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A Comprehensive Evaluation of Vehicle Intelligent Barrier Avoidance Function under Special Roads Based on G1-CRITIC

Xuewen Zhang [1,2,*], Qi Zhan [2], Wei Zhou [2] and Zhichao Liu [2]

[1] Doctoral Program on Major National Projects, Southeast University, Nanjing 210096, China
[2] Research Institute of Highway Ministry of Transport, Beijing 100088, China
* Correspondence: xw.zhang@rioh.cn; Tel.: +86-13601145743

Abstract: As one of the core functions of the autonomous driving of vehicles under special roads, the intelligent barrier avoidance function plays an important role in improving traffic efficiency and ensuring driving safety. Scientific, reasonable, and comprehensive evaluation methods can provide the basis for intelligent vehicles before their use. The comprehensive evaluation index system is constructed for the avoidance ability and avoidance mode of intelligent vehicles against different barriers. The weights of qualitative indicators that are difficult to quantify are determined based on the order relation analysis (G1) method, and the weights of quantitative indicators are determined based on the CRITIC (criteria importance though intercriteria correlation) method. The overall system is comprehensively and quantitatively evaluated through the grey correlation degree method. The correctness of the evaluation method is verified via testing. According to the comprehensive evaluation method studied, the comprehensive evaluation result of the test vehicle is obtained. The intelligent barrier avoidance function of negative barriers is superior to that of positive barriers. The integrated evaluation method can obtain evaluation results of vehicle performance in different test scenarios.

Keywords: intelligent vehicles; intelligent barrier avoidance function; G1 method; CRITIC method; grey correlation degree method

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1. Introduction

The roads on which vehicles drive are generally divided into structured roads and unstructured roads. Structured roads refer to roads with clear road markings, a single environment, and distinct geometric features, such as highways and urban arteries. In a broad sense, structured roads can be understood as unobstructed road environments with flat ground and good visual effects for white line navigation. Unstructured roads refer to roads with unclear road boundaries, complex environments, and diverse road shapes that have a low degree of structural such as urban nonmain roads and rural streets. Compared with structured roads, unstructured roads also have the characteristics of exhibiting diverse types and states of barriers and surface coverage, as well as complex and variable road conditions, all of which increase the difficulty for intelligent vehicles to perceive the environment.

Vehicles have been developing in intelligent and directions. The testing and evaluation of intelligent vehicles are the basic guarantee to achieving the safe use of transport. According to the degree of interaction between the test environment and external traffic elements and the degree of test risk, the test and evaluation can be divided into four stages, including a closed-environment normative test, a closed-environment validation test, a limited open-environment validation test, and an open-environment demonstrative validation [1]. Closed-environment normative testing has the lowest degree of interaction and test risk compared to the other phases. The purpose of this test is to assess the performance of the vehicle by its performance in various aspects. This phase of testing does not allow access to other vehicles and related elements and is conducted in a dedicated closed environment. The test conditions are defined, the test methods, instruments and results are reproducible, and the test results are precise values of physical quantities. Closed-environment validation tests are also conducted in dedicated closed environments and require the performance of multiple tests to obtain probabilistic indicators. Part of the limited open-environment validation test allows other vehicles and related elements to enter and exit the area in order to evaluate the safety, reliability and other performance of the vehicle. Open-environment demonstration validation is conducted in a completely open real-traffic environment to improve the environmental synergy between the vehicle, the road, traffic facility equipment and other traffic participants. Although the scenarios, test methods, test results, and relative difficulty of the four phases are different, they are all essential and have means of providing technical guarantees of the safety, reliability, and use of intelligent vehicles.

At present, the research on the testing and evaluation system for intelligent vehicles in special roads is not perfect, and the intelligent barrier avoidance function of vehicles cannot be assessed. As one of the core functions of autonomous driving, the intelligent function of barrier avoidance plays an important role in improving traffic efficiency and ensuring driving safety. Therefore, establishing a scientific and reasonable comprehensive evaluation method for application to the vehicle intelligent barrier avoidance function under special roads is of great significance. Testing and evaluation before the actual use of the vehicle is of great significance in the process of verifying function and ensuring driving safety.

The premise of a comprehensive evaluation is to build an evaluation index system, and the selection of indexes should follow the principles of feasibility and scientific. Integrated evaluations are centered on obtaining the evaluation results of the subject through the use of the appropriate methodology. The process mainly includes calculating the index weight and establishing a comprehensive evaluation model. According to the source of data, the methods for calculating weights can be divided into three categories, including the subjective method, objective method, and combination weighting method [2]. According to the knowledge and experience of experts in the corresponding fields, the subjective method compares, assigns, and calculates the importance of the evaluation indicators to determine the weight. Examples include the analytical hierarchy process (AHP) [3], the expert survey method (Delphi) [4], and the order relationship analysis (G1) method [5]. Subjective weight depends too much on expert experience. The objective method uses mathematical methods to calculate weights according to the quantitative relationship between the initial data of indicators. Examples include principal component analysis [6], factor analysis [7], the entropy method [8], and the CRITIC (criteria importance though intercriteria correlation) method [9]. If the measured data are not typical and universal, there may be an unreasonable weight distribution. The combined weighting method combines the weights obtained using the subjective and objective methods according to different preference coefficients. It not only retains the information expression of expert experience and knowledge and the subjective intention of decision-makers in the subjective method, but it also retains the information of the internal relationship between indicators and evaluation objects in the objective method. It has the effect of offering complementary advantages, and the evaluation results are relatively more scientific and reasonable. The multiple evaluation indicators are synthesized into a whole comprehensive evaluation by establishing a comprehensive evaluation model. The main methods include the grey correlation method [10], TOPSIS (technique for order preference by similarity to an ideal solution) method [11], BP (back propagation) network [12], and fuzzy comprehensive evaluation method [13].

