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基于自然驾驶数据的匝道行驶典型场景聚类分析

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摘要：匝道行驶由于存在潜在的车辆间交通冲突，对自动驾驶汽车来说是一项挑战，因此，有必要对匝道的典型场景开展研究，以便应用于自动驾驶汽车的开发和测试。基于自然驾驶数据(naturalistic driving data，NDD)研究了匝道行驶典型场景。首先，通过对车辆在匝道上交互时的3个主要元素进行定义，包括初始状态(initial state，S)、驾驶动作(driving action，A)和交互性能(interaction performance，P)，并以此来描述车辆的交互行为；然后，选取用于表征A和P的变量作为聚类特征，通过基于Calinski-Harabasz(CH)指数的K-means聚类方法获得8种聚类结果，根据聚类结果对各变量进行分析，得到4种典型的交互方式；再后，通过分析表征初始状态的变量，运用置信椭圆提取典型的逻辑场景；最后，基于逻辑场景随机选择两个具体场景对自动驾驶系统(autonomous driving system，ADS)进行测试和评估。结果表明，运用研究获得的匝道行驶典型场景进行测试，可揭示自动驾驶汽车与其他交互车辆间的交互能力，说明基于NDD并运用聚类分析方法生成的匝道行驶典型场景是有效的。

关键词：自动驾驶汽车；自然驾驶数据；匝道行驶典型场景；聚类分析

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Clustering Analysis of Typical Ramp Scenarios Based on Naturalistic Driving Data

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Abstract: Ramp driving poses a big challenge to autonomous vehicles, on which there are potential traffic conflicts between vehicles. Therefore, it is necessary to study ramp scenarios for development and testing. In this paper, typical ramp scenarios are studied based on naturalistic driving data (NDD). First, three major elements are defined to describe the interaction between vehicles on the ramp, including the initial state (S), the driving action (A) and the interaction performance (P). Next, variables to characterize the A and the P are selected to be clustering features, and then 8 kinds of categories are obtained by the K-means clustering method based on the Calinski-Harabasz (CH) index. Then, according to the clustering results, 4 kinds of typical interaction modes are obtained by analyzing the variables above. Afterwards, by analyzing the variables that characterize the S, typical logical scenarios are extracted by the confidence ellipse. Finally, based on the logical scenarios, two concrete scenarios are selected to test and evaluate the autonomous driving system (ADS). The results show that testing with typical ramp scenarios can reveal the social cooperation capabilities of autonomous vehicles. Therefore, it is effective to generate typical ramp scenarios by clustering analysis based on NDD.

Key words: autonomous vehicle; naturalistic driving data; typical ramp scenarios; clustering analysis

With the development of technology, intelligent vehicles have gradually had the high-level autonomous driving function. As it has the capability to predict interactive trends and implement interactive behaviors[1], the harmony with traffic and its evaluation theory[2] attract an increasing amount of attention. Because of the multifarious potential traffic conflicts between the vehicles on the main road and the merging vehicle on the ramp, ramp driving poses

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a big challenge to autonomous vehicles. Thus, the ramp scenario could be used to test and evaluate the harmony with traffic of vehicles more effectively[3]. Therefore, it is necessary to study typical ramp scenarios.

The knowledge-based and the data-based methods for generating test scenarios are the two mainstreams. The research team of Technische Universität Braunschweig used the ontology method to generate test scenarios according to the knowledge of experts and traffic laws[4-5]. In addition, the data-based method is used by most research institutions recently[6-7], and the scenarios generated by this method could reflect the conditions of real traffic. Therefore, interactive modes will be analyzed based on naturalistic driving data of ramp in this paper, so as to select typical scenarios.

Relevant researches on interaction modes of ramp have been conducted recently. LIU proposes a lane-change prediction model of ramp based on the BP neural network[8]. Kita, believing that the probability of lane change obeys the logistic model, develops a gap-acceptance model to predict the lane change behavior[9]. However, these models only aim to determine whether to change lanes, which could not reflect the complex interaction behavior of vehicles. In view of this, SUN studies the multi-classification model and has subjectively defined the merging behavior based on the response of the main-road vehicle (e.g., normal lane change, forced lane change, and cooperative lane change), thereby constructing a decision tree classification mode[10]. Hidas[11] and Alexandra[12] divide the lane change behavior into three types similarly including normal lane change, forced lane change, and cooperative lane change. In these researches, the analysis of the merging behavior is mostly based on subjective judgment, which lacks the analysis based on naturalistic driving data of ramp.

In this paper, three major elements are defined to describe the interaction between vehicles on the ramp, including the initial state (S), the driving action (A), and the interaction performance (P). In addition, typical interaction modes are analyzed by using the clustering method based on the variables that characterize the driving action and the interaction performance, and typical ramp scenarios are extracted based on the distribution of variables that characterize the initial state. The results show that testing with typical ramp scenarios can reveal the social cooperation capabilities of autonomous vehicles. Therefore, it is effective to generate typical ramp scenarios by clustering analysis based on NDD.

1 Clustering analysis of typical interaction mode

In order to study the typical interaction mode on the ramp, firstly, interaction samples are selected based on naturalistic driving data (NDD). Secondly interaction types of vehicles on the ramp are defined and analyzed statistically based on NDD. Finally, typical interaction modes are studied by clustering analysis based on the samples of typical interaction types.

1.1 Collection of naturalistic driving data

The NDD is collected on a ramp of expressway G50 in Shanghai by drone. The original data is 4 hours of video captured by aerial photography. The view of NDD is shown in Fig. 1. And the definition of roads and vehicles in the ramp scenario is shown in Fig. 2. After data collection, effective interaction samples are selected based on the following principles: ① The driving behavior of merging vehicle is reasonable; ② There is no congestion on the ramp or the main-road.

Fig.1 View of NDD

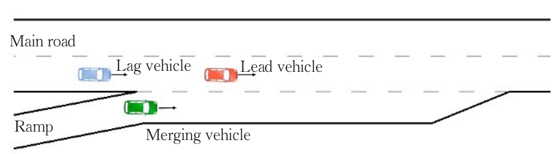

Fig.2 Definition of roads and vehicles in the ramp scenario

A total of 1252 interaction samples are selected to research the interaction modes of vehicles on the ramp.

1.2 Extraction of typical interaction type

The interaction type refers to the interaction behavior between the merging vehicle and the main-road vehicle in the confluence area. According to differences in the congestion of the ramp and the main-road, driving path of the merging vehicle, driving behavior of the merging vehicle and traffic condition on the main-road, 4 kinds of interaction types are defined. Simultaneously, the 1 252 samples of different interaction types are statistically analyzed. The distribution of interaction types is shown in Fig. 3.

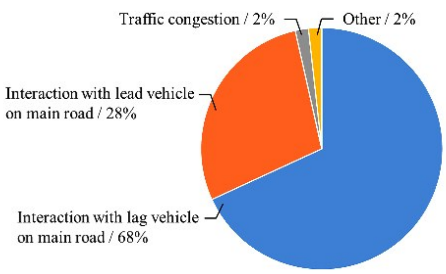

Fig.3 Distribution of interaction types (N=1 252)

The interaction of the lagging vehicle on the main-road means there is only one lagging vehicle on the main-road when merging. The interaction of the leading vehicle on the main-road means there is only one leading vehicle on the main-road when merging. The other types include no interaction, illegal driving, and so on.

According to the statistical results in Fig. 3, samples of the interaction type with the lagging vehicle on the main road are the most, accounting for 68.13% of the total samples. This kind of interaction type can effectively demonstrate the harmony with traffic of autonomous vehicles, due to the complexity and diversity of behaviors and interaction modes of it. Therefore, this interaction type is selected as a typical type for research. Then, the NDD of typical interaction types is used for clustering analysis to study interaction modes.

1.3 Clustering analysis of interaction mode

1.3.1 Selection of clustering variables

Clustering variables are important for clustering analysis. Redundant or too few clustering variables will affect the clustering effect[13].

In this paper, three major elements abbreviated as SAP are defined to describe the interaction between vehicles on the ramp, including the initial state (S), the driving action (A), and the interaction performance (P). The diagram of SAP is manifested in Fig. 4 in which, the initial state (S) refers to the initial position and the initial speed of the merging vehicle and the vehicle on the main-road. The driving action (A) refers to the acceleration, deceleration, and lane change during interaction in the confluence area. The interaction performance (P) refers to the potential risk between the merging vehicle and the vehicle on the main-road when merging, which could be characterized by time to collision (TTC), time headway (THW), desired reaction time (DRT) and so on[14].

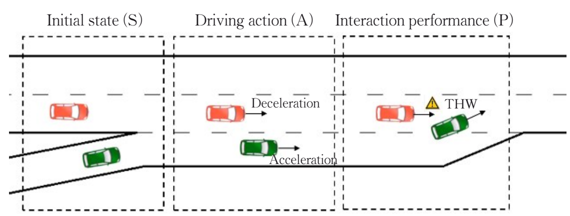

Fig.4 SAP of interaction between vehicles

Studies on the prediction model of the merging behavior show that interaction modes are mainly determined by the driving behavior and the merging performance when merging[15]. Therefore, the variables that characterize the A and the P are selected as the clustering variables, which are shown in Tab. 1. After the clustering analysis, the variables that characterize the S are used to extract the typical ramp scenarios based on the clustering results.

1.3.2 Clustering method

Because of the large sample size of the typical interaction type, the K-means clustering method based on the CH (Calinski-Harabasz) index is used to analyze the typical interaction modes, which avoids the problem of the selection of categories.

(1) K-means clustering method. For the sample data set $X=\{x_1, x_2, \cdots, x_i, \cdots, x_n\}$ and clustering numbers K, firstly, the clustering algorithm could select K samples randomly, and these samples are

Tab.1 Clustering variables

Element	Variables	Symbol	Meaning
S	Merging gap	D	distance between the lagging vehicle and the leading vehicle along the direction of the main−road
	Relative speed	ΔV	speed difference between the merging vehicle and the vehicle on the main−road
A	Speed difference of the merging vehicle	ΔV_{mv}	difference between the speed when merging and the speed at the S
	Speed difference of the vehicle on the main−road	ΔV_{mrv}	difference between the speed when merging and the speed at the S
P	Merging Position	P	distance from the ramp to the position when merging
	THW of the vehicle on the main−road when merging	T_{THW}	ratio of the two−vehicle distance to the speed of the vehicle on the main−road

regarded as the clustering centers. Then, the Euclidean distances between the remaining samples and the clustering centers are calculated, and the remaining samples are assigned to the nearest category. Finally, the clustering centers of each category are recalculated. The above steps will continue until the optimal convergence condition is reached. The convergence condition is expressed as follows:

$$\max\left|p_k - m_k\right| \leqslant \sigma \quad (k=1,2,\cdots,K) \tag{1}$$

where: p_k is the new clustering center of the k-th category; m_k is the previous clustering center of the k-th category. σ is the allowable error value of the clustering center.

(2) CH index refers to the ratio of inter-class dispersion and intra-class compactness, and the function is expressed as follows:

$$\begin{cases} \mathrm{CH}(k)=\dfrac{B_{\mathrm{trace}}}{k-1}\Big/\dfrac{W_{\mathrm{trace}}}{N-k} \\ B_{\mathrm{trace}}=\sum_{j=1}^{k} n_j \left\| z_j - z \right\|^2 \\ W_{\mathrm{trace}}=\sum_{j=1}^{k}\sum_{x_i\in z_j}\left\| x_i - z_j \right\|^2 \end{cases} \tag{2}$$

where: B_{trace} is the trace of the covariance matrix of the inter-class data; W_{trace} is the trace of the covariance matrix of the intra-class data; N is the total sample number of the sample data set; k is the number of clustering categories. Larger the value of CH index, the better the clustering effect.

Rezaee[16] believes that the optimal number of clustering categories should be between 2 and $\sqrt{N}$. Where, N is the total number of sample data. Firstly, k is assigned to be 2. Secondly, K-means algorithm is invoked to obtain the clustering result, and the value of the CH index is calculated based on the clustering result. Finally, k is added by 1, and the clustering result and the value of CH index are recalculated until the k is equal to integer not greater than $\sqrt{N}$.

1.3.3 Clustering result

The clustering results from 348 samples are shown in Fig. 5. When k is 8, the value of the CH index is max, and the clustering effect is best. And then, the sample size of each category is counted, which are shown in Tab. 2.

According to the statistical results in Tab. 2, category No. 2 and category No. 5 are removed

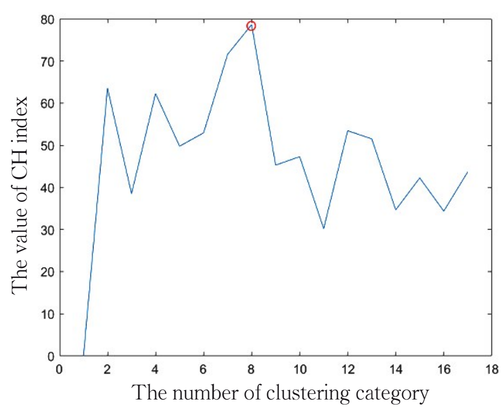

Fig.5 Value of CH index

Tab.2 Sample size of each category

Category	Number	Proportion/%
1	35	10.06
2	13	3.74
3	58	16.67
4	46	13.22
5	19	5.46
6	44	12.64
7	76	21.84
8	57	16.38

because of accounting for a small proportion of samples. In the end, there are 6 kinds of categories in this typical interaction type, and the samples of these categories accounting for 90.80% of samples. In order to analyze and understand the feature of the typical categories and the difference between the typical categories, the clustering variables for each category is made statistics, and the statistical results are shown in Tab. 3. Where, the bold number refers to the feature of variable with the most samples.

In order to determine the interaction mode of the typical category, 4 kinds of the interaction modes are defined based on whether there is a cooperative behavior and the potential collision risk when merging. The cooperative behavior refers to the acceleration and deceleration during interaction in confluence area. The interaction modes are defined in Tab. 4.

Tab.3 Statistical results of each category

Index	Value	1	3	4	6	7	8
P	Head (0~75 m)	1	**56**	0	**34**	**39**	**49**
	Middle (75~150 m)	**27**	2	**34**	10	37	8
	End (>150 m)	7	0	12	0	0	0
ΔV_{mrv}	Acceleration (>3 m/s)	2	1	0	0	4	5
	Stability (−3~3 m/s)	**28**	15	**26**	1	**63**	**41**
	Deceleration (<−3 m/s)	5	**42**	20	**43**	9	11
ΔV_{mv}	Acceleration (>3 m/s)	**27**	1	2	7	0	**41**
	Stability (−3~3 m/s)	8	**55**	**44**	**37**	**76**	16
	Deceleration (<−3 m/s)	0	2	0	0	0	0
T_{THW}	With risk (<1 s)	**23**	10	**31**	**30**	26	16
	Without risk (>1 s)	12	**48**	15	14	**50**	**41**

Tab.4 Definition of interaction modes

Merging performance	Cooperative behavior	No cooperative behavior
With potential risk	Successful cooperative lane change (SCLC)	Weak−interaction lane change (WLC)
Without potential risk	Unsuccessful cooperative lane change (USCLC)	Forced lane change (FLC)

In Categories No. 1 and No. 6, because TTHW is less than 1, the potential risk between the merging vehicle and the vehicle on the main road is high. In terms of the driving action, there are cooperative behaviors that increase the merging gap in both categories. Therefore, Categories No. 1 and No. 6 belong to USCLC. The difference between the two categories is that in Category No. 1, the merging vehicle accelerates to try to increase the merging gap, and in Category No. 6, the vehicle on the main road decelerates to try to increase the merging gap.

In Categories No. 3 and No. 8, because TTHW is greater than 1, the potential risk between the merging vehicle and the vehicle on the main road is low. In terms of driving action, there are cooperative behaviors that increase the merging gap in both categories. Therefore, Categories No. 3 and No. 8 belong to SCLC. The difference between the two categories is that in Category No. 3, the vehicle on the main road decelerates to increase the merging gap, and in Category No. 8, the merging vehicle accelerates to increase the merging gap.

In Category No. 4, the potential risk between the merging vehicle and the vehicle on the main road is high. Moreover, there are no cooperative behaviors that increase the merging gap. Thus, Category No. 4 belongs to FLC.

In Category No. 7, the potential risk between the merging vehicle and the vehicle on the main road is low. Moreover, there are no cooperative behaviors that increase the merging gap. Therefore, Category No. 7 belongs to WLC.

1.3.4 Analysis and discussion

The density of scatter plot could reflect the distribution of variables in a continuous area. Therefore, the characteristics of the variables can be analyzed. In order to understand the difference between the interaction mode and the interaction mechanism, the distribution of variables that characterize the S for different interaction modes are analyzed by the density of scatter plot, and the result is shown in Fig. 6 where the variables include the merging gap and the relative speed between the merging vehicle and the vehicle on the main road at the S.

Compared with other interaction modes, initial relative speed is a lower(median is −2 m/s) between the merging vehicle and the vehicle on the main road in WLC, and the merging gap is also large (median is larger than 50 m). Therefore, the merging vehicle and the vehicle on the main road could drive normally without

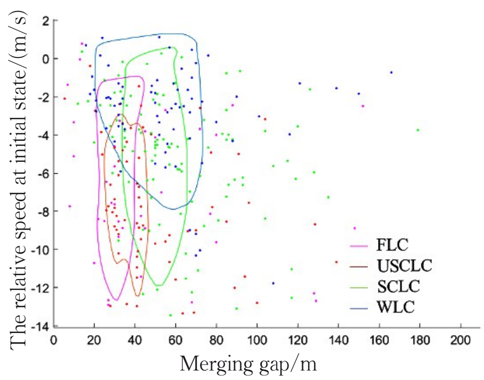

Fig.6 Density of scatter plot

any behavior that could increase the merging gap.

Compared with the FLC and USCLC, initial relative speed is a higher (median is −5 m/s) in SCLC, but the merging gap is large (median is larger 50 m). Therefore, there is enough space for the merging vehicle and the vehicle on the main road to carry out the cooperative behavior, thereby the merging vehicle could drive without collision risk.

In USCLC and FLC, the initial relative speed is high (median is −8 m/s), and the merging gap is small (median is less than 30 m). Therefore, there is not enough space for the merging vehicle and vehicle on the main road to increase the merging gap and reduce the relative speed, thereby there is a large potential collision risk between the merging vehicle and the vehicle on the main road.

2 Extraction of typical ramp scenario

Typical ramp scenarios could be understood as the scenarios that appear frequently in the real world and could include different interaction modes. In order to extract the typical ramp scenarios, the distribution of scenario parameters for different interaction modes is analyzed by the method of confidence ellipse based on the clustering results. The confidence ellipses of different interaction modes at a confidence of 75% are shown in Fig. 7. The variables that characterize the S are selected as scenario parameters.

According to Fig. 7, the typical logical scenario[17] of the ramp is the scenario whose parameters are set in the gray area. In this scenario, there are different interaction modes in the real world, including FLC, SCLC, USCLC, and WLC. This feature allows the vehicle in this scenario to freely choose the interaction mode according to its own strategy. Therefore, this scenario is of great significance for testing and evaluation of harmony with traffic for autonomous vehicles.

In addition to the merging gap and the relative speed, scenario parameters also include the initial speed of the merging vehicle, the initial speed of the leading vehicle on the main road, and the distance between the merging vehicle and the lagging vehicle on main road. Based on the samples distributed in the gray area in Fig. 7, the scenario parameters are made statistics, which are listed in Tab. 5. The diagram of the test scenario is shown in Fig. 8 where vehicle A is the merging vehicle, vehicle B is the leading vehicle on the main-road, and vehicle C is the lagging vehicle on the main road.

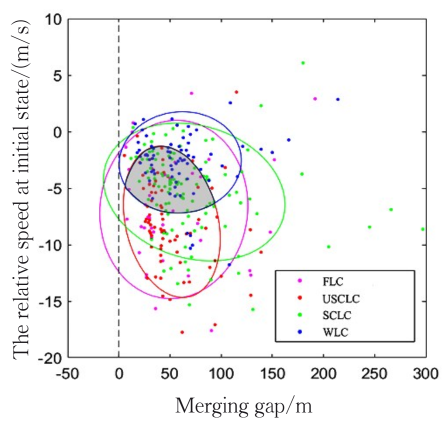

Fig.7 Confidence ellipses of interactive modes at a confidence of 75%

Tab.5 Statistical results of the parameters

Parameter	Symbol	Unit	Range
Initial speed of vehicle A	V_{A0}	m/s	[11.1, 20.6]
Relative speed between vehicle A and vehicle C	ΔV	m/s	[−6.7, −1.8]
Initial speed of vehicle B	V_{B0}	m/s	[11.5, 28.2]
Merging gap	D_0	m	[26.0, 68.0]
Distance between vehicle A and vehicle C	D_{L0}	m	[0.0, 69.0]

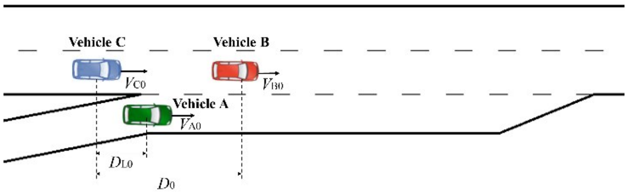

Fig.8　Diagram of the test scenario

3　Application of typical test scenario

3.1　Simulation test

A hardware-in-the-loop simulation platform is constructed based on the virtual test drive (VTD). First, a ramp scene is constructed in the simulation environment, which consists of a two-lane main road and an acceleration lane of 226 m. Next, two concrete scenarios [17] are selected based on the logical scenarios in Tab. 5. The scenario parameters of the concrete scenarios are presented in Tab. 6. Furthermore, vehicles A, B and C are driven by the autonomous driving system (ADS) with autopilot function such as obstacle avoidance and path planning. Finally, the interaction performance of vehicle A is tested and evaluated by a mapping model of harmony with traffic.

Tab.6　Parameters of concrete scenarios

Parameter	Symbol/Unit	Concrete scenario No. 1	Concrete scenario No. 2
Initial speed of vehicle A	V_{A0}/(m/s)	13.3	13.1
Relative speed between vehicle A and vehicle C	ΔV/(m/s)	−3.2	−5.2
Initial speed of vehicle B	V_{B0}/(m/s)	12.8	13.9
Merging gap	D_0/m	21.0	86.0
Distance between vehicle A and vehicle C	D_{L0}/m	9.0	39.0

3.2　Results and analysis

Using the data of the simulation test, the harmony with traffic of vehicle A is evaluated by the back propagation neural network (BPNN) mapping model for evaluation[2]. The evaluation results (5-point scale) are shown in Tab. 7.

Tab.7　Evaluation results (5-point scale)

Scenario	Score of harmony with traffic
Concrete scenario No. 1	2.1
Concrete scenario No. 2	2.9

Taking concrete scenario No. 1 as an example, in Fig. 9, when T=0, the distance between vehicle A (green car) and vehicle C (blue car) and the distance between vehicle B (red car) and vehicle C are short. When T=4 s and 8 s, vehicle C changes lane before vehicle A merges, and avoids the direct interaction with vehicle A, thereby, vehicle C drives at a constant speed. When T=4 s, 8 s and 12 s, there is not a long distance between vehicle A and vehicle B, but vehicle A also drives normally without adjusting speed to increase the merging gap. When T=14 s, vehicle A decelerates significantly to reduce speed, and merges slowly into the slow lane of the main road. The merging position is at the end of the acceleration lane. From the entire process, it can be seen that vehicle A is too conservative to guarantee its own driving efficiency and comfort. Therefore, the score of harmony with traffic that is obtained by the BPNN mapping model is low.

