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Research on the Quantitative Evaluation of the Traffic Environment Complexity for Unmanned Vehicles in Urban Roads

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ABSTRACT The primary goal of the paper is to explore the human-vehicle-road interaction mechanism in the traffic environment and evaluate the traffic environment complexity for unmanned vehicles in urban roads. In particular, we propose the quantitative evaluation models of the traffic environment complexity for unmanned vehicles in urban roads in the paper. Specifically, the structure system of the complex traffic environment in urban roads is dissected from the aspect of human-vehicle-road, laying the basis for proposing influencing factors of traffic environment complexity. We divide the complex traffic environment into the static traffic environment and the dynamic traffic environment in light of relative static and dynamic characteristics of various environmental elements. For the complexity of the static traffic environment, the quantitative evaluation model is established by the grey relation analysis method that converts static environment complexity into the relation degree of static complexity's influencing factors. For the complexity of the dynamic traffic environment, the quantitative evaluation model is established based on the improved gravitation model that introduces the concepts of equivalent mass and the contribution degree of the unmanned vehicles' driving strategy. Besides, we evaluate the traffic environment complexity in the designed scenario by quantitative models proposed in the paper and existing evaluation models of traffic environment complexity in urban roads. The calculating process and results show that the proposed quantitative models of traffic environment complexity are more convenient and more reasonable, which provide a new idea and a method to evaluate the traffic environment complexity.

INDEX TERMS Traffic environment complexity, unmanned vehicles, quantitative evaluation model, static traffic environment, dynamic traffic environment.

I. INTRODUCTION

The unmanned vehicle is the product of the in-depth integration of the automotive industry with new-generation information technologies such as artificial intelligence, Internet of Things, and high-performance computing. In recent years, it has been the main direction for the development of intelligence and network connectivity in the global automotive industry and transportation fields, which is expected to achieve in public roads within a few years [1]–[3]. Unmanned vehicles are always in a complex traffic environment from R&D, production access to the testing process. For unmanned vehicles, the complex traffic environment affects the entire driving working process, including environment perception, planning decision, and control execution. The traffic environment complexity reflects the influencing degree of the complex traffic environment on unmanned vehicles. Therefore, it is necessary to analyse the complex traffic environment and quantify the traffic environment complexity for unmanned vehicles. Moreover, it is of great significance to research on the quantitative evaluation of the traffic environment complexity in urban roads for the design and specifications of the test environment, traffic command and control, and road traffic safety [4], [5].

The American National Institute of Standards and Technology proposed and established the ALFUS framework for the autonomous level of unmanned systems in 2003, which comprehensively evaluated and classified various unmanned

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systems (including unmanned vehicles). The ALFUS framework regarded the environment complexity as one of the three crucial factors that also included task complexity and human-computer interaction degree. Moreover, the environment complexity was quantitatively classified as a simple environmental condition, a medium environmental condition, a complex environmental condition, and an extreme environmental condition [6], [7]. Some researchers mainly discuss the influence of the complex traffic environment on drivers in terms of research on the traffic environment complexity. In [8]–[11], researchers designed the traffic environments with different traffic parameters in the simulated environments. They carried out the driving tests in order to study the relationship among the workload, the mental load of drivers, and traffic environment complexity. Oviedo-Trespalacios *et al.* [12], Ma *et al.* [13] designed distracted driving tests for drivers in different traffic environments to explore the relationship between distracted drivers and different traffic conditions. Aiming at researching the interaction methods and behaviours between drivers and vehicles, Li [14] designed three early warning modes from the aspects of vision, touch, and hearing, and investigated the driver's subjective experience. From the perspective of driving comfort and safety, Liu [15] established an evaluation index system that is used to evaluate the influence of the roadside environment on driving behaviours.

Some researchers have conducted quantitative research on the traffic environment complexity. According to the analysis method of road roughness and the principle of Analytic Hierarchy Process, Zhao *et al.* [16], [17] proposed a new road-feature-based multi-parameter road complexity calculation model of the off-road environment which regarded three-dimensional scale, average slope, and adhesion characteristics of travelable area as road indicators. Based on the analysis of the combat environment in the new version of the US Army's ''Outline of Operations'', Li *et al.* [18] defined the typical working environment of unmanned vehicles in rural areas. They divided the environment complexity into six evaluation aspects, including road environment, obstacles in the lane, road coverage, road damage, light and shadow, and imaging blur. They also established an evaluation index system of the typical environment complexity in rural areas. For urban roads, some studies [19]–[23] divided the urban traffic environment into the static environment and the dynamic environment roughly, and they proposed the calculation model of urban environment complexity to quantify the complexity of urban traffic environment based on information entropy. However, the model ignored the variability and diversity of participants in the traffic environment. Fan [24] described the concept of complexity factors and established a conceptual model of the complexity of the dynamic traffic environment based on time to collision. Zhang [25] considered the development of complexity theory in the field of the airspace traffic environment and put forward the evaluation method by using the parameters of the traffic environment. Meanwhile, he established model of the complexity of the dynamic traffic environment based on the gravitation model that regarded the relative speed and the relative distance as parameters. However, he did not give a clear description of some parameters.

In summary, researchers have less research on the quantitative models of traffic environment complexity for unmanned vehicles. Primary problems in the research on the complex traffic environment contain the incomplete consideration of complex traffic environment's influencing on driving, lack of expression on the interaction and dynamic changes about the traffic environment and vehicle status, and ambiguous description on the interaction mechanism among human, vehicles and roads. These problems limit the practical application of quantitative models. In the actual unmanned driving environment, the traffic environment composes of multiple elements, but the influence of multiple elements is not a simple addition of each element's influence. Hence, we must use scientific methods to judge the complexity level of the traffic environment.

To deal with the abovementioned problems, the quantitative evaluation model of the traffic environment complexity for unmanned vehicles in urban roads is studied in the paper. The main contribution of the paper is summarised below. Firstly, in order to consider the influence of complex traffic environment on unmanned driving comprehensively, the structure system of the complex traffic environment in urban roads is dissected from the aspect of human-vehicle-road. According to relative static and dynamic characteristics of various environmental elements, the complex traffic environment contains the static traffic environment and the dynamic traffic environment. Secondly, we propose influencing factors of the static environment complexity in light of the static traffic environment's composition. Since the static environment complexity reflects in the relation degree of static complexity's influencing factors, the quantitative model of the complexity of the static traffic environment for unmanned vehicles is established by the grey relation analysis method to describe the influence of static environment on unmanned vehicles clearly. Thirdly, we propose influencing factors of the dynamic environment complexity in light of the dynamic traffic environment's composition. The quantitative model of complexity of the dynamic traffic environment is established based on the improved gravitation model to express the temporal and spatial variation characteristics of dynamic elements, which introduces the concepts of equivalent mass and contribution degree of the unmanned vehicles' driving strategy. Finally, the proposed quantitative models are compared with some existing evaluation models of urban traffic environment complexity in a designed scenario to verify the proposed quantitative models.