In terms of the evaluation of intelligent vehicles, Sun [14] built an evaluation index system from three aspects, namely, safety, intelligence, and ride comfort. Then, the author calculated the weight based on the EAHP (extended analytical hierarchy process) method, and comprehensively evaluated the intelligent behavior of driverless vehicles through gray correlation analysis. Zhao [15] established an evaluation index system based on typical working conditions, such as intersections and car following, and evaluated them through the entropy–cost function method. Although subjective factors were excluded, the system relied too much on the measured data and did not have universality. Huang [16] evaluated the overall performance of the driverless vehicle through the AHP–entropy method and fuzzy comprehensive evaluation. To avoid the complexity of the AHP calculation and the possibility of failing the consistency test, Li [17] analyzed the test content of the China Smart Car Future Challenge, built an evaluation index system from the four aspects of safety, systematicity, stability, and speed, and calculated the weight based on the G1 method and entropy method. The G1 method is an improved weighting method based on AHP that avoids the complex process of constructing judgment matrices and consistency checks. However, the entropy method ignores the internal relationship between indicators. CRITIC method has better applications in other comprehensive evaluation fields, such as power grid [18] and mining [19], compared with the entropy method, which considers the conflict and contrast degree of evaluation indicators. The driverless vehicle is in the development stage, and so the subjective assessment of experts cannot be excessively relied on in the function evaluation process. Additionally, the measured data of indicators cannot be completely relied on.

Firstly, this paper focuses on the closed-environment normative test, the evaluation object is the intelligent barrier avoidance function of the vehicle under special roads, and the performance of the function is evaluated by measuring the specific physical quantities of each index. For indicators that can obtain data, the CRITIC method of objective weighting is used to determine the weight. For qualitative indicators that are difficult to quantify, the G1 method is used to determine the weight in order to avoid the single influence of subjective and objective factors in the evaluation method. A complex evaluation index system can be regarded as a grey system. To reduce the influence of subjective factors in the final evaluation result, the grey correlation analysis method is chosen as the evaluation method, which provides a basis for the application of vehicles.

2. Materials and Methods

2.1. Construction of Evaluation Index System

2.1.1. Test Programs

In order to ensure the safe driving of intelligent vehicles on special roads, vehicles should have the ability to sense and identify the barriers in front of them. Additionally, they should be able to make decisions and perform actions such as bypassing, braking, and crossing according to the volume, location, and other characteristics of the barriers. Therefore, the test items should include positive and negative barrier-oriented perception and recognition ability, as well as intelligent barrier avoidance through detour, braking, and crossing.

1. Positive and negative barriers

Barriers are divided into positive barriers and negative barriers according to their vertical distance from the ground. Positive barriers refer to objects that are higher than the ground for a certain distance and hinder vehicle driving, while the phrase negative barriers refers to terrain that is lower than the ground for a certain distance and endangers vehicle driving. In unstructured roads, common positive barriers include rocks and trees, while common negative barriers include ditches, pits, and valleys. Different from positive barriers, negative barriers have high concealment and danger, and their identification is difficult. Failure in identification is likely to lead to accidents. Therefore, the test programs and evaluation system are first divided into the ability to avoid positive barriers and negative barriers.

2. Recognition and perception of barriers

The recognition and perception ability of intelligent vehicles with regard to barriers in intelligent driving is the premise and foundation of planning and implementing barrier avoidance functions. The evaluation is conducted using the minimum perceived distance and the maximum perceived distance. The vehicle is equipped in the no-load state in order to approach and stay away from barriers at the lowest speed of automatic driving to measure the perceived distance.

3. Intelligent barrier avoidance through detour

If the barriers on the front side occupy the current lane and the adjacent lanes allow space to continue to drive safely, the vehicle can avoid barriers through the detour. The vehicle starts from a standstill and approaches the barrier at a steady test speed. The test ends when the vehicle successfully changes lanes to overtake the barrier and returns to traveling in the original lane. If the distance between the vehicle and the barrier is less than the safe distance, the vehicle still fails to go around, or a collision occurs, the test ends. A schematic diagram of the test scenario is shown in Figure 1.

