An IVIS Typical Scene Generation Algorithm Based on Traffic Big Data

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ABSTRACT

With the increasing development of automatic driving technology, the construction of virtual simulation scenes libraries for automatic driving vehicles, as well as the optimization of coverage of functions and redundancies based on the current scenes libraries, has become a problem that needs to be solved in process of the establishing the Intelligent Vehicle-Infrastructure System (IVIS) test and evaluation system, especially facing the uncountable inexhaustible library of actual traffic scenes. The construction of a standardized general test scene library covering typical scene applications, to provide a complete closed loop for automated driving vehicle testing also becomes a necessity.

Based on the traffic big data, this paper takes the intelligent vehicle road system IVIS as the background, and aims to use scene essential factors, which are indecomposable factors obtained by scene decomposition, to describe the traffic scenes data, with feature extraction algorithm notion of unsupervised learning and nonlinear dimensionality reduction as a reference. Choosing traffic cell modelling, this paper adopts the idea of essential factors as the core and raises a vectorization process of scenes data as a foundation of subsequent research of the generation algorithms.

On the basis of primitive scene decomposition, two core goals are set: study the typical test scenes of IVIS High-fidelity and flexible reconstruction technology and research on the scalable and easy-to-test generation technology of IVIS extreme test scenes. With scene vectorization process as the fundament, this paper attempts to select and optimize a suitable clustering algorithm, to use an improved density clustering algorithm called OIR-DBSCAN, to generate IVIS typical scenes, and accordingly ensure the generalizability and timeliness of the IVIS test.

CCS CONCEPTS

• **Computing methodologies**; • **Machine learning**; • **Machine learning approaches**;

KEYWORDS

Intelligent vehicle-infrastructure system, Essential factors, Clustering algorithm, Scene generation

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1 INTRODUCTION

In today's age of information explosion, the technology used for autonomous vehicles in the field of intelligent transportation is changing rapidly. However, there has been no corresponding breakthrough in the development of test and evaluation technologies for autonomous vehicles [1].

Traditional vehicle performance testing is no longer sufficient to meet the increasing demand for autonomous driving testing [2]. So, on this basis, unlike the real vehicle testing environment where adequate space is highly demanded and numerous real vehicles may be damaged, the virtual testing method based on traffic scene data has huge technical advantages, both in terms of testing efficiency and testing costs. [3]

Although the importance of the simulated test scenes are proposed, due to the inexhaustible nature of real traffic scenes, the industry does not yet have an applicable solution. Therefore, this paper focus on raising a new method to generate the typical IVIS test scenes, as an important tool for future autonomous vehicle testing and verification.

1.1 Intelligent Vehicle-Infrastructure System

The concept of Intelligent Vehicle-Infrastructure System (IVIS) represents the latest technological frontier of transportation. Unlike the traditional approach where the vehicle is the only intelligent body and the core of the test, the IVIS concept means that the existing test treats the intelligent driving vehicle as one element and the surrounding environment, including the current road and road test equipment, as the other element, treating them equally and therefore allowing for greater similarity to the reality during the test. [4]

However, due to the convenience of the preceding process in traditional testing, IVIS products are less likely to be rolled out or used on a large scale in the current situation; in this regard, the complete set of test equipment for IVIS product access certification, as well as the supporting professional test site, play a vital role in influencing the overall situation. Therefore, it is important to maximize the coverage of the test and evaluation functions of the scenes, at a low cost in terms of time and money, and with limited site resources.

Considering the purpose of autonomous driving testing, which is through functional testing within a given scene, the final evaluation

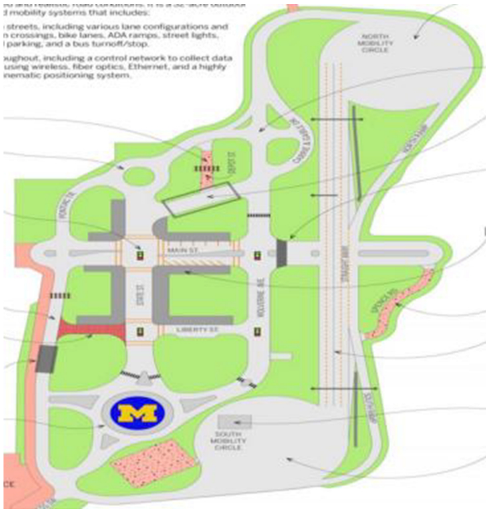

Figure 1: Autonomous Driving Simulation Test Scene.

of the autonomous vehicle is derived, in terms of functionality and comfort, and most importantly, safety, and other aspects, which can thus be used as important indicators for assessing autonomous vehicles, in terms of functional completeness and safety performance and various aspects.

