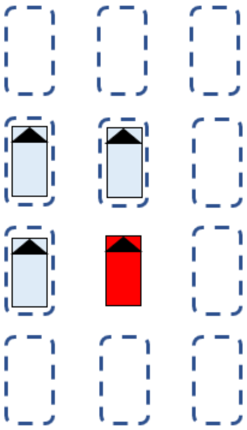
Method for quantitative evaluation of traffic complexity on the highway



Semester Thesis

at the Department of Mechanical Engineering of Technical University of Munich

Supervised by Prof. Dr.-Ing. Markus Lienkamp

Thomas Ponn, M. Sc.

Chair of Automotive Technology

Submitted by Xiao Yu, B. Sc.

Boltzmannstraße 15

85748 Garching bei München

Submitted on 13.11.2019

Description of the work

Method for quantitative evaluation of traffic complexity on the highway

Numerous tests are necessary before an automated function of a vehicle can be launched on the market. In order to select the most representative test scenarios, which can cover as many factors as possible, so that the testing process can be more effective and efficient, the complexity of the environment around an automated vehicle will be analysed quantitatively to offer an objective view of the traffic situation.

The following tasks are to be completed by Ms Xiao Yu

- Literature research of relevant topics
- Derivation of factors contributing to complexity
- Implementation of influence factors
- Analysis of results obtained through application of implemented method

Each step of the work should be documented in a clear form. The candidate undertakes to finish the semester thesis independently and to indicate the scientific tools used by her.

The submitted work remains as the examination document in the ownership of the chair.

Release: 13.05.2019

Submit: 13.11.2019

Prof. Dr.-Ing. M. Lienkamp

Supervisor: Thomas Ponn, M. Sc.

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Herr/Frau: **Yu, Xiao**

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Garching, den 13.11.2019

Xiao Yu, B. Sc.

Expression of thanks

I am very grateful for having this opportunity writing the semester thesis at Chair of Automotive Technology. Sincere thanks to my supervisor Thomas Ponn, M. Sc., who has offered a lot of useful advices and encouragement for the accomplishment of this work.

Garching, 13.11.2019

Xiao Yu

Inhaltsverzeichnis

List of Abbreviations

SAE	Society of Automobile Engineers
AV	Automated Vehicle
ACC	Adaptive Cruise Control
LKA	Lane Keeping Assistance
AEB	Automatic Emergency Brake
V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Network
V2P	Vehicle-to-Pedestrian
V2V	Vehicle-to-Vehicle
N-FOT	Naturalistic Field Operational Tests
NDS	Naturalistic Driving Studies
FOT	Field Operational Tests
AHP	Analytical Hierarchical Process
TTC	Time-to-Collision
MSM	Minimal Safety Margin
TTB	Time-to-Brake
CV	Constant Velocity
CA	Constant Acceleration
CTRV	Constant Turn Rate and Velocity
CTRA	Constant Turn Rate and Acceleration
CSAV	Constant Steering Angle and Velocity
CCA	Constant Curvature and Acceleration
RMS	Root Mean Square
GNN	Graph Neural Network
GAT	Graph Attention Network
GCN	Graoh Convolutional Network

Formula characters

Formula characters	Uni	Description
$v_{\mathrm{ego,x}}$	m/s	Longitudinal
d_{safe}	m	Safety distance
$\boldsymbol{f}$	-	Normalized values of influence factors
$\boldsymbol{w}$	-	Weighting vector for influence factors
x_{ego}	m	x-coordinate of ego-vehicle
$width_{\mathrm{ego}}$	m	Length of ego-vehicle
ROI_{start}	m	x-coordinate of starting point of ROI
ROI_{end}	m	x-coordinate of end point of ROI
t_period	s	Time period for prediction of surrounding traffic
nof	-	Number of frames for prediction of surrounding traffic
v_{endf}	-	Frame number of the last frame of vehicle v
$\boldsymbol{v\_traj}_{actual,x}$	-	Vector containing the x-coordinates of actual trajectory of a predicted surrounding vehicle v
$\boldsymbol{v\_traj}_{actual,y}$	-	Vector containing the y-coordinates of actual trajectory of a predicted surrounding vehicle v
$\boldsymbol{v\_traj}_{predict,x}$	-	Vector containing the x-coordinates of predicted trajectory of a predicted surrounding vehicle v
$\boldsymbol{v\_traj}_{predict,y}$	-	Vector containing the y-coordinates of predicted trajectory of a predicted surrounding vehicle v
$x_{neighbour,0}$	m	x-coordinate of initial position of a predicted surrounding vehicle
$v_{neighbour,x,0}$	m/s	Initial longitudinal velocity of a predicted surrounding vehicle
$a_{neighbour,x,0}$	m/s^2	Initial longitudinal acceleration of a predicted surrounding vehicle
$\boldsymbol{deviation}_{longituidinal}$	m	Vector containing longitudinal deviation over all predicted frames
$\boldsymbol{deviation}_{lateral}$	m	Vector containing lateral deviation over all predicted frames
$\boldsymbol{deviation}_{euclidean}$	m	Vector containing Euclidean distance of deviation all over predicted frames

$time\_gap_{label}$	s	Time-to-collision of ego-vehicle in longitudinal direction to surrounding vehicle with corresponding label
BS_{front}	m²	Blind spot caused by a vehicle in front of ego-vehicle
$BS_{leafleading}$	m²	Blind spot caused by vehicle labelled “leftleading”
$BS_{middleleading}$	m²	Blind spot caused by vehicle labelled “middleleading”
pa_{ego}	-	Possible actions of ego-vehicle
pa_{nb}	-	Possible actions of neighbour-vehicle
$variable_{norm}$	-	Values of influence factor after normalization
C_{scene}	-	Complexity of a scene
$C_{scenario}$	-	Complexity of a scenario

1 Introduction

As a traditional industry, the automobile industry nowadays is facing a lot of new challenges, which appear with the development of telecommunication technology, global climate change, change of consumers' demand and attitudes, etc. New development trends caused by the influence of these factors are summarized with an acronym 'C.A.S.E.', indicating Connectivity, Autonomous, Sharing and Electrification. Lots of capital and effort have been and will continue being put in the research field of autonomous driving (also known as self-driving), not only for the reason, that its development can make our traffic transportation more secure and comfortable, but also because its realization will redefine our way of traveling and bring revolutionary changes to our daily life.

In the first part of this chapter, a brief introduction of autonomous driving will be given, in which the definition of different levels of self-driving are explained. In the second part, the motivation of this thesis will be clarified. Then in the third part, the goal of the thesis is going to be elaborated and the structure of the work will be shown.

1.1 Autonomous driving

In 2014, SAE International (Society of Automobile Engineers) categorized different degrees of self-driving into six levels, known as J3016 [1]. Since then, this categorization has become the most often referenced standard while assessing the performance of an automated vehicle.

The categorization begins with level 0, where there is no automation. Tasks like acceleration, deceleration, steering, braking, etc. all need to be conducted manually. Vehicles at level 1 are equipped with some assistant functions. At this level, part of control can be taken over by vehicles. However, the driver keeps monitoring the environment around vehicle and is ready to take control of the vehicle back at any time. One example of the assistant systems is ACC (Adaptive Cruise Control), which helps the vehicle to maintain a safety distance from the front vehicle by adjusting its speed. Other assistant systems like LKA (Lane Keeping Assistance), AEB (Automatic Emergency Brake), Parking Assistance are also available from many automobile producers on the market now. Level 2 refers to partial automation, this is also what nowadays most automobile producers can already offer. For vehicles at this level, the system takes full control of the vehicle while permanent monitoring of the environment and immediate interference in case of emergency from the driver are required. Level 3 is defined as conditional automation. One biggest difference to the last two levels is that, the vehicle no longer requires the driver's permanent attention and can monitor the environment on its own. The system can make decisions like lane change or braking according to its own judgement. The driver is able to engage in other activities besides driving. However, the driver still needs to be ready for interference if the system requires, that the control needs to be taken over by the driver. Vehicles reaching level 4 are highly automated and the driver may leave the driver's seat. Highly automated driving mode can only be activated under certain circumstances. Beyond these circumstances interference from the driver is still required. Level 5 is described as complete automation, where no human attention and interference are no longer needed under any condition.

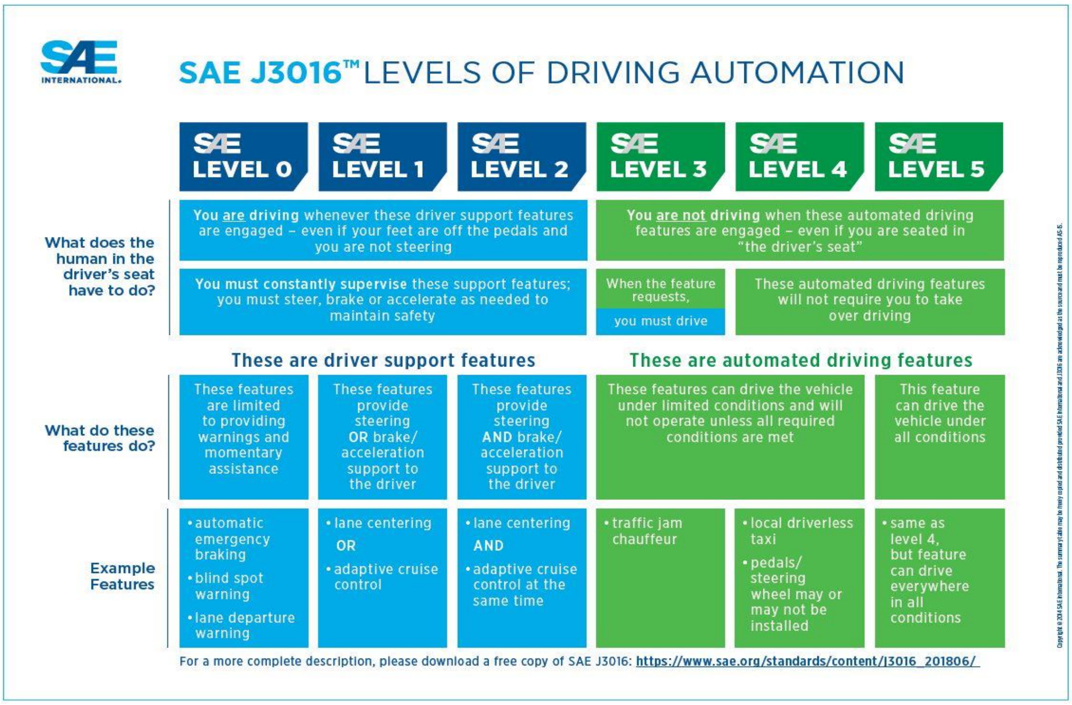


Figure 1.1: Levels of automation [1]

1.2 Relevance of the work

As the level goes higher, less attention from human is required for the monitoring of the environment, tasks will be step-by-step taken over by the automatic system. Therefore, the capability of the vehicle to sense the environment is essential, which includes identifying the driving lanes, understanding traffic signals and various road signs, monitoring the states and behaviours of other traffic participants like avoiding the pedestrians, keeping a safe distance to the front vehicle, etