restriction policy, in order to improve the accuracy of the model, the genetic algorithm is used to optimize the evaluation weight of the model to improve the evaluation accuracy of the model.

2.4. Evaluation model optimization

In order to improve the evaluation weight in the evaluation model of the urban public transportation restriction policy, the objective function to minimize is firstly established.

$$minf(a) = \sum_{i=1}^{n} \sum_{j=1}^{m} |X(i,j) - Z(i)|^k$$
$$s.t. \sum_{j=1}^{m} a(j) = 1 \tag{11}$$

where $X(i,j)$ represents the evaluation score data matrix, $Z(i)$ represents the evaluation index function, and $a(j)$ represents the weight of the evaluation method.

The genetic algorithm is used to complete the global optimization, and the candidate solutions corresponding to the problem are coded. The candidate solutions here refer to the evaluation results. After coding, only the chromosomes composed of coding are operated, which is beneficial to reduce the interference of other items, to improve the evaluation efficiency. In the coding process, it is combined with the traffic index grades in Table 3 above to establish 5 grades, which are coded as 00, 01, 10, 11 and 101 respectively. Figure 1 is the coding structure diagram of the ant colony.

In order to improve the application performance of the ant colony algorithm, the knowledge rule theory is introduced in the effect evaluation of the ant colony algorithm. It can be seen from Figure 1 that η_i represents the encoding value of the i-th attribute, and its calculation formula is:

$$\eta_i = \sum_{i,j=1} \tau_{ij}^{\alpha} \times \varsigma_{ij}^{\beta} \tag{12}$$

where τ_{ij}^{α} represents the forward target of the ant; ς_{ij}^{β} represents the mutation position of the ant, where α and β both represent the pheromone intensity.

Whether the coding condition is included in the knowledge rule is judged by the parameter ψ_p, and its expression is:

$$\psi_p = \begin{cases} \psi_p, p \in K_d \\ 0, p \notin K_d \end{cases} \tag{13}$$

where K_d represents the knowledge rule base. In the formula, the former item indicates that the coding condition is included in the knowledge rule base, and the latter item indicates that the coding condition is not included in the knowledge rule base.

According to the coding results, the optimal genetic individual selection is realized by selecting the appropriate operator, and the optimal genetic individual corresponds to the evaluation index of the implementation effect of the policy, that is, selecting the appropriate evaluation index. In this paper, the optimal genetic individual is obtained by means of two-generation competitive ranking, that is, the genetic individual is divided into female and male individuals, which are respectively expressed as follows:

$$X_1(k) = [x_1(k), x_1(k+1), \ldots, x_1(k+N-1)] \tag{14}$$
$$X_2(k) = [x_2(k), x_2(k+1), \ldots, x_2(k+N-1)] \tag{15}$$

Select one-half of the excellent individuals in formula (14) and formula (15), and place them in the matching pool for the next crossover operation.

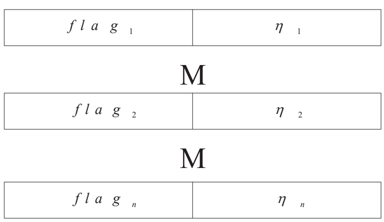

Fig. 2 - Coding structure diagram

In the crossover operation, it is necessary to follow the principle that the same sex cannot be paired, that is, only females and males can be paired, and the best ones will be eliminated during the pairing process. So far, the optimization of the principal component evaluation model is completed, and the accuracy of the evaluation model is improved.

3. Experimental analysis

In order to verify the application effect of the urban public transport restriction policy evaluation method based on genetic algorithm designed in this paper, the method of literature [7] and literature [16] are selected as the comparison methods, and the method of this paper is compared and analyzed, and the comparison results and conclusions are obtained.

3.1. Experimental environment design

In the experiment, a section of traffic network is selected as the experimental site. There are both three-phase signal intersections and four-phase signal intersections in the traffic network. The public transport lines are numbered by numbers, which are 1, 2, 3, 4 and 5 respectively. Figure 2 is the plan of the transportation network. Since the traffic index is an important index to evaluate the road congestion of urban public transport, by analyzing the regional traffic index, the road operation can be obtained, and the change of the traffic operation can be analyzed according to the index. Through a period of 3 months, the traffic conditions of the traffic network were monitored and observed, and the traffic conditions in the study area during this period were obtained. Combined with the traffic congestion index in the evaluation index proposed in Section 2.2, the traffic index situation on a certain weekday is analyzed, and the traffic change characteristics in this area are obtained. Figure 4 shows the distribution curve of the traffic index on weekdays.

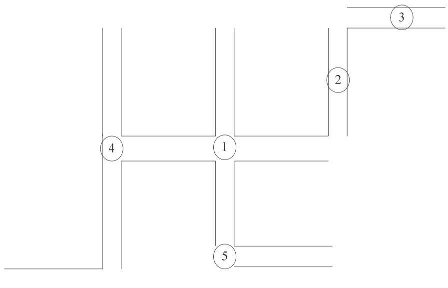

Fig. 3 - Plan of traffic network in the experimental area

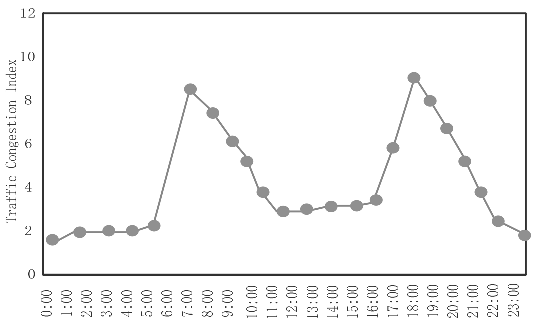

Fig. 4 - Distribution curve of traffic index on working days

According to figure 3, 8 a.m. and 6 p.m. are the peak traffic hours, followed by 7 a.m. and 9 p.m. and 5 and 7 p.m. the traffic congestion is alleviated in the rest of the time. According to the above analysis, the traffic peak area in the study area in working days.

According to the characteristics of the above experimental environment and transportation network, Swarm for Java is used as the simulation platform to compare the evaluation effects of different methods, and the accuracy of the evaluation results and the evaluation time are used as the experimental indicators to analyze the application effects of the three methods.

3.2. Analysis of comparative results

Taking the accuracy of the evaluation results as the experimental index, the evaluation effects of different methods are compared, and the results are shown in Figure 5. It can be seen from Figure 5 that the accuracy of the evaluation results in the method of Chen et al. [7] and Xi et al. [16] increases slowly with multiple iterations, but the highest value of the accuracy of the evaluation results is not higher than 75%. The accuracy of the evaluation results of the method in this paper reaches the highest value of more than 90%. It can be seen that the evaluation results of the method in this paper are more accurate, and can effectively evaluate the traffic conditions in the experimental area, providing help for traffic dredging and traffic congestion relief.

Taking the evaluation time as the experimental index, the evaluation results of different methods are compared, and the results are shown in Figure 6.

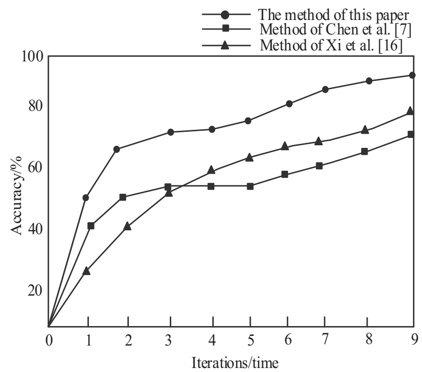

Fig. 5. - Comparison of the accuracy of the evaluation results of different methods

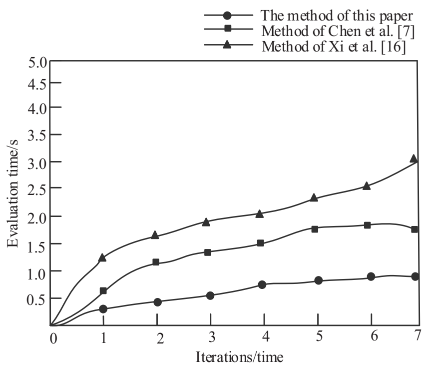

Fig. 6 - Time-consuming comparison of evaluation of different methods