Due to the uncertainties associated with real-life scene testing, the construction of virtual scenes is often the first step in testing the functionality of a self-driving car with the help of simulation before the real-life functional tests are carried out.

1.2 Typical Scene Generation Based on Essential Factors

Based on the above description, the major concern of the research is how to reproduce real scenes credibly in virtual scenes and simulations, taking into account the inexhaustible nature of real traffic scenes. [5] The research aims to adopt techniques for the high-fidelity and flexible reconstruction of typical IVIS test scenes and to develop a mixed reality-based test scene construction system to solve the key common problems of construction, verification and evaluation and deployment optimisation of extreme test scenes for IVIS systems.

In the research of the above problems, a standardized common test scene library covering typical scene applications and extreme scene conditions is identified to be established to provide support for IVIS product access, enabling a complete closed-loop to be formed for the autonomous driving vehicle testing process at the same time. An example of an autonomous driving test scene is shown in the figure 1 [6].

Based on the research background overview, in general, this paper has the following aims.

Firstly, adopt a non-linear dimensionality reduction and unsupervised learning feature extraction algorithm to decompose and to extract the minimum elements for a given traffic scene input. [7] While ensuring the interpretability and practical significance, the extracted scene primitive elements will be used as the basis for the

Figure 2: Construction of Simulation Test Scenes Based on Real Traffic Data.

subsequent traffic scene reconstruction to realise the real traffic scene and the sample and the construction of the pathway between real traffic scenes and sample data. [8-9] Secondly, the virtual simulation environment with similar probability distribution as the real traffic scenes is generated as closely as possible and used as the basis for the subsequent deployment of IVIS scenes. To ensure the transferability of test results, the basic tool considered is the construction of a traffic test scene based on real data as shown in the figure 2 [6].

To ensure the universality and timeliness of the IVIS test, the typical scenes are extracted from the scene library generated based on real scene data and used as the base scene library for subsequent autonomous vehicle testing.

2 SCENE VECTORIZATION

As a test scene for an intelligent vehicle road system (IVIS), the traffic scene, which is on an equal footing with the autonomous vehicle under test, should also be considered as a target for scene generation, in addition to its static factors, such as the dynamic factors of the intelligent body. On this basis, we can first split the problem into the generation of the parameters for the scene, i.e. the generation of the following parameters.

$$\theta_{env} = \left(\theta_{static}, \theta_{dynamic}\right)$$

θ_{env} is the overall traffic scene environment parameter, while θ_{static} and $\theta_{dynamic}$ are the static and dynamic part of the parameter, respectively. It is worth noting that the static parameters include the coordinates, speed, acceleration, lane conditions, ambient state, road conditions, weather conditions and other factors of the various components of the scene at the beginning of the phase. While the dynamic parameters, which do not refer to changing parameters such as speed, represents the parameters of the intelligence that will change dynamically according to the observed traffic conditions, such as the controller of the autonomous vehicle, the neural network parameters, etc.

2.1 Feature Extraction and Essential Factors

The basic idea of the paper is to adopt the "Extract-Build-Optimise" technique, which is based on the existing traffic scene database and uses non-linear dimensionality reduction and unsupervised learning methods to study the extraction of primitives and the

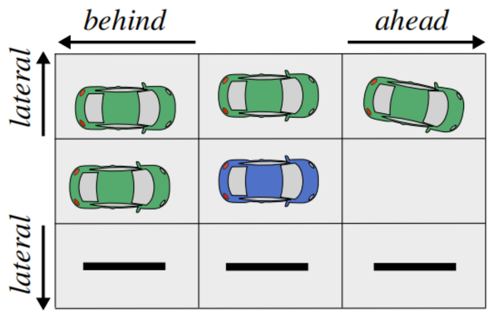

Figure 3: Nine-Square Grid Modeling of Traffic Scenes.

subsequent parameterisation of road traffic elements under typical and extreme scene conditions.