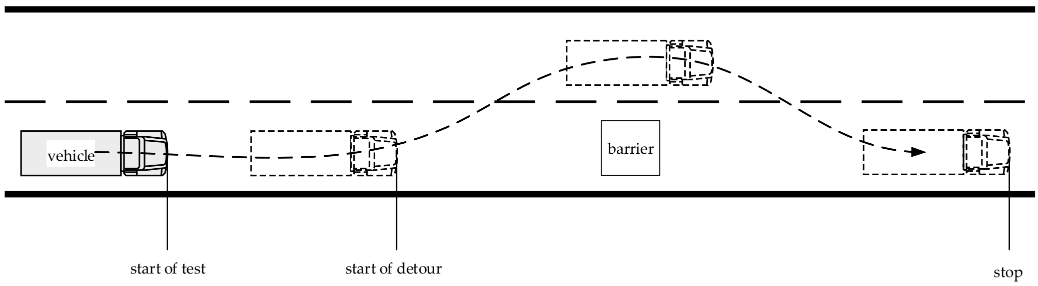

Figure 1. Test diagram of intelligent barrier avoidance through detour.

4. Intelligent barrier avoidance through braking

If the barriers completely occupy the driving space in front, the vehicle avoids the barriers by braking. The vehicle starts from a standstill and approaches the barrier at a steady test speed. The test ends when the vehicle successfully stops in front of the barrier. If the distance between the vehicle and the barrier is less than the safe distance and it still fails to brake, or if a collision occurs, then the test ends. A schematic diagram of the test scenario is shown in Figure 2.

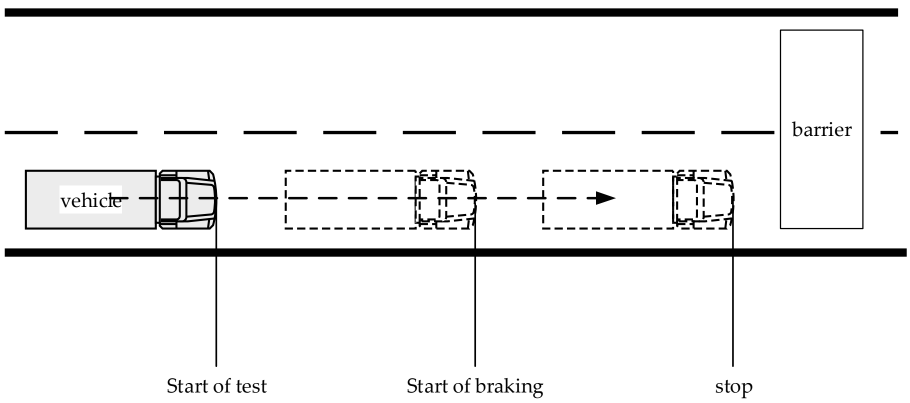

Figure 2. Test diagram of intelligent barrier avoidance through braking.

5. Intelligent barrier avoidance through crossing

If the height or depth of the current barrier allows crossing, then the vehicle can cross the barrier. The vehicle starts from a standstill and approaches the barrier at a steady test speed. The test ends when the vehicle successfully crosses the barrier or stops during the crossing. A schematic diagram of the test scenario is shown in Figure 3.

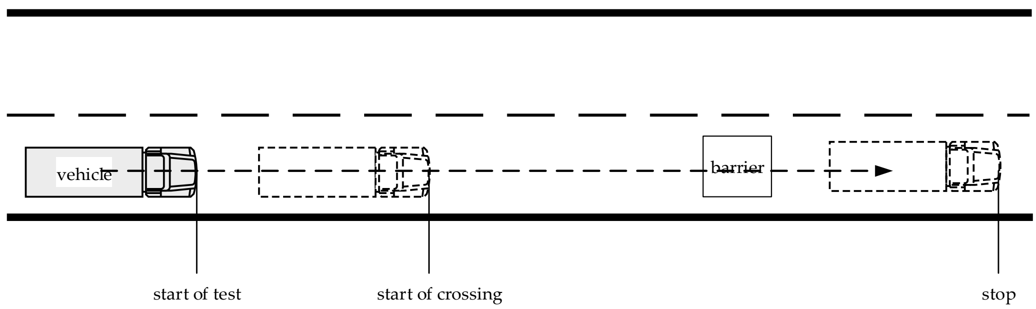

Figure 3. Test diagram of intelligent barrier avoidance through crossing.

2.1.2. Test Environment and Barriers

The test site is selected to be a two-lane straight road that is straight, dry, and has good adhesive ability. The site has a width of no less than 7 m and a length of approximately 200 m. The test environment will be dry, without rain and snow. The vehicle will be tested under the load conditions specified by the manufacturer, without any adjustments being made after the start of the test. Therefore, the influence of road surface, environment and other factors will not be considered in the test or evaluation.

In order to conduct a comprehensive evaluation of the intelligent barrier avoidance function of the vehicle under special road conditions, the size of the barriers is set according to functions such as braking, crossing, and detour when the vehicle is facing the barriers. By setting barriers of different sizes, the goal of accurately triggering the different intelligent barrier avoidance functions of the test vehicle is achieved during the test. The dimensions of the barriers used for testing and the corresponding test scenarios are shown in Table 1. The test vehicle was subjected to three trials under each test scenario.