II. STRUCTURE SYSTEM OF THE COMPLEX TRAFFIC ENVIRONMENT FOR UNMANNED VEHICLES IN URBAN ROADS

The complex traffic environment for unmanned vehicles in urban roads composes of various environmental elements, such as traffic lights, signs, markings, vehicles, and pedestrians. According to relative static and dynamic characteristics and meaning attributes of environmental elements, environmental elements is classified as static elements and dynamic elements. Different from that of the traditional traffic environment (including the driving environment, the meaningful traffic environment, and the social traffic environment), the classification of the complex traffic environment in the paper includes the static traffic environment and the dynamic traffic environment. Static elements refer to regional environmental elements without position movement or status change within a certain time, such as road types, buildings, and weather. They constitute a static traffic environment. Dynamic elements refer to all the moving elements that may affect the driving behaviour of unmanned vehicles, such as same-lane vehicles and roadside pedestrians. They constitute a dynamic traffic environment.

A. STATIC TRAFFIC ENVIRONMENT IN URBAN ROADS

The static traffic environment of unmanned vehicles in urban roads has the characteristics that do not alter under certain conditions. The composition of the static traffic environment for unmanned vehicles in urban roads is visible in Fig. 1.

Road conditions are the core content of the static traffic environment in urban roads, which consist of road sections, intersections, tunnels, bridges and culverts. Road sections include straight sections, turning sections and road grades. According to "Technical code for urban road engineering" [26], road grades include express roads, arterial roads, sub-arterial roads, and access roads. Intersections contain grade crossings and interchanges. The types of grade crossings include cross-shaped crossings, T-shaped crossings, roundabouts and other types. Interchanges include hub interchanges, general interchanges, and separated interchanges.

Traffic facilities are hardware facilities in the static traffic environment. Traffic facilities consist of traffic signals and traffic safety facilities on the ground of "Code for design of urban road traffic facilities" [27]. To be specific, traffic signals contain traffic lights, traffic signs, and traffic markings. Traffic signs include indication signs, prohibition signs, warning signs, guide signs, and tourist area signs. Traffic markings mainly include indication markings, prohibition markings and warning markings. Generally, traffic safety facilities include safety fences, isolation facilities, anti-glare facilities, and induction facilities.

The surrounding scenes of the road consist of roadside buildings, plants, and topography that contains plains, basins, plateaus, mountainous regions, and hills. As for unmanned vehicles, climate conditions primarily make a difference to perception and visibility of sensors and slippery road conditions, thereby affecting unmanned driving. Climate conditions consist of day, night, and weather which includes sunny days, rain, snow, fog, etc.

The electromagnetic environment becomes more and more complex with the wide application of a large number of frequency devices. Unmanned vehicles are equipped with plenty of sensors, and they connect and exchange data with pedestrians, vehicles, and roads through wireless signals. The electrical and electronic systems of unmanned vehicles and wireless communication are very likely to be affected by the surrounding electromagnetic environment.

B. DYNAMIC TRAFFIC ENVIRONMENT IN URBAN ROADS

The dynamic traffic environment in urban roads mainly refers to vehicles and pedestrians in an urban traffic environment. The composition of the dynamic traffic environment for unmanned vehicles in urban roads is visible in Fig. 2.

According to "Technical specifications for power-driven vehicles operating on roads" [28], power-driven vehicles contain automobiles, motorcycles, trailers, wheeled mobile machinery for special purpose, and tractor transport units. Non-power-driven vehicles include bicycles, tricycles, electric bicycles, animal-powered vehicles, and motoriszed wheelchairs for the disabled on the ground of "Traffic Safety Law". Pedestrians consist of children, young men, young women, the elderly and pregnant women in light of their age, physical characteristics, and cognitive ability of traffic [29].

III. QUANTITATIVE EVALUATION MODEL OF THE TRAFFIC ENVIRONMENT COMPLEXITY

The traffic environment complexity is the description and evaluation of the surrounding environment in the driving process of unmanned vehicles. It is closely related to the traffic environment, which is a physical parameter for evaluating the influencing degree of the traffic environment on unmanned vehicles. From the perspective of the inherent influencing factors that lead to the complexity of the traffic environment, the establishment of an evaluation model for the traffic environment complexity is a bridge to study the interaction between the participants and the traffic environment where participants locate. The working process of an unmanned vehicle, including environment perception, planning decision, and control execution, is finished by the unmanned driving system itself. In fact, the whole working process of unmanned driving is similar to that of manual driving. Therefore, we study the influencing factors of traffic environment complexity for unmanned vehicles from the perspective similar to manual driving. In manual driving, the complex traffic environment affects the driver's psychology. However, we do not need to take into account the influence of the static traffic environment on the driver's psychology in unmanned driving. The complex traffic environment in urban roads composes of the static traffic environment and the dynamic traffic environment. Thus, the traffic environment complexity for unmanned vehicles in urban roads also composes of two parts in the paper.

A. QUANTITATIVE MODEL OF COMPLEXITY OF THE STATIC TRAFFIC ENVIRONMENT

The complexity of the static traffic environment results from the relation degree of influencing factors of the static environment complexity. Hence, the grey relation analysis method