Once the scenes are decomposed into essential factors, the combination of the essential factors and their internal coupling allows us to express more types and sizes of traffic scenes more easily, forming a good pavement for the subsequent research.

In this regard, for each input scene data, the existing scene is continuously quadratic to the smallest unit of which is maximumly divided is retained, and the rest ones continue to repeat the operation [10] until the current input of the existing scene completely becomes the smallest constituent unit. At this point, these basic units, formed by the algorithm's continuous segmentation, can be used as the core for the next step, the reverse of scene generation and representation.

For scene construction, we must define the fundamental elements of the scene, and for any scene, we wish to concretely represent the abstract scene using the obtained scene primitives, in this way completing the data structure description of the variables in the environment.

2.2 Traffic Scene Modeling

Having identified the use of primitive ideas to disentangle the problem, the question of how to model it concretely also becomes a matter for consideration. Wolf et al. proposed a nine-box format for modelling [11], i.e. for the currently moving vehicle, consider dividing it, together with its surroundings, into a nine-box space, with the current vehicle as to the core. Vehicles directly in front, directly behind, left in front, left behind, right in front, right behind, right to the left and right to the right are taken into account for their driving decisions and environmental interactions. This is shown in the figure 3 [12].

While modelling in the nine-box format provides a more complete picture of vehicle-environment interactions, at larger data scales, it also has a correspondingly larger number of redundant situations - in most normal traffic situations, a vehicle will not be surrounded by eight vehicles travelling around it; similarly, most vehicles in a traffic scene will not be in a relatively. In the same way, most vehicles in a traffic scene are not relatively stationary. Therefore, except the vehicles directly in front and behind, the core vehicle in motion, with multiple driving vehicles to its left or right, is in a changing position relative to the main vehicle, and is hardly ever to the left or right, and if it is, it is usually not maintained as a state for long.

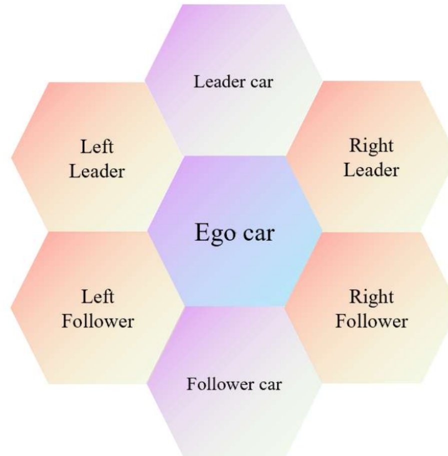

Figure 4: Traffic Scene Unit Cell Modeling.

Considering the above scene, we choose another modelling approach - traffic scene cellular modelling - as the basic model. In this way, not only is the space in front of the main vehicle but also the space to the left and right thereof is arranged in two relative positions. In this way, not only is the information about the interaction between the vehicle under test and the space of the moving traffic environment not lost but most of the redundant data could be removed. The details are shown in the figure 4 [5].

Ultimately, based on the crystalline modelling of the traffic scenes, in the actual vectorisation process, the presence of the element of the central main vehicle driving state can be taken into account and its decision space scope reduced and simplified to the traffic scene environment space on one side.

Specifically, the description and composition sample set of the IVIS scene, using the decomposed essential factors, is characterised in the form of vectors. The vectors are as follows.

2.3 Traffic Scene Vectorized Expression

[[Host Vehicle Elements], [Traffic Participant Elements], [Road Elements], [Traffic Signal Elements], [Environment Elements], [IVIS Logical Relationship/Interaction Mode], [Other Parameters]]

Because more than one element exists for each component, each component is thus set up as a vector again, as follows:

[Host Vehicle Elements] contains three components, which are the main vehicle speed, travel state and acceleration with or without limits.

Considering the desire for the main vehicle speed to have as little impact on the vector as possible, and also to have less impact on the scene vector once the vehicle speed reaches a larger value, the larger unit of measure is used, and the main vehicle speed is set based on the actual vehicle speed with a value of $\sqrt{\frac{v_{Real}}{60}}$.