Table 1. Types, sizes, and testing scenarios of barriers.

Type	Testing Scenario	Size (Length × Wide × High *)
Positive barriers	detour	1 m × 1 m × 1 m
	span	7.5 m × 0.3 m × 0.3 m
	brake	7.5 m × 0.5 m × 1 m
Negative barriers	detour	1.5 m × 1.5 m × −0.5 m
	span	7.5 m × 1.0 m × −0.3 m
	brake	7.5 m × 1.5 m × −0.5 m

* With regard to the dimensions of the height of the barrier, a positive number is used to indicate the height above the road surface, while a negative number is used to indicate the height below the road surface.

2.1.3. Evaluation Indicator System

The evaluation indicator system is a prerequisite for testing and evaluation. In order to ensure that the results of the comprehensive evaluation are comprehensive, scientific and accurate, the evaluation index system is constructed on the basis of the principles of safety, feasibility, systematicity and scientific quality, as shown in Table 2. The evaluation index system includes three levels. The subject of the evaluation is the intelligent barrier avoidance function of the vehicle. The function layer is the ability to avoid positive barriers and the function of avoiding negative barriers. The element layer corresponding to each functional layer includes four indicators, namely, the recognition and perception of barriers, and intelligent barrier avoidance through detour, braking, and crossing. The third level consists of specific evaluation indicators.

Table 2. Evaluation index system of intelligent barrier avoidance function.

Function (A)	Element (B)	Index (C)
avoid positive barriers (A1)	recognition and perception of barriers (B1)	minimum perceived distance (C1) maximum perceived distance (C2) perceptual speed (C3)
	intelligent barrier avoidance through detour (B2)	test speed (C4) maximum lateral acceleration (C5) longitudinal average acceleration (C6) detour distance (C7) maximum lateral offset (C8)
	intelligent barrier avoidance through braking (B3)	braking test speed (C9) TTC of the time of triggering braking (C10) braking distance (C11) distance from barriers when parking (C12) maximum braking acceleration (C13) average braking acceleration (C14) braking error test speed (C15) braking error rate (C16)
	intelligent barrier avoidance through crossing (B4)	test speed (C17) TTC of the time of trigger crossing (C18) crossing distance (C19) maximum longitudinal acceleration (C20) longitudinal average acceleration (C21) maximum pitch angle (C22) maximum vertical acceleration (C23) average speed of barrier crossing (C24)
avoid negative barriers (A2)	recognition and perception of barriers (B5)	minimum perceived distance (C25) maximum perceived distance (C26) perceptual speed (C27)
	intelligent barrier avoidance through detour (B6)	test speed (C28) maximum lateral acceleration (C29) longitudinal average acceleration (C30) detour distance (C31) maximum lateral offset (C32)
	intelligent barrier avoidance through braking (B7)	braking test speed (C33) TTC of the time of triggering braking (C34) braking distance (C35) distance from barriers when parking (C36) maximum braking acceleration (C37) average braking acceleration (C38) braking error test speed (C39) braking error rate (C40)
	intelligent barrier avoidance through crossing (B8)	test speed (C41) TTC of the time of trigger crossing (C42) crossing distance (C43) maximum longitudinal acceleration (C44) longitudinal average acceleration (C45) maximum pitch angle (C46) maximum vertical acceleration (C47) average speed of barrier crossing (C48)

2.2. Comprehensive Evaluation Method

2.2.1. G1 Method

1. Determine the order relationship between indicators

The new ranking of the original indicator set is determined by experts. If indicator x_a is important relative to x_b, then this is denoted as $x_a > x_b$. Based on this, a new order relationship is obtained.

2. Determine relative importance

The relative importance q_j between adjacent indicators is assigned based on Table 3, where q_j is the ratio of the weights of the two adjacent indicators, as shown in Formula (1).

$$q_j = \frac{w_{s(j-1)}}{w_{sj}}, \tag{1}$$

where $j = n, n-1, \cdots, 2$. n is the number of indicators at the corresponding level.

Table 3. Reference for assigning relative importance of adjacent indicators.

q_j	Meaning
1.0	*i* is as important as *j*
1.2	*i* is slightly more important than *j*
1.4	*i* is obviously more important than *j*
1.6	*i* is strongly more important than *j*
1.8	*i* is extremely more important than *j*

3. Calculation of subjective weights

The calculation formula for subjective weight w_{sj} is shown in Formula (2). According to the recursive relationship, the subjective weights of other indicators can be obtained, as shown in Formula (3).

$$w_{sj} = \left(1 + \sum_{j=2}^{n} \prod_{j=2}^{n} q_j\right)^{-1}, \tag{2}$$

$$w_{s(j-1)} = q_j w_{sj}, \tag{3}$$

where $j = n, n-1, \cdots, 2$.