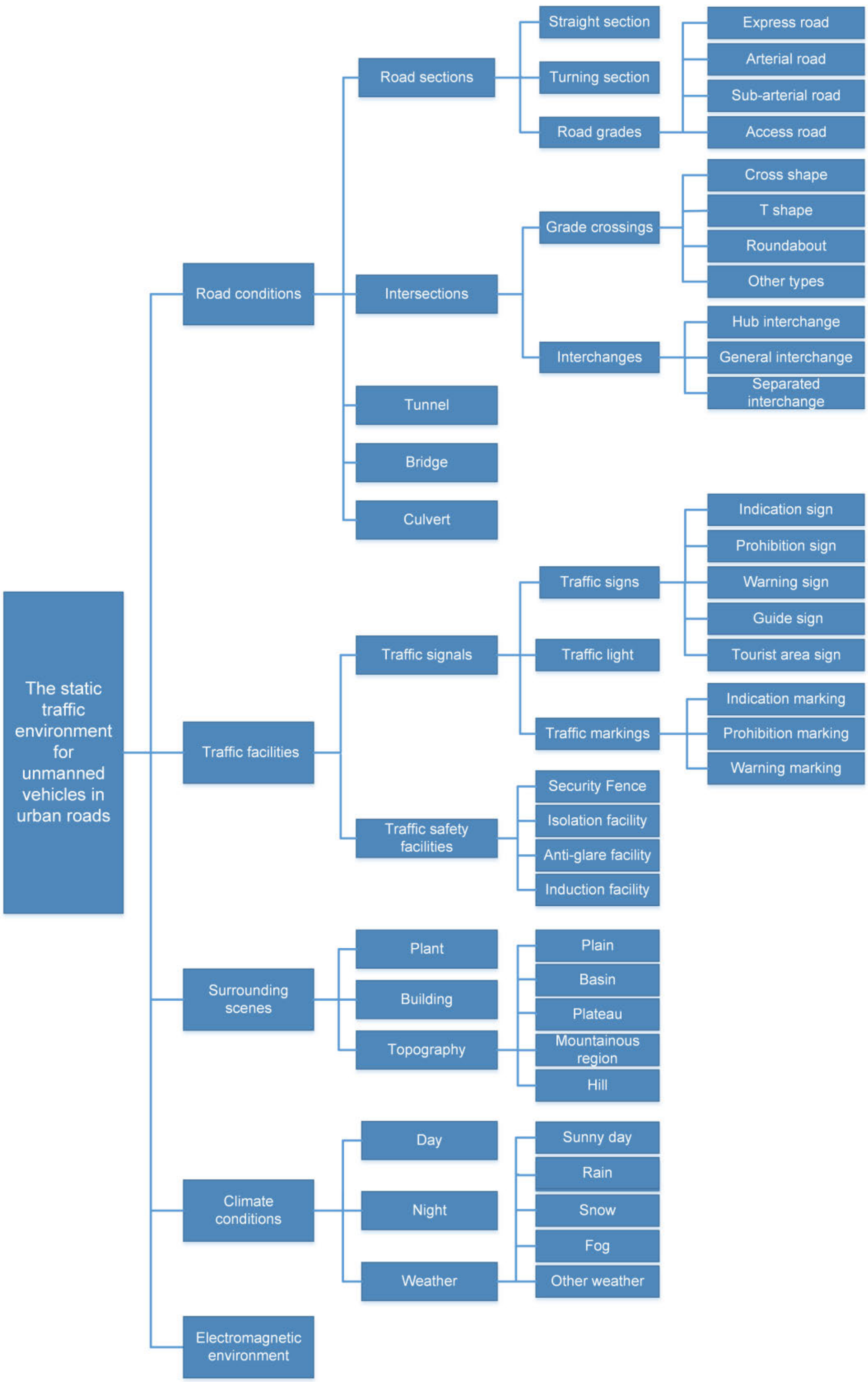

FIGURE 1. **Composition of the static traffic environment for unmanned vehicles in urban roads.**

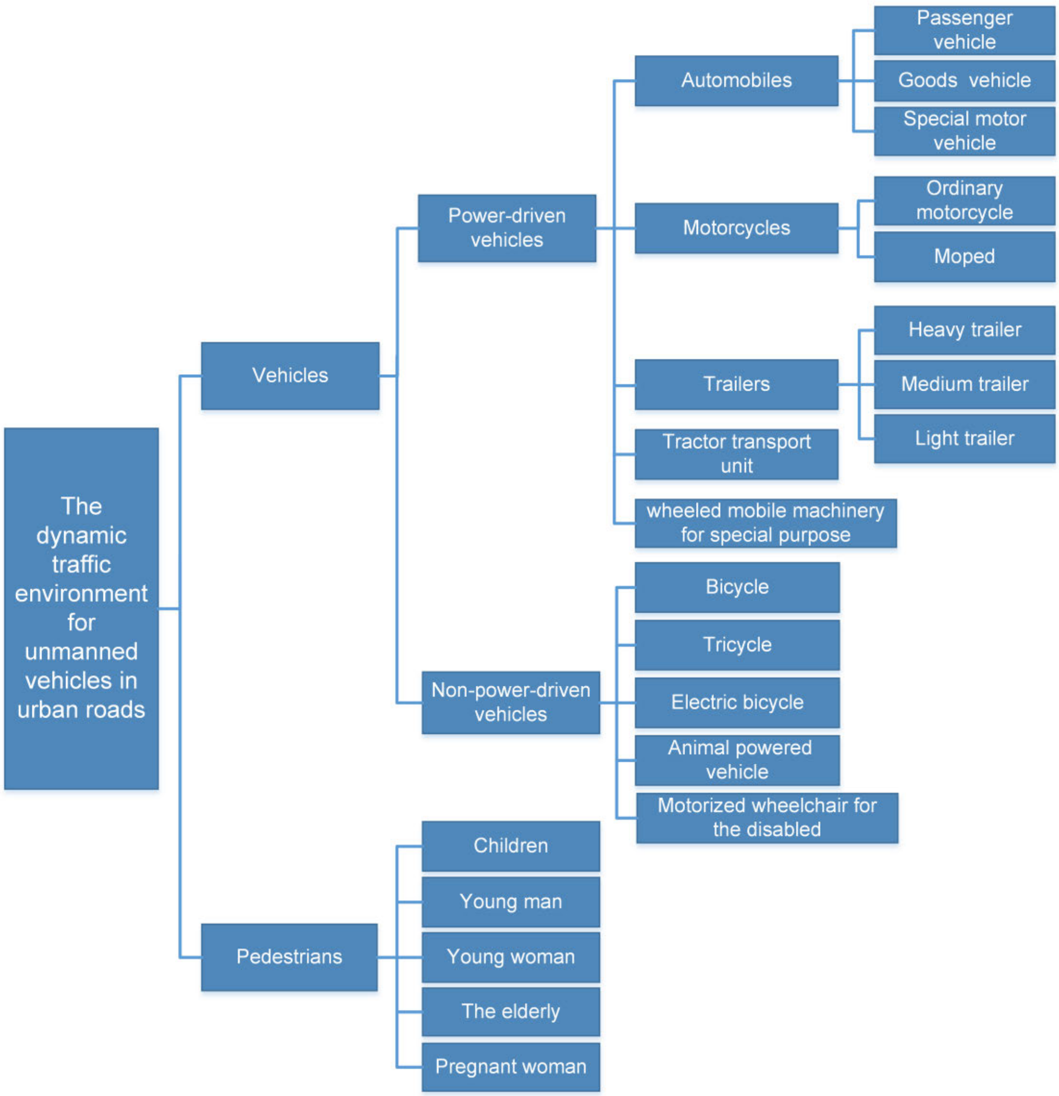

FIGURE 2. **Composition of the dynamic traffic environment for unmanned vehicles in urban roads.**

can be used to establish a quantitative model of complexity of the static traffic environment for unmanned vehicles in urban roads to evaluate the static traffic environment.

1) INFLUENCING FACTORS OF STATIC ENVIRONMENT COMPLEXITY

The influencing factor of the static environment complexity refers to the factor that has some influence on the complexity of the static traffic environment. The static elements primarily affect environment perception and friction coefficients for unmanned vehicles in urban roads.

According to the composition of static environmental elements, the influencing factors of the static environment complexity are shown in Table 1.

2) GREY RELATION ANALYSIS

The grey system theory is a new theory created by Professor Julong Deng for the analysis of the grey system patterns with unclear information in the field of control [30], [31]. The grey relation analysis process based on the grey system is a process of sequence comparison on the foundation of the grey and uncertainty between factors' interaction. The relation degree reflects the relationship between factors in the light of factors' sample data. The grey relation analysis combines qualitative analysis and quantitative analysis in systems, and there will be no inconsistency between qualitative results and quantitative results obtained by the grey relation analysis method. At the same time, the grey relation analysis method does not restrict the number of samples. It is very suitable for the situation that information is incomplete.