For better unification, it is desired to characterise the behaviour of reversing and steering in the same mode as the driving state during scene vectorisation, therefore, the introduction of an acceleration

vector set is considered, where the driving state is characterised by a combination of longitudinal and lateral acceleration value as $[a_{Vertical}, a_{Horizontal}]$, and the value is the actual acceleration value a_{Real}.
The values are $[0, 0]$ for unrestricted acceleration, and $[a_{Lower}, a_{Upper}]$ for the combination of the lower and upper values of the actual acceleration.
The [Traffic Participant Elements] contains two components, the follower vehicle attribute and the non-motorised vehicle and pedestrian attribute, which are categorised and considered as an example:
For collision avoidance purposes, all rear-end vehicles should be taken into account as remote vehicles:
When going straight or reversing, consider one vehicle to the front and one to the left and right, and when considering vehicles to the left or right, set a lateral relative position threshold, giving priority to vehicles that reach the threshold, and when the threshold is not reached, give priority to the closest relative position relative to the vehicle travelling in the forward direction.
When turning left or changing lanes to the left, only the vehicle in front and up to two vehicles to the left need to be considered, using these three as remote vehicles, and the same when turning right or changing lanes to the right or making a U-turn.
Thus, in [Traffic Participant Elements]:
Remote vehicles are ranked according to their influence on the driving situation of the main vehicle, with priority given to remote vehicles in the same lane for specific reference, and then from left to right.
The remote vehicle attributes are [Remote Vehicle Speed, Remote Vehicle Acceleration, Remote Vehicle Position, Remote Vehicle Priority], and similarly to the master vehicle:
The remote vehicle speed is taken as $\sqrt{\frac{v_{Real}}{60}}$, the acceleration is taken as its actual value, and the remote vehicle position corresponds to [Lateral Relative Position, Longitudinal Relative Position].
The lateral relative position is {left $= -1$, right $= 1$, same lane $= 0$}, the longitudinal relative position is {front $= 1$, back $= -1$, side by side $= 0$}, if $[0, 0]$ means there is no corresponding remote vehicle; if the remote vehicle has priority to pass then the value is inf, otherwise the value is 0.
The non-motorized vehicle and pedestrian attributes are {Non-motorized Vehicle and Pedestrian Position, Non-motorized Vehicle and Pedestrian Relative Speed Direction}, where the position corresponds to that of the remote vehicle, i.e. [Lateral Relative Position, Longitudinal Relative Position], where:
Lateral relative position is {left $= -1$, right $= 1$, same road $= 0$}, longitudinal relative position is {front $= 1$, rear $= -1$, side-by-side $= 0$}, if $[0,\ 0]$ means there is no corresponding non-motorized vehicle and pedestrian.
The relative velocity direction is [Lateral Relative Velocity Direction, Longitudinal Relative Velocity Direction], where lateral relative velocity direction is {relative left $= -1$, relative right $= 1$, relative same road $= 0$}, longitudinal relative velocity direction is {relative forward $= 1$, relative backward $= -1$, relative side by side $= 0$}, if $[0,\ 0]$ means relative stationary or non-existent, for non-motorised vehicles or pedestrians need not be considered.

The [Road Elements] contains four components, namely road linearity, motorway attributes, road section attributes and road width, where the road linearity attribute is the radian value representation of the curvature of the road.
Motorway attributes are [One/Both Ways, Number of Lanes], where one way = 1 and two ways = 2 and the number of lanes is the true number.
The road section attribute is {ordinary road section = 1, section entry/exit = 5, four-branch fork = 10}.
Road width values are the actual road width values.
The value is 0 if there is no traffic signal and 10 if there is.
The [Environment Elements] contains three components, namely weather attributes, scene closure and traffic flow control attributes. Considering the effect of weather on sight lines and road conditions, an enumeration assignment is made so that the weather attribute is {sunny = 0, windy = 0.5, cloudy = 1, foggy = 1.5, dusty = 3, rainy = 4, snowy = 5, hail = 9}.
The period attribute is [day= 1/night= 0, with lighting= 1/without lighting= 0, with tunnel= -1/without tunnel= 0], then the actual data processing can be considered to sum this item, i.e. equivalent to the actual situation, with lighting at night $\approx$daytime.
The [Other Parameters] contain a component $\sqrt{\frac{3.6D}{10v_{max}}}$, D i.e. the distance between the device under test and the smart body.
After digitization according to the above classification rules, it can be imported into the subsequent processing algorithm.