2.2.2. CRITIC Method

The CRITIC method considers the conflict and contrast degree of evaluation indicators compared with the entropy method [20], That is, the weight is determined by calculating the standard deviation and correlation coefficient of evaluation indicators, which includes the following steps.

1. Dimensionless processing

Because the evaluation indicator units are different, and as positive indicators and negative indicators will appear in the evaluation process, dimensionless processing is required. Formula (4) is used for positive indicators with higher indicator values and Formula (5) is used for negative indicators with lower indicator values.

$$X_j = \frac{x_j - \min x}{\max x - \min x}, \tag{4}$$

$$X_j = \frac{\max x - x_j}{\max x - \min x}, \tag{5}$$

where x_j represents the j-th original measured data of index x, and X_j represents the dimensionless data of index x.

2. Calculation of the standard deviation of each index

$$\sigma_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(X_{ij}-\overline{X_j}\right)^2}, \tag{6}$$

where $\overline{X_j}$ is the average of the measured data of index x_j, and m is the quantity of the measured data of the index. σ_j is the standard deviation of the measured data of the index.

3. Establishment of correlation coefficient matrix

The correlation coefficient matrix Z of indicators of n is calculated as shown in Formula (7).

$$z_{ij} = \frac{\sum_{i=1}^{n}\left(X_i-\overline{X_i}\right)\left(X_j-\overline{X_j}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i-\overline{x_i}\right)^2\sum_{j=1}^{m}\left(x_j-\overline{x_j}\right)^2}}, \tag{7}$$

where z_{ij} is the linear correlation coefficient between index x_i and index x_j.

4. Calculation of the information amount

The formula for calculating the information content C_j of each indicator is shown in Formula (8).

$$C_j = \sigma_j\sum_{i=1}^{m}\left(1-z_{ij}\right), \tag{8}$$

where C_j is the amount of information contained in indicator x. The greater the amount of information is, the greater the role and weight of this indicator in the overall evaluation indicator system will be.

5. Calculation of weight

The calculation formula of objective weight w_{oj} is shown in Formula (9).

$$w_{oj} = \frac{C_j}{\sum_{j=1}^{n} C_j}. \tag{9}$$

2.2.3. Grey Correlation Degree Method

1. Determine evaluation indicators

List the values of various indicators for different test times or vehicles, assuming that there are n evaluation indicators in m tests, and obtain the evaluation matrix $(x_{ij})_{m\times n}$.

2. Determine reference sequence

Due to some test data errors in different tests of vehicles under the same test project, the sequence values of the reference sequence x_0 are composed of test conclusions for each indicator.

3. Dimensionless processing

Use the mean method to perform dimensionless processing on the values of each indicator.

$$X_i(j) = \frac{x_i(j)}{x_j}, \tag{10}$$

$$x_j = \frac{1}{m}\sum_{i=0}^{m} x_i(j), \tag{11}$$

where $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$. $x_i(j)$ is the j-th index value of the i-th test, x_j is the average value of the j-th indicator, and $X_i(j)$ is the dimensionless indicator value.

4. Calculate the correlation coefficient between the comparison sequence and the reference sequence

The correlation coefficient calculation between the comparison sequence and the reference sequence is shown in Formula (12).

$$\xi_i(j) = \frac{\min_i \min_j |X_0(j) - X_i(j)| + \rho \max_i \max_j |X_0(j) - X_i(j)|}{|X_0(j) - X_i(j)| + \rho \max_i \max_j |X_0(j) - X_i(j)|}, \tag{12}$$

where $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$. ρ is the resolution coefficient, taken between (0,1), and the resolution coefficient is generally taken as 0.5.

5. Calculate grey correlation degree

If the test is conducted multiple times on the same vehicle, the maximum correlation coefficient of different test times will be used as the correlation degree of the corresponding indicator γ_j, $j = 1, 2, \cdots, n$, which is the score of the indicator.

6. Calculate the score of multiple indicators

The weighted average of the correlation degree (indicator score) with the corresponding weights of the indicators is used to obtain the score of the upper-level indicator in the multi-layer indicators. If the evaluation index system has three or more layers, multiple calculations are performed until the highest-level index score is obtained.

$$E = \sum_{j=1}^{n} \gamma_j W_j. \tag{13}$$

3. Comprehensive Evaluation

The correctness of the comprehensive evaluation model for the intelligent barrier avoidance function of vehicles is verified under special road conditions based on test results, and the performance of the test sample vehicles in the test is evaluated comprehensively.

3.1. Indicator Weight

In the evaluation index system, the various indicators of the functional and element layers are not easily quantified directly, and so the G1 method is used to determine the weight of the indicators. The various indicators in the indicator layer can be quantified using numerical values, and the CRITIC method is used to determine the weight of the indicators.

3.1.1. G1 Method for Calculating Subjective Weights

Taking the element layer and indicator layer under A1 as an example on the basis of expert scoring, subjective weights are obtained using the G1 method. All indicators are reordered according to their importance, and the order relationship between the element layer and indicator layer under A1 is obtained. The relative importance between adjacent indicators in the indicator layer can be obtained according to the rational assignment method. The weight values corresponding to each indicator in the new sequence relationship can be calculated. And the results of the calculations are shown in Table 4.