The basic principle is that the degree of data's changes by comparing each sequence with the reference sequence is applied to judge the influence of each factor on the reference sequence. Since the relation degree is the relevance degree between factors of the comparison sequence and the reference sequence, it has more than one value. The information

TABLE 1. Influencing factors of static environment complexity.

Influencing factors of static environment complexity	Description
Road grades	Express road, arterial road, sub-arterial road, access road
Road surfaces	Dry, wet, iced
Pavement structures	Asphalt, non-asphalt
Road alignment	Linear, non-linear
Road types	Road sections, intersections, tunnel, bridge, culvert
Traffic facilities	Signs, markings, signal lights
Illuminance	Day, night
Weather conditions	Sunny day, rain, snow, fog
Topographic features	Plain, basin, plateau, mountainous region, hill
Surrounding scenes	Building, plant
Electromagnetic signals	Interference of surrounding electromagnetic signals

which the relation degree involves is too scattered to facilitate overall comparison. Therefore, it is necessary to concentrate these values of relation degree into one value, that is, the average value as the quantitative expression of the relation degree between the comparison sequence and the reference sequence. The complexity of the static traffic environment is the result of interaction among many influencing factors which interact uncertainly and complicatedly, so the relation degree between the influencing factors of the static environment complexity is able to show the complexity of the static traffic environment. The greater the relation degree is, the greater the complexity will be, and vice versa.

3) MODEL CONSTRUCTION

We construct the quantitative model of the complexity of the static traffic environment for unmanned vehicles by the grey relation analysis method. Specific steps are as follows.

a: DETERMINATION OF THE COMPARISON SEQUENCE

The influencing factors of static environment complexity contain road grades, road surfaces, pavement structures, road alignment, road types, traffic facilities, illuminance, weather conditions, topographic features, surrounding scenes, and electromagnetic signals. Those influencing factors compose the comparison sequence, and attribute values of each influencing factor are assigned by using expert scoring.

b: DIMENSIONLESS PROCESSING

According to different attributes of influencing factors, influencing factors are divided into "positive" indicators and "negative" indicators. The greater attribute values of positive indicators are, the greater their influence will be. The dimensionless processing of the *jth* positive indicators is given as:

$$y_j = \frac{x_j - \min x_j}{\max x_j - \min x_j} \tag{1}$$

where x_j is the value of this influencing factor, j is the serial number of the influencing factor and $j = 1, 2, \ldots, $ n.

The smaller attribute values of negative indicators, the smaller their influence will be. The dimensionless processing of the *jth* negative indicators is given as:

$$y_j = \frac{\max x_j - x_j}{\max x_j - \min x_j} \tag{2}$$

The range of influencing factors' attribute values is [0, 1] through dimensionless processing.

c: CALCULATION OF THE RELATION DEGREE

The relation degree is calculated as:

$$c_j = \frac{\min_j \left|y_j - Y^+\right| + \varepsilon \max_j \left|y_j - Y^+\right|}{\left|y_j - Y^+\right| + \varepsilon \max_j \left|y_j - Y^+\right|} \tag{3}$$

$$Y^+ = \max_{1 \le j \le n} y_j \tag{4}$$

where c_j is the relation degree, ε is the resolution coefficient, and Y^+ is the ideal optimal reference sequence. The smaller ε is, the greater the discernibility and difference between relation degrees will be. Usually, ε is 0.5. In the paper, $Y^+ = [1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1]$. It means that complexity of the static traffic environment reaches to maximum when both attribute values of influencing factors are 1.

d: QUANTIFICATION OF THE COMPLEXITY OF THE STATIC TRAFFIC ENVIRONMENT

Based on the grey relation analysis method, the complexity of the static traffic environment is calculated as:

$$C_s = 1/n \sum_{j=1}^{j=n} c_j \tag{5}$$

where C_s is the complexity value of the static traffic environment for unmanned vehicles.

After completing the steps above, we can achieve the quantitative evaluation of complexity of the static traffic environment.

B. QUANTITATIVE MODEL OF COMPLEXITY OF THE DYNAMIC TRAFFIC ENVIRONMENT

The gravitation model is a spatial interaction model, which researchers mainly apply in predicting and analysing spatial interaction. The complexity of the dynamic traffic environment is a function of time and space, so we employ the gravitation model to describe the complexity of the dynamic traffic environment for unmanned vehicles in urban roads.

1) INFLUENCING FACTORS OF DYNAMIC ENVIRONMENT COMPLEXITY

The influencing factors of dynamic environment complexity are capable of affecting the complexity of the dynamic traffic environment. In light of dynamic environmental elements, the main influencing factors of dynamic environment complexity consist of variability (changes in speed and relative distance), relevance (interaction of dynamic elements), diversity (such as power-driven vehicles, non-power-driven

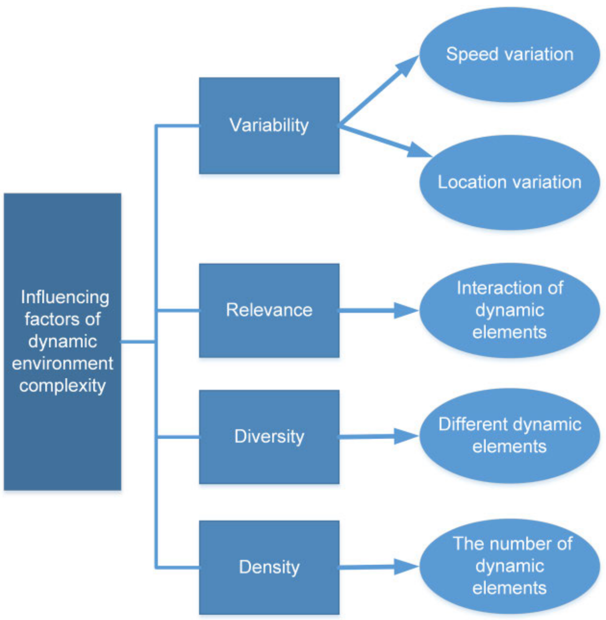

FIGURE 3. Composition of the influencing factors of dynamic environment complexity.

vehicles, and pedestrians), and density of dynamic elements (the number of dynamic elements) in Fig. 3.

2) IMPROVED GRAVITATION MODEL

The gravitation model is expressed as:

$$F = \mathrm{G}M_1M_2\Big/S^2 \tag{6}$$

where F is the gravitation of the two objects, M_1 and M_2 are the mass of the two objects, S is the distance between them, and G represents the constant of gravitation.

Due to real-time changes in the dynamic traffic environment, we express the complexity of the dynamic traffic environment by instantaneous influence and cumulative influence. The instantaneous influence is called the instantaneous dynamic complexity. Similarly, the cumulative influence is called the cumulative dynamic complexity.