3 TYPICAL SCENE GENERATION

Due to the uncertainties in real-world scene testing, simulations and virtual scenes are often used to initially test the functionality of autonomous vehicles before real-world testing. To improve the testing efficiency of autonomous vehicles in virtual simulation scenes generated based on real data, it is difficult to avoid the need to remove redundant scenes and identify representative scenes to guide the construction of test scenes and test environments.
And since real traffic scenes are inexhaustible and difficult to reproduce credibly, we develop a mixed reality-based test scene construction system to study the high-fidelity and flexible reconstruction technology of IVIS typical test scenes, solve key common problems such as the construction, verification evaluation and deployment optimization of IVIS system test scenes, and can consider starting from clustering algorithms to realize the generation and deployment of typical scenes.

3.1 Algorithm Selection

K-Means clustering [13] requires the number of clusters to be specified in advance, and can only target spherical clusters, which is difficult to achieve for large scale IVIS traffic scenes without a priori knowledge.
The hierarchical clustering algorithm [14], on the other hand, is not very suitable for traffic scenes with high dimensionality and, is not conducive to solving the problem at hand due to its long computing time when the data size increases at the same time.
Therefore, density-based clustering algorithms are a more appropriate choice when considering the actual deployment of scenes and how closely they interact with each other. As a well-known density clustering algorithm, the DBSCAN algorithm [15] can achieve

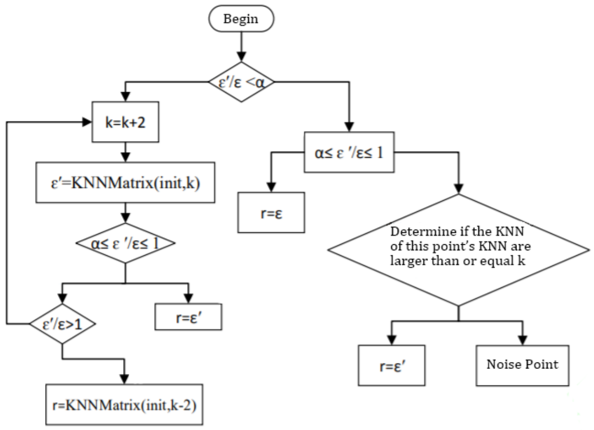

Figure 5: OIR-DBSCAN Clustering Algorithm Flow.

the need to measure the closeness of the inscribed input samples by setting the clustering cluster neighborhood distance parameter, regardless of the shape of the sample clusters.

The DBSCAN algorithm finds the corresponding solution as the process of finding clusters that satisfy both connectivity and maximality, i.e.

For a core object x, the set of all samples that are reachable by its density is denoted as

X={x‘∈ D|x‘ is density-reachable by x}

Then X is the target cluster.

3.2 Improved DBSCAN Algorithm

Considering the specific implementation, the basic DBSCAN algorithm, with its global parameters, is less typical of the results obtained for datasets with uneven density.

Therefore, for the existing IVIS traffic scene dataset, an improved OIR-DBSCAN algorithm is used, with the addition of initial point optimization, and the link of adaptive clustering radius for different clusters, as shown in the figure 5Denote the inverse $k-$nearest neighbors of x as $R_k(x) = R$, which satisfies the following conditions.

Usually take $k = 1$, i.e. y is the reverse nearest neighbor of $x \Leftrightarrow x$ is the nearest neighbor of y.

And for clustering initial points, also modified from random selection accordingly to, pick the point with the smallest value in the list, and for any point, the specific calculation process is

$$Value\,(init) = \frac{1}{m_{init}} + \sum_{i=0}^{k-1} \text{KNNMatrix}\,(init, i)\,(m_{init} \neq 0)$$

After obtaining the point with the smallest value in the list and making it the initial point for clustering, the following steps are repeated iteratively: start clustering from the first initial point, delete the samples that already have labels at the end, select the initial point for clustering at the start of the next iteration and repeat the above operation until the end of clustering.