Table 4. Subjective weights at the element and index levels under indicator A1.

q_j	Relative Importance of Adjacent Indicators	Subjective Weights Corresponding to Indicators
B1, B2, B4, B3	1.4, 1.2, 1.4	36.56%, 26.12%, 21.77%, 15.55%
C3, C2, C1	1.2, 1.4	41.18%, 34.31%, 24.51%
C5, C4, C6, C7, C8	1.4, 1.2, 1.2, 1	26.47%, 18.91%, 15.76%, 13.13%, 13.13%
C10, C9, C15, C13, C16, C11, C14, C12	1.4, 1, 1.2, 1, 1.2, 1.4, 1.2	20.99%, 14.99%, 14.99%, 12.49%, 12.49%, 10.41%, 7.44%, 6.20%
C18, C17, C20, C23, C22, C21, C24, C19	1.4, 1.2, 1, 1, 1.2, 1.2, 1	20.74%, 14.81%, 12.34%, 12.34%, 12.34%, 10.29%, 8.57%, 8.57%

The weights of indicators C25–C48 are the same as the above, while the weights corresponding to indicators A1, A2, A11, A12, C49, C50, and C51 at other levels are 54.55%, 45.45%, 45.45%, 54.55%, 34.31%, 41.18%, and 24.51%, respectively.

3.1.2. CRITIC Method for Calculating Objective Weights

Dimensionless processing is performed on the three experimental data points of the indicator layer. Positive indicators include C2, C3, C4, C9, C10, C11, C12, C15, C17, C18, and C21, while C1, C5, C6, C7, C8, C13, C14, C16, C19, C20, C22, C23, and C24 are negative indicators. The standard deviation and correlation coefficient of the indicators are calculated via the use of the CRITIC method to obtain the indicator layer weights, as shown in Tables 5–12.

Table 5. Calculation Results of CRITIC Weights for Indicator C1–C3.

Indicator	σ	z	C	w_o
C1	0.507	2.018	1.024	23.59%
C2	0.563	2.045	1.152	26.54%
C3	0.546	3.969	2.165	49.87%

Table 6. Calculation Results of CRITIC Weights for Indicator C4–C8.

Indicator	σ	z	C	w_o
C4	0.500	1.962	0.981	13.74%
C5	0.522	6.245	3.263	45.72%
C6	0.544	1.720	0.936	13.11%
C7	0.503	2.138	1.076	15.07%
C8	0.515	1.711	0.882	12.36%

Table 7. Calculation Results of CRITIC Weights for Indicator C9–C16.

Indicator	σ	z	C	w_o
C9	0.513	7.559	3.875	16.03%
C10	0.502	5.044	2.532	10.47%
C11	0.504	5.038	2.542	10.51%
C12	0.536	9.996	5.355	22.15%
C13	0.501	9.244	4.631	19.16%
C14	0.512	5.236	2.681	11.09%
C15	0.501	5.108	2.560	10.59%
C16	0.000	7.000	0.000	0.00%

Table 8. Calculation Results of CRITIC Weights for Indicator C17–C24.

Indicator	σ	z	C	w_o
C17	0.519	6.294	3.265	10.62%
C18	0.502	8.920	4.481	14.58%
C19	0.545	5.732	3.124	10.17%
C20	0.549	10.251	5.625	18.30%
C21	0.541	8.470	4.585	14.92%
C22	0.503	6.383	3.211	10.45%
C23	0.571	5.758	3.286	10.69%
C24	0.549	5.749	3.154	10.26%

Table 9. Calculation Results of CRITIC Weights for Indicator C25–C26.

Indicator	σ	**z**	**C**	w_o
C25	0.000	2.000	0.000	0.00%
C26	0.506	1.775	0.899	47.64%
C27	0.556	1.775	0.988	52.36%

Table 10. Calculation Results of CRITIC Weights for Indicator C28–C32.

Indicator	σ	z	C	w_o
C28	0.548	2.321	1.271	14.04%
C29	0.503	2.189	1.100	12.16%
C30	0.540	7.247	3.915	43.27%
C31	0.566	2.940	1.665	18.40%
C32	0.508	2.159	1.097	12.13%

Table 11. Calculation Results of CRITIC Weights for Indicator C33–C40.

Indicator	σ	**z**	**C**	w_o
C33	0.512	6.527	3.342	12.21%
C34	0.501	6.505	3.261	11.92%
C35	0.529	6.123	3.240	11.84%
C36	0.521	9.809	5.115	18.69%
C37	0.501	6.483	3.247	11.86%
C38	0.575	9.033	5.193	18.97%
C39	0.500	7.938	3.971	14.51%
C40	0.000	7.000	0.000	0.00%

Table 12. Calculation Results of CRITIC Weights for Indicator C41–C48.