In a specific scenario, we regard gravitation's magnitude between the unmanned vehicle p and the dynamic element q as the complexity of the dynamic traffic environment for the unmanned vehicle p in the process of driving. Thus, the quantitative model of the instantaneous dynamic complexity for the unmanned vehicle p is defined as:

$$C_d = \left|\mathrm{G}RM_pM_q\Big/S_{pq}^2\right| \tag{7}$$

where C_d is the quantitative result of the instantaneous dynamic complexity, M_p and M_q represent the equivalent mass of the unmanned vehicle p and the dynamic element q respectively, R is the contribution degree of the driving strategy for the unmanned vehicle p, S_{pq} is the distance between the unmanned vehicle p and the dynamic element q, that is, the relative distance, and G is an undetermined coefficient. In actual traffic scenarios, an appropriate threshold can be set for the instantaneous dynamic complexity to reduce the amount of calculation and remove the influence of unnecessary dynamic elements.

It is noteworthy that the instantaneous dynamic complexity is a scalar.

a: EQUIVALENT MASS

When we adopt the gravitation model to establish the quantitative model of complexity of the dynamic traffic environment, M_1 and M_2 in (6) become equivalent mass. The equivalent mass is a function of actual mass, types and speeds of the unmanned vehicle and dynamic elements [32]. According to the 2004 World Bank and World Health Organization's report [33], the number of traffic accidents is related to the second power of the average road speed in developing countries. Hence M_p and M_q is defined as:

$$M_p = T_pm_p\left[1 + \mathrm{k}_1\left(V_p\cos\theta_p\right)^2\right] \tag{8}$$

$$M_q = T_qm_q\left[1 + \mathrm{k}_1\left(V_q\cos\theta_q\right)^2\right] \tag{9}$$

where T_p and T_q represent the types of the unmanned vehicle p and the dynamic element q, V_p and V_q are the speeds of p and q, and the movement direction of the unmanned vehicle p is specified as positive. θ_p and θ_q are the angles between the relative distance and the respective movement direction, and the clockwise direction is defined as positive. The range of θ_p and θ_q is $[0, \pi]$. m_p and m_q are the actual mass of the unmanned vehicle p and the dynamic element q. k_1 is an undetermined coefficient. In particular, the equivalent mass is the product of the object type and the actual mass when the object is stationary.

b: CONTRIBUTION DEGREE OF THE DRIVING STRATEGY

When studying the behaviour of drivers, researchers usually classify the attributes of drivers as the over-cautious, the cautious, the robust, the impulsive, and the offensive [34]. Different unmanned vehicles also own different attribute. In the paper, we introduce the contribution degree of the driving strategy to reflect this kind of attribute of unmanned vehicles. The contribution degree of the driving strategy is defined as:

$$R = \begin{cases} \mathrm{r}\exp\left(\dfrac{V_p\cos\theta_p + V_q\cos\theta_q}{\mathrm{k}_2V_p\cos\theta_p}\right), & \cos\theta_p\cos\theta_q < 0 \\ \mathrm{r}, & \cos\theta_p\cos\theta_q = 0 \\ \mathrm{r}\exp\left(\dfrac{\mathrm{k}_2V_p\cos\theta_p}{V_p\cos\theta_p + V_q\cos\theta_q}\right), & \cos\theta_p\cos\theta_q > 0 \end{cases} \tag{10}$$

where R is the contribution degree of the driving strategy, r and k_2 are the undetermined coefficients, and $(V_p\cos\theta_p + V_q\cos\theta_q)$ is the relative speed between the unmanned vehicle p and the dynamic element q.

Providing that $\mathrm{r} = 1$ and $\mathrm{k}_2 = 1$, the functional relation of contribution degree of the driving strategy is obtained as

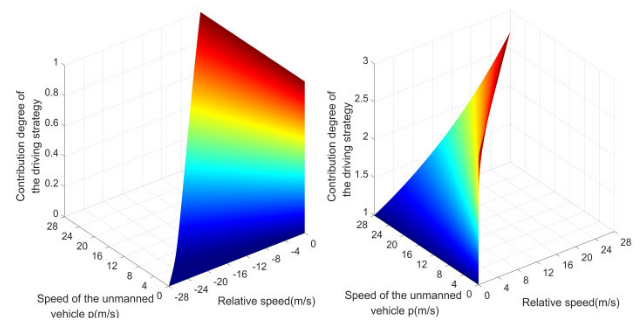

FIGURE 4. Functional relation of contribution degree of the driving strategy when $\cos\theta_p\cos\theta_q < 0$.

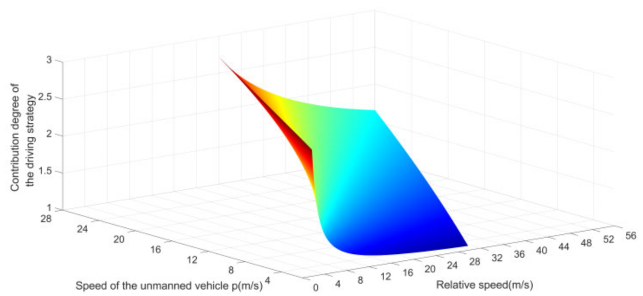

FIGURE 5. Functional relation of contribution degree of the driving strategy when $\cos\theta_p\cos\theta_q > 0$.

shown in Fig. 4 and Fig. 5, where we consider that maximum design speed of urban roads in China is 100km/h.

In Fig. 4, when the relative speed is less than 0, the contribution degree of the unmanned vehicle's driving strategy is not greater than 1. When the relative speed is greater than or equal to 0, the contribution of the unmanned vehicle's driving strategy is not greater than the value of the natural logarithm's base. When the unmanned vehicle p and the dynamic element q move towards each other in Fig 5, the contribution degree of the unmanned vehicle's driving strategy is not greater than the value of the natural logarithm's base.

The cumulative dynamic complexity should be equal for different vehicles in the same scenario, so we adopt time integral to calculate the cumulative dynamic complexity. The cumulative dynamic complexity is defined as:

$$C'_d = \int \left| \mathrm{G}RM_pM_q \Big/ S_{pq}^2 \right| dt \tag{11}$$

where $C_d^{'}$ is the cumulative dynamic complexity.

IV. VALIDATION AND DISCUSSION

In order to verify the proposed quantitative evaluation models of traffic environment complexity, we evaluate the traffic environment complexity in the designed scenario by models proposed in the paper and existing models of urban traffic environment complexity, and compare the calculating process and the result of each model. We design a car-following scenario to display a situation that the speeds of the two vehicles are equal clearly and intuitively. The calculating process and results show that the proposed quantitative models of traffic environment complexity are more convenient and more reasonable.

A. DESIGNED SCENARIO

According to the competition scenario of the 2018 World Intelligent Driving Challenge, we design a car-following scenario in Fig. 6. The vehicle q travels at a constant speed of 14m/s. $V_p = 12$m/s and $S_{pq} = 10$m at $t = 0$s. Whereafter, the unmanned vehicle p accelerates with an acceleration of 1m/s^2 until it follows the vehicle q at the same speed as the vehicle q.