For five types of scenes: security, efficiency, information service, formation vehicles and commercial vehicles, respectively, DBSCAN

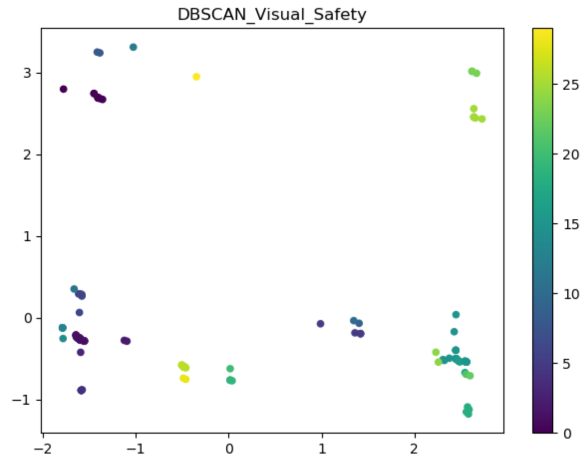

Figure 6: Generation of Typical Security Scenes under DBSCAN Algorithm.

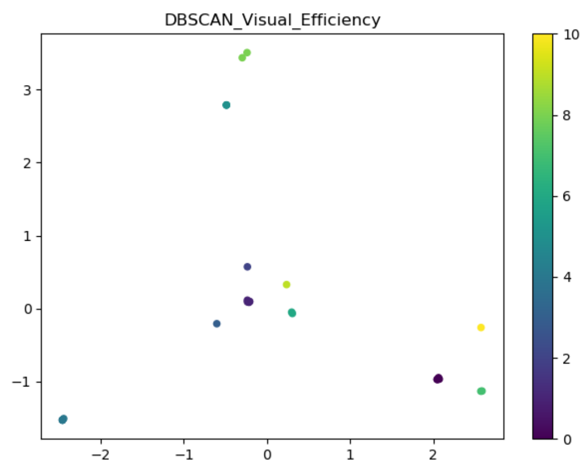

Figure 7: Generation of Typical Efficiency Scenes under DBSCAN Algorithm.

cluster analysis can be performed to obtain typical scene generation results. The legend and silhouette scores are shown as follows:

As shown in figure 6, the security class has 170 original scenes in total, 30 typical scenes can be obtained, and the resulting silhouette score is SC = 0.879.

As shown in figure 7, The efficiency class has 30 original scenes in total, 11 typical scenes can be obtained, and the resulting silhouette score is SC = 0.802

As shown in figure 8, The information service class has 57 original scenes in total, 7 typical scenes can be obtained, and the resulting silhouette score is SC = 0.884.

As shown in figure 9, The formation vehicles class has 58 original scenes in total, 5 typical scenes can be obtained, and the resulting silhouette score is SC = 0.835.

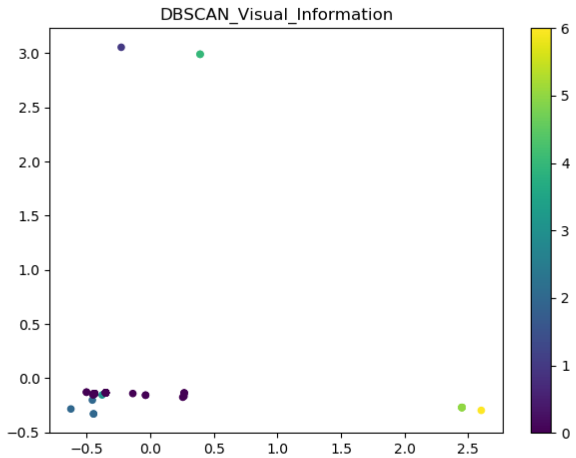

Figure 8: Generation of Typical Information Service Scenes under DBSCAN Algorithm.

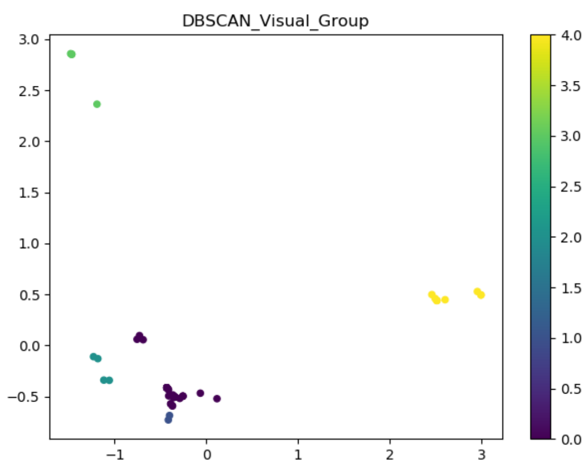

Figure 9: Generation of Typical Formation Vehicles Scenes under DBSCAN Algorithm.

As shown in figure 10, The commercial vehicles class has 25 original scenes in total, 4 typical scenes can be obtained, and the resulting silhouette score is SC = 0.803.

4 CONCLUSION

As the most basic core principle idea of this article, by drawing on the idea of non-linear dimensionality reduction and unsupervised learning feature extraction algorithm, the idea of scene primitives as the smallest element after scene decomposition is proposed. It should be noted that the primitive idea has become the basis of the subsequent scene generation algorithm. In order to better match with the optimization of the redundancy coverage of the scene library, after horizontal comparison, this paper selects the road traffic unit cell modeling, combined with the primitive idea, as the description of the IVIS scene. In specific applications, a rule flow

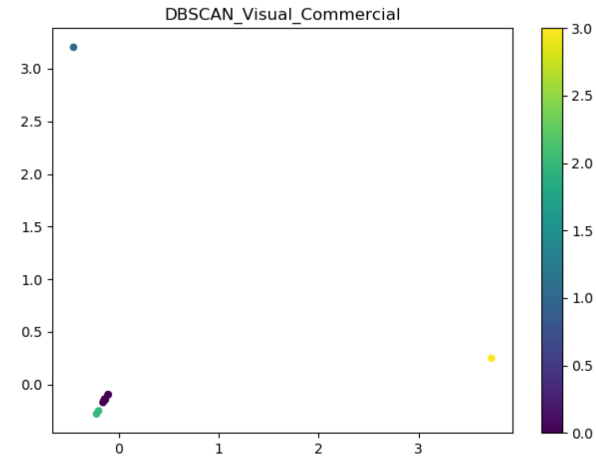

Figure 10: Generation of Typical Commercial Vehicles Scenes under DBSCAN Algorithm.

for vectorization of scene primitive data has also been proposed, which reduces the redundancy of description data in the existing scene library.

In terms of typical scene generation algorithms, in order to improve the test efficiency of IVIS test evaluation scenes for autonomous vehicles while ensuring test safety, for virtual simulation scenes generated based on existing scene libraries and real data, it is necessary to Data redundancy is removed. After preliminary investigation and experimentation, an improved density clustering OIR-DBSCAN algorithm with adaptive radius was finally selected to find representative scenes and guide the construction of test scenes and test environments.

5 PROSPECT

As the most basic core principle idea of this article, by drawing on the idea of non-linear dimensionality reduction and unsupervised learning feature extraction algorithm, the idea of scene primitives as the essential elements after the scene decomposition is proposed. It should be noted that the essential elements have become the basis of the subsequent scene generation algorithm. In order to better match with the optimization of the redundancy coverage of the scene library, after horizontal comparison, this paper selects the road traffic unit cell modeling, combined with the essential elements, as the description of the IVIS scene. In specific applications, a rule flow for vectorization of data expressed by the essential elements has also been proposed, which reduces the redundancy of description data in the existing scene library.

In terms of typical scene generation algorithms, it is necessary to remove the data redundancy, in order to improve the test efficiency of IVIS test evaluation scenes for autonomous vehicles while ensuring testing safety, for virtual simulation scenarios generated based on existing scenario libraries and real data. After preliminary investigation and experimentation, an improved density clustering OIR-DBSCAN algorithm with adaptive radius was finally selected to find representative scenarios and guide the construction of test scenarios and test environments.

Based on the idea of the essential elements, the proposed IVIS test and evaluation scene data vectorization rules can be better applied to the tasks of current research topics. However, as a relatively new field, there are still many rules related to scene the essential elements. The large development and research space are a vast blue ocean. Whether it is for the construction of the simulation platform or for the optimization of the function and redundancy coverage of the IVIS scene, the improvement of this part will become a continuous work.

For the research of typical scene generation algorithm in this paper, although the improved OIR-DBSCAN algorithm based on density clustering is initially selected, it will continue to explore related algorithms in order to write the typical scene generation algorithm that best meets the current research problem. Similarly, on the basis of the improvement of primitive rules, the sensitivity of the algorithm to the data scale and its robustness to the change of the scene state will be both included in the further research in the follow-up.

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