Indicator	σ	**z**	**C**	w_o
C41	0.553	8.067	4.459	13.64%
C42	0.500	7.097	3.550	10.86%
C43	0.536	9.477	5.076	15.53%
C44	0.507	7.501	3.803	11.64%
C45	0.537	6.478	3.478	10.64%
C46	0.548	6.505	3.564	10.91%
C47	0.548	7.901	4.327	13.24%
C48	0.528	8.383	4.423	13.54%

Among the weights of various indicators, the weights of C16, C25, and C40 are 0, and the three test data points of C16 and C40 are all 0 and meet the test requirements, making it impossible to obtain relevant information about the indicators from the data. In this research, C25 did not undergo the minimum perception distance test and there was no data record. However, this does not mean that these three indicators are not important. Compared to other indicators at the same level, the weights of C5 and C40 are too high. The observation of experimental data reveals abnormal data, and the above indicators need to be corrected in conjunction with subjective weights.

3.1.3. Calculate Combination Weights

Combining the subjective and objective weights of the indicator layer to correct incorrect test data and information that cannot be reflected in the data, while also reducing the impact of subjective factors, obtains the combined weight. The weights of other levels of indicators are subjective, and the final weights of the indicator layer are shown in Table 13.

Table 13. Indicator layer weight.

Indicator	w_s	w_o	W
C1	24.51%	23.59%	24.05%
C2	34.31%	26.54%	30.43%
C3	41.18%	49.87%	45.53%
C4	18.91%	13.74%	16.33%
C5	26.47%	45.72%	36.10%
C6	15.76%	13.11%	14.44%
C7	13.13%	15.07%	14.10%
C8	13.13%	12.36%	12.75%
C9	14.99%	16.03%	15.51%
C10	20.99%	10.47%	15.73%
C11	10.41%	10.51%	10.46%
C12	6.20%	22.15%	14.18%
C13	12.49%	19.16%	15.83%
C14	7.44%	11.09%	9.27%
C15	14.99%	10.59%	12.79%
C16	12.49%	0.00%	6.25%
C17	14.81%	10.62%	12.72%
C18	20.74%	14.58%	17.66%
C19	8.57%	10.17%	9.37%
C20	12.34%	18.30%	15.32%
C21	10.29%	14.92%	12.61%
C22	12.34%	10.45%	11.40%
C23	12.34%	10.69%	11.52%
C24	8.57%	10.26%	9.42%
C25	24.51%	0.00%	12.26%
C26	34.31%	47.64%	40.98%
C27	41.18%	52.36%	46.77%
C28	18.91%	14.04%	16.48%
C29	26.47%	12.16%	19.32%
C30	15.76%	43.27%	29.52%
C31	13.13%	18.40%	15.77%
C32	13.13%	12.13%	12.63%
C33	14.99%	12.21%	13.60%
C34	20.99%	11.92%	16.46%
C35	10.41%	11.84%	11.13%
C36	6.20%	18.69%	12.45%
C37	12.49%	11.86%	12.18%
C38	7.44%	18.97%	13.21%
C39	14.99%	14.51%	14.75%
C40	12.49%	0.00%	6.25%
C41	14.81%	13.64%	14.23%
C42	20.74%	10.86%	15.80%
C43	8.57%	15.53%	12.05%
C44	12.34%	11.64%	11.99%
C45	10.29%	10.64%	10.47%
C46	12.34%	10.91%	11.63%
C47	12.34%	13.24%	12.79%
C48	8.57%	13.54%	11.06%

3.2. Comprehensive Evaluation of Grey Correlation Degree

Using the test conclusions (mean) from three sets of test data as a reference sequence, the correlation coefficient is calculated. The calculation results of indicator layer indicators C1–C48 are shown in Tables 14–21. Among them, the indicator C25 for intelligent driving towards negative barriers was not tested for minimum distance and had no test data, as it was synchronized with the barrier avoidance test. When calculating the correlation coefficient, the C25 value was not substituted and was directly set to 1.

Table 14. Correlation coefficient results for Indicator C1–C3.

Indicator	Test 1	Test 2	Test 3	γ_j
C1	1.000	0.446	0.506	1.000
C2	0.707	0.351	0.403	0.707
C3	0.683	0.642	0.686	0.686

Table 15. Correlation coefficient results for Indicator C4–C8.

Indicator	Test 1	Test 2	Test 3	γ_j
C4	0.824	0.335	0.492	0.944
C5	0.435	1.000	0.859	0.667
C6	0.998	0.949	0.986	1.000
C7	0.503	0.459	0.468	0.520
C8	0.913	0.570	0.924	0.823

Table 16. Correlation coefficient results for Indicator C9–C16.

Indicator	Test 1	Test 2	Test 3	γ_j
C9	0.862	0.665	0.659	0.687
C10	0.910	0.333	0.485	0.814
C11	0.932	0.875	0.911	0.927
C12	0.886	0.606	0.914	0.861
C13	0.980	0.927	0.938	0.976
C14	0.998	0.886	0.961	0.977
C15	0.913	0.561	0.695	0.983
C16	1.000	1.000	1.000	1.000

Table 17. Correlation coefficient results for Indicator C17–C24.