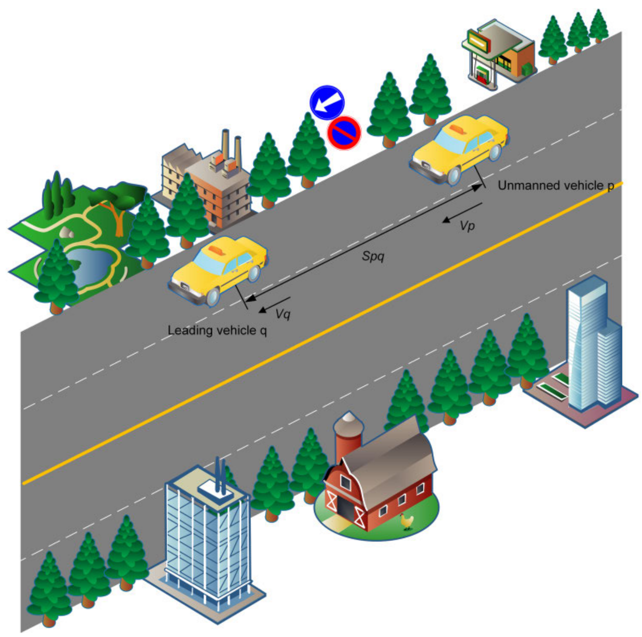

FIGURE 6. A car-following scenario.

In the car-following scenario shown in Fig. 6, elements of the static traffic environment in the urban road consist of the straight section, the sub-arterial road, the prohibition sign, the indication sign, prohibition markings, indication markings, plants, buildings, the plain, the sunny day, and weak electromagnetic interference. The road has a dry surface, a non-asphalt structure, and linear alignment. Due to studying the influencing factors of the traffic environment complexity from the perspective similar to manual driving, we can assign the values of environmental elements by expert scoring. In fact, the weights, scores, and attribute values of static elements obtained by expert scoring in the paper come from the 2018 World Intelligent Driving Challenge.

B. EVALUATION OF COMPLEXITY OF THE STATIC TRAFFIC ENVIRONMENT

We respectively use the quantitative model of static environment complexity based on grey relation analysis proposed in the paper and the existing model based on information entropy [19] to evaluate the static environment complexity in the designed scenario.

1) EXISTING MODEL BASED ON INFORMATION ENTROPY

In the existing model based on information entropy, the model is expressed as:

$$C_s = \beta \times (\alpha_1 \sum X_1 + \alpha_2 \sum X_2 + \alpha_3 \sum X_3 + \alpha_4 \sum X_4) \tag{12}$$

where X_1, X_2, X_3, and X_4 are the corresponding total scores of the composition of the urban static traffic environment. α_1, α_2, α_3, and α_4 are the corresponding weights of composition, and β is the coefficient of the static environment complexity.

Firstly, we need to determine the composition of the static traffic environment and number each node, as shown in Fig. 7.

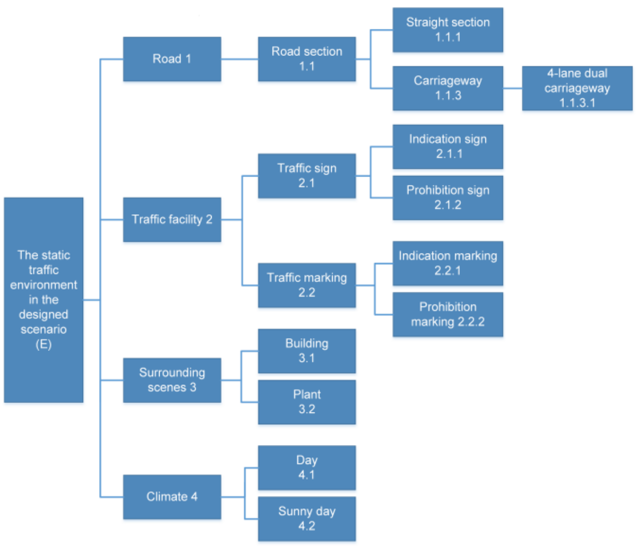

FIGURE 7. Composition of the static traffic environment and each node's number.

Secondly, we count the number of input nodes and output nodes which each node has from left to right in Fig. 7 and group nodes according to the number of input nodes and output nodes. Table 2 presents the nodes' grouping.

TABLE 2. Nodes' grouping.

The number of input nodes	The number of output nodes	Nodes	The number of nodes with the same number of input nodes and output nodes
0	1	{ E }	1
1	0	{1.1.1, 1.1.3.2,2.1.1, 2.1.2, 2.2.1,2.2.2,3.1, 3.2, 4.1, 4.2}	10
1	1	{1,1.1.3 }	2
1	2	{1.1, 2,2.1,2.2,4}	5
1	3	{3}	1
Total			19

Thirdly, according to the calculation of the first-order entropy of the graph, the complexity coefficient of the static environment is:

$$\beta = -\left(2 \times \frac{1}{19} \times \ln \frac{1}{19} + \frac{2}{19} \times \ln \frac{2}{19} + \frac{5}{19} \times \ln \frac{5}{19} + \frac{10}{19} \times \ln \frac{10}{19}\right) = 1.236$$

Finally, the static environment complexity is calculated by (12):

$$C_s = 20.136$$

In the model based on information entropy, the range of static environment complexity is 0 to 100. By contrast, the static environment complexity in the designed scenario is relatively low.

2) QUANTITATIVE MODEL OF STATIC ENVIRONMENT COMPLEXITY BASED ON GREY RELATION ANALYSIS

Based on the grey relation analysis, we quantify the static environment complexity for the unmanned vehicle in the designed scenario.

The determined comparison sequence is:

$Y_j = [0.667\ 0\ 0\ 0\ 0\ 0.304\ 0\ 0\ 0\ 1\ 0]$

According to (3) and (4), the relation degree is:

$r_j = [0.600\ 0.333\ 0.333\ 0.333\ 0.333\ 0.418\ 0.333\ 0.333\ 0.333\ 1\ 0.333]$

According to (5), the complexity of the static traffic environment in the scenario is:

$C_s = 0.426$

$\min_j |y_j - Y^+| = 0$ and $\max_j |y_j - Y^+| = 1$, so the range of static environment complexity is 0.333 to 1. That is to say, the static traffic environment in the designed scenario is relatively simple.

The model of static environment complexity based on information entropy takes static elements as the influencing factors of the static environment complexity. However, it does not consider the influence of road surfaces, pavement structures and electromagnetic signals. Road surfaces and pavement structures directly affect the friction coefficient of the road, thereby affecting unmanned driving. Electromagnetic signals have an influence on the working process in unmanned driving. The quantitative model of static environment complexity proposed in the paper take into account these three influencing factors. Moreover, compared with that of model based on information entropy, the calculating process of the quantitative model based on grey relation analysis proposed in the paper is more convenient and simpler.