In order to analyze the difference in driving behavior between ADS and a human driver. Taking concrete scenario No. 1 as an example (see Fig. 9), the interaction performance of ADS and that of human driver in real traffic is compared, whose result is shown in Tab. 8.

Tab.8　Comparison of interaction performance between human driver and ADS in concrete scenario No. 1

Interaction Performance		Human driver	ADS
Interactive mode		FLC	USCLC
Vehicle A	Performance	High	Low
	Driving action	Merging into the main road at the middle of the acceleration lane	Merging into the main road at the end of the acceleration lane
Vehicle C	Performance	Low	High
	Driving action	Decelerate	Lane change

It can be seen from the above test and evaluation results that typical ramp scenarios could be used to reveal the social cooperation capabilities of autonomous vehicles. Therefore, it is effective to generate typical ramp scenarios by clustering analysis based on NDD.

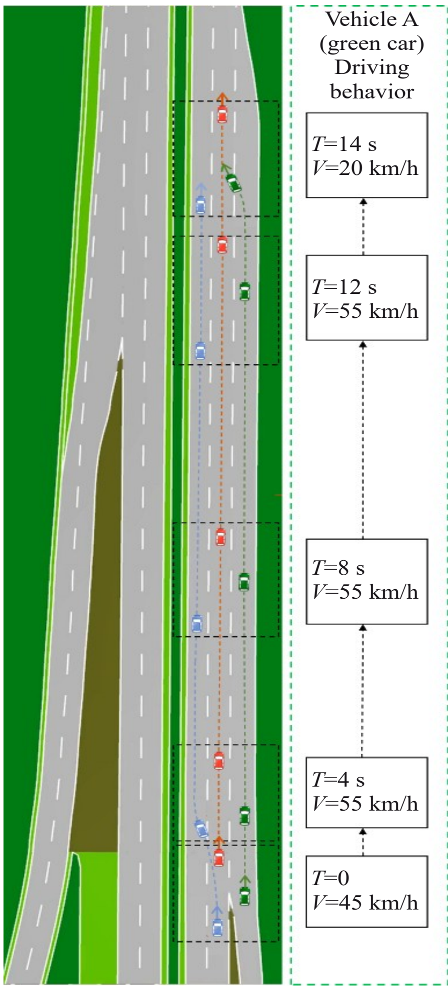

Fig.9 Test process of concrete scenario No.1

4 Conclusions

In order to extract typical ramp scenarios, typical interaction modes are studied by clustering analysis based on NDD. Typical logical scenarios are extracted based on the clustering results. In addition, two concrete scenarios derived from logical scenarios are selected to test and evaluate ADS. The conclusions are listed as follows:

(1) Clustering analysis of the interaction between vehicles through major element SAP is an effective way to extract the typical interaction mode and scenarios of ramp driving based on NDD.

(2) By selecting the variables to characterize the A and the P as clustering features, including the speed differences, the merging position, and the THW, 8 kinds of categories are obtained by the K-means clustering method based on CH index. Moreover, 4 kinds of typical interaction modes distinguished by whether there are cooperative behavior and potential risk are obtained by analyzing the variables above.

(3) The variables that characterize the S are selected as scenario parameters, such as the relative speed between the merging vehicle and the main-road vehicle, the merging gap, the speed of the merging vehicle and so on. The distribution of those scenario parameters is analyzed by confidence ellipse. According to this, typical logical scenarios are extracted.

(4) The results of the ADS test and evaluate based on the concrete scenarios derived from logical scenarios show that testing with typical ramp scenarios can reveal the ADS's capability of harmony with traffic, which can reflect the social cooperation capabilities of autonomous vehicles.

In the future, the sample data in the type of interaction with the leading vehicle on the main road will be considered, which is the second major type as shown in Fig. 3. Besides, a more comprehensive typical ramp scenario will be built by analyzing multifarious interaction modes.

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