Indicator	Test 1	Test 2	Test 3	γ_j
C17	0.891	0.978	0.670	0.857
C18	0.719	0.420	0.333	0.629
C19	0.576	0.453	0.517	0.967
C20	0.988	0.998	0.923	0.972
C21	0.882	1.000	0.959	0.960
C22	0.973	0.881	0.832	0.901
C23	0.961	0.974	0.861	1.000
C24	0.994	0.964	0.857	0.980

Table 18. Correlation coefficient results for Indicator C25–C26.

Indicator	Test 1	Test 2	Test 3	γ_j
C25	1.000	1.000	1.000	1.000
C26	0.911	1	0.732	1.000
C27	0.911	1	0.732	1.000

Table 19. Correlation coefficient results for Indicator C28–C32.

Indicator	Test 1	Test 2	Test 3	γ_j
C28	0.987	0.450	0.428	1.000
C29	1.000	0.843	0.886	0.987
C30	0.997	0.962	0.961	0.998
C31	0.998	0.338	0.334	0.919
C32	0.998	0.665	0.674	0.986

Table 20. Correlation coefficient results for Indicator C33–C40.

Indicator	Test 1	Test 2	Test 3	γ_j
C33	0.782	0.908	0.589	0.897
C34	0.825	0.537	0.446	0.734
C35	0.821	0.931	0.333	0.576
C36	0.902	0.851	0.702	0.813
C37	0.974	0.570	0.402	0.994
C38	0.976	0.997	0.989	1.000
C39	0.857	0.905	0.611	0.889
C40	1.000	1.000	1.000	1.000

Table 21. Correlation coefficient results for Indicator C41–C48.

Indicator	Test 1	Test 2	Test 3	γ_j
C41	0.716	0.521	0.579	0.979
C42	0.513	0.657	0.834	1.000
C43	0.576	0.413	0.334	0.580
C44	0.946	0.958	0.941	0.991
C45	0.812	1.000	0.971	0.966
C46	0.742	0.921	0.837	0.927
C47	0.729	0.899	0.347	0.738
C48	0.943	0.791	0.428	0.769

According to the scores and weights of various indicators, the comprehensive scores of each level under the percentage system are calculated in sequence, as shown in Table 22.

Table 22. Comprehensive evaluation results of intelligent barrier avoidance function of the test vehicle.

Target	Function (A)	Score	Element (B)	Score
intelligent barrier avoidance function	A1	79.99	B1	76.79
			B2	71.74
			B3	88.68
			B4	89.07
	A2	92.9	B5	100.00
			B6	91.94
			B7	85.47
			B8	87.42

4. Discussion

The comprehensive evaluation score clearly reflects the overall situation of the intelligent barrier avoidance function of the test vehicle and the differences in each specific function. The overall score for the intelligent barrier avoidance function of the test vehicle under special roads is 87.03, and some of the functions of this vehicle can still be improved. The intelligent barrier avoidance function of the test vehicle facing negative barriers has a higher score than that facing positive barriers. This indicates that in the same scenario, the test vehicle's ability to avoid negative barriers is better than its ability to avoid positive barriers. The difference between the two scores may be influenced by the test data, with some indicators scoring too high and subjective weights only partially corrected. Among the intelligent barrier avoidance functions facing positive barriers, the score of the intelligent barrier crossing function is the best, being significantly superior to that of detour. In the intelligent barrier avoidance function for negative barriers, the ability to recognize and perceive barriers and the intelligent barrier avoidance function through detour are superior to those of braking and crossing. The scores of each function can reflect the functional differences in the same scene, providing a targeted basis for improving the intelligent barrier avoidance function of the test vehicle.

The test evaluation in this paper only verifies the correctness and validity of the proposed method. Due to the limitation of the number of test samples, the test results (mean values) are selected as the reference sequence in the comprehensive evaluation study, which cannot further evaluate the advantages and disadvantages of vehicle functions. In subsequent research, the law of the test results can be studied through multiple-vehicle tests to obtain the optimal limit value of each index, and a more reasonable reference sequence can be set accordingly. Along these lines, further research on the evaluation score of the advantages and disadvantages of the interval can be used as the basis for the comprehensive evaluation. The evaluation method can then be applied to compare the functional advantages and disadvantages of different vehicles.

5. Conclusions

To comprehensively evaluate the intelligent barrier avoidance function of vehicles under special road conditions, a complete evaluation index system for this function was first constructed. Then, based on the G1 method and CRITIC method, the weights of the indexes were calculated in a hierarchical manner and the grey correlation degree comprehensive evaluation model was established. Finally, it was validated by the test data of the vehicle when tested on special roads. The results indicate that the comprehensive evaluation method studied in this paper can provide reasonable evaluation results for the intelligent barrier avoidance function of vehicles, and the evaluation results can provide a basis for the improvement and application of intelligent vehicles.

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