C. EVALUATION OF COMPLEXITY OF THE DYNAMIC TRAFFIC ENVIRONMENT

In this part, we evaluate the complexity of the dynamic traffic environment by quantitative model of dynamic environment complexity based on the improved gravitation model proposed in the paper, the model based on time to collision [24], and the model based on the gravitation model [25]. To be sure, researchers consider influencing factors that contain variability, relevance, the number and diversity of dynamin elements in the model based on time to collision and the model based on the gravitation model.

1) EXISTING MODELS OF DYNAMIC ENVIRONMENT COMPLEXITY

In the existing model based on time to collision (TTC), the instantaneous dynamic complexity is defined as:

$$C_d = 1/TTC = |V_p - V_q|/S_{pq} \tag{13}$$

Fig. 8 presents the relationship among the instantaneous dynamic complexity of the unmanned vehicle p, speed and distance between vehicles.

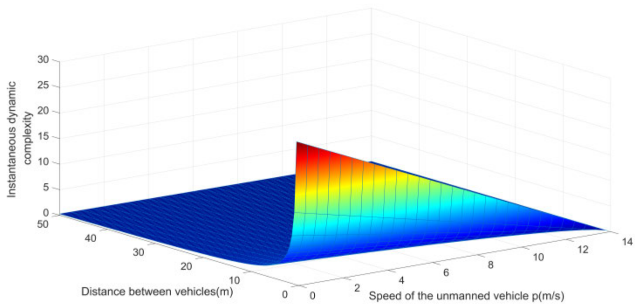

FIGURE 8. Functional relationship among the instantaneous dynamic complexity, speed and distance between vehicles based on time to collision.

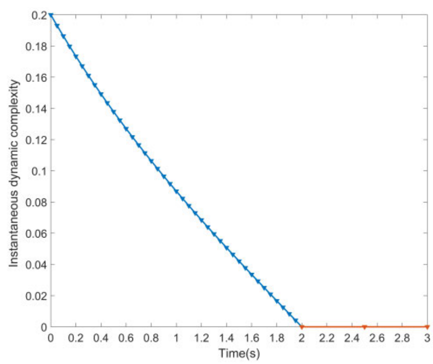

FIGURE 9. Variation curve of the instantaneous dynamic complexity with time based on time to collision.

Fig. 9 is the variation curve of the instantaneous dynamic complexity with time.

In the existing model based on the gravitation model, the instantaneous dynamic complexity is defined as:

$$C_d = \left|\lambda(V_p - V_q)f(p, q)/{S_{pq}}^2\right| \tag{14}$$

where λ is the correction parameter and λ = 100. *f(p, q)* is the difference before and after the dynamic element affects the speed of the unmanned vehicle. *f(p, q)* is represented by the acceleration of the unmanned vehicle in the paper.

Fig. 10 shows the relationship among the instantaneous dynamic complexity of the unmanned vehicle p, speed and distance between vehicles.

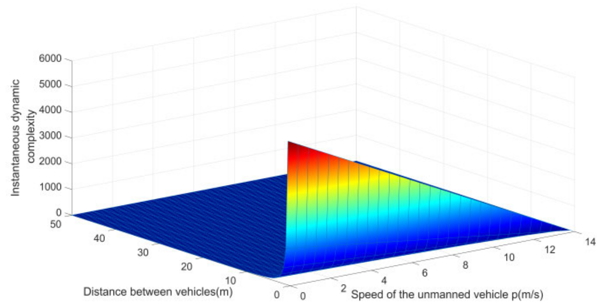

FIGURE 10. Functional relationship among the instantaneous dynamic complexity, speed and distance between vehicles based on the gravitation model.

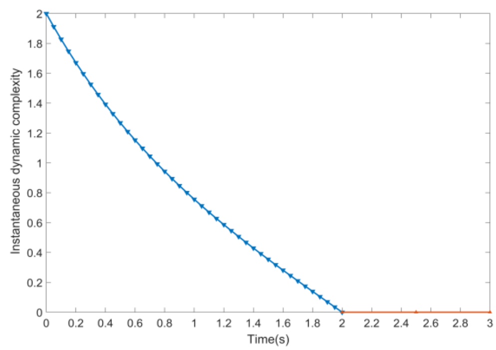

FIGURE 11. Variation curve of the instantaneous dynamic complexity with time based on the gravitation model.

Fig. 11 is the variation curve of the instantaneous dynamic complexity with time.

2) QUANTITATIVE MODEL OF DYNAMIC ENVIRONMENT COMPLEXITY BASED ON THE IMPROVED GRAVITATION MODEL

In the car-following scenario shown in Fig. 6, $\theta_p = 0$ and $\theta_q = \pi$. We apply the proposed quantitative model of dynamic environment complexity to calculate the complexity of the dynamic traffic environment.

According to (7)–(10), the instantaneous dynamic complexity for the unmanned vehicle p is expressed as:

$$C_d = \frac{\mathrm{Gr}}{S^2}\exp\left(\frac{V_p\cos\theta_p + V_q\cos\theta_q}{\mathrm{k}_2 V_p\cos\theta_p}\right)T_p m_p \left[1 + \mathrm{k}_1\left(V_p\cos\theta_p\right)^2\right] \times T_q m_q\left[1 + \mathrm{k}_1\left(V_q\cos\theta_q\right)^2\right] \tag{15}$$

For illustration purpose, the following set of parameters are chosen: G=10^{-6}, $k_1 = 1$, $\mathrm{k}_2 = 0.1$, r=1, $m_p = 1500$kg, $m_q = 1500$ kg, $T_p = 1$, $T_q = 1$.

The instantaneous dynamic complexity of the unmanned vehicle p is:

$$C_d = 46.35\exp\left[(V_p - 14)/V_p\right]\left(1 + 0.1V_p^2\right)/S^2 \tag{16}$$

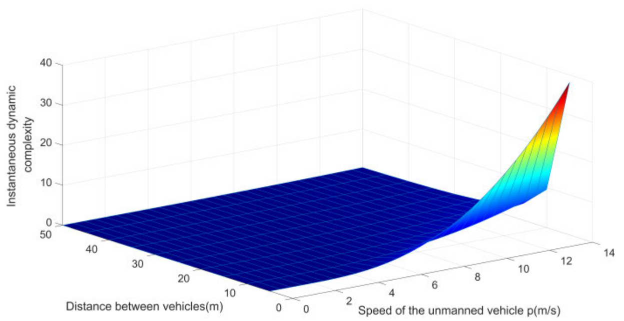

FIGURE 12. Functional relationship among the instantaneous dynamic complexity, speed and distance between vehicles based on the improved gravitation model.

Fig. 12 presents the relationship among the instantaneous dynamic complexity of the unmanned vehicle p, speed and distance between vehicles.

The instantaneous dynamic complexity of the unmanned vehicle p is also expressed as:

$$C_d = \frac{46.35\exp\left[(t-2)/(t+12)\right]\left(15.4+2.4t+0.1t^2\right)}{\left(10+2t-0.5t^2\right)^2} \tag{17}$$

Fig. 13 is the variation curve of the instantaneous dynamic complexity with time.

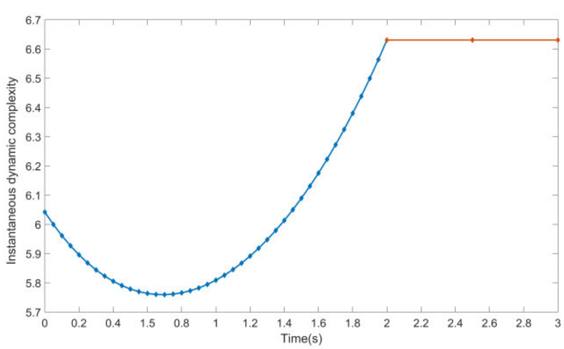

FIGURE 13. Variation curve of the instantaneous dynamic complexity with time based on the improved gravitation model.

3) COMPARATION ANALYSIS

In Fig. 8, Fig. 10, and Fig. 12, the instantaneous dynamic complexity of the unmanned vehicle p and the variation amplitude decrease gradually with the speed of the unmanned vehicle p and the distance between vehicles increasing on the whole.

In Fig. 13, the instantaneous dynamic complexity of the unmanned vehicle p decreases firstly and then increases with time t. This kind of change trend results from the difference in the increasing amplitude of the numerator and the denominator in (16). When the unmanned vehicle p accelerates at a constant acceleration, both speed of the unmanned vehicle p and distance between vehicles increase. Before C_d reaches the lowest point, the variation curve shows that the increasing amplitude in the square of the distance between vehicles is greater than that in the numerator. After the lowest point of C_d, the variation curve shows that the increasing amplitude in the square of the distance between vehicles is less than that in the numerator.

Obviously, since the unmanned vehicle p and the vehicle q travel at the same speed and the distance between vehicles is constant after $t = 2$s, the variation curve of the instantaneous dynamic complexity does not change any longer in Fig. 13. The instantaneous dynamic complexity is 6.6306. The speed of the unmanned vehicle p keeps at 14m/s, and the distance between vehicles is 12m. Whereas, the instantaneous dynamic complexity becomes zero after $t = 2$s in Fig. 9 and Fig. 11. That is to say, the vehicle q does not have an influence on the unmanned vehicle p, which is inconsistent with the fact. In consequence, compared with the model based on time to collision and the model based on the gravitation model, the quantitative model of dynamic environment complexity based on the improved gravitation model proposed in the paper is more reasonable and more effective.

V. CONCLUSION AND FUTURE WORK

The research aims to reveal the human-vehicle-road interaction mechanism for unmanned vehicles and evaluate the traffic environment complexity in urban roads quantitatively. The main working in the paper is summarised as the following points:

1) According to the structural system of human-vehicle-road, we analyse the structure system of the complex traffic environment and relative static and dynamic characteristics of urban roads in the round. We dissect static and dynamic elements as comprehensively as possible, laying a foundation for influencing factors of traffic environment complexity. In this way, the complex traffic environment is classified as the static traffic environment and the dynamic traffic environment.
2) We study the quantitative evaluation models of traffic environment complexity for unmanned vehicles in urban roads from two parts. The grey relation analysis method is applied to establish the quantitative model of complexity of the static traffic environment. The relation degree of influencing factors of the static environment complexity reflects the complexity of the static traffic environment. Moreover, the greater the relation degree is, the greater the complexity will be.
3) For the complexity of the dynamic traffic environment, we take the temporal and spatial variation characteristics of dynamic elements into consideration. After analyzing the influencing factors in all directions, we improve the gravitation model. The quantitative model of complexity of the dynamic traffic environment for unmanned vehicles is proposed based on the improved gravitation model. Meanwhile, we define the

TABLE 3. Scores, weights, and attribute values about traffic facilities.

Description	Weights of difficulty degree	Description	Weights of difficulty degree	Description	Scores of difficulty degree	Weights of difficulty degree	Attribute values
Traffic facilities	0.320	Traffic sign	0.376	Indication sign	89.000	0.238	0.810
				Prohibition sign	80.000	0.214	0.655
				Warning sign	70.000	0.186	0.423
				Guide sign	70.000	0.186	0.483
				Tourist area sign	70.000	0.186	0.483
		Traffic marking	0.416	Indication marking	79.000	0.316	0.638
				Prohibition marking	82.000	0.330	0.690
				Warning marking	88.000	0.354	0.793
		Traffic light	0.208		42.000		0.000

TABLE 4. Scores, weights, and attribute values about the road.

Description	Weights of difficulty degree	Description	Weights of difficulty degree	Description	Weights of difficulty degree	Description	Scores of difficulty degree	Weights of difficulty degree	Attribute values
Road (road conditions)	0.300	Road section	0.210	Straight section	0.278		14.600		0.000
				Turning section	0.452		23.700		0.107
				Carriageway	0.270	2-lane dual carriageway	23.300	0.412	
						4-lane dual carriageway	11.600	0.205	
						8-lane dual carriageway	11.100	0.196	
						10-lane dual carriageway	10.600	0.187	
		Intersection	0.376	Grade crossing	0.562	Cross-shaped grade crossing	58.000	0.274	0.508
						T-shaped grade crossing	42.000	0.198	0.321
						Roundabout	40.000	0.186	0.297
						Other grade crossing	72.000	0.342	0.672
				Interchange	0.438		41.000		0.309
		Tunnel	0.232				58.000		0.508
		Bridge and culvert	0.182				45.000		0.356

concept of equivalent mass and the contribution degree of the unmanned vehicles' driving strategy and give a detailed calculation method.

4) In order to verify the proposed quantitative evaluation models in the paper, we evaluate the traffic environment complexity in the designed car-following scenario by quantitative evaluation models proposed in the paper and existing evaluation models of urban traffic environment complexity. Compared with the existing evaluation models, the proposed quantitative model of the static environment complexity is more convenient and simpler, and the proposed quantitative model of the dynamic environment complexity is more reasonable and more effective.

The quantitative evaluation models of traffic environment complexity for unmanned vehicles in the paper provide a new idea and a method for the evaluation of the traffic environment complexity to some extent. However, there are no clear methods to determine the values of some parameters in the models. In the next step, the research work will mainly focus on how to determine the parameters and calculate the whole traffic environment complexity for a given scenario.

APPENDIX

APPENDIX 1

See Table 3.

APPENDIX 2

See Table 4.

APPENDIX 3

See Table 5.

TABLE 5. Scores, weights, and attribute values about surrounding scenes and the climate.

Description	Weights of difficulty degree	Description	Scores of difficulty degree	Weights of difficulty degree	Attribute values
Surrounding scenes	0.120	Building	29.900	0.598	0.598
		Plant	20.200	0.402	0.402
		Building and plant	50.000		1.000
		None	0.000		0.000
Climate (climate conditions)	0.260	Day	18.450	0.200	0.000
		Night	31.000	0.342	1.000
		Sunny day	12.664	0.116	0.000
		Rain/snow/fog	37.336	0.342	1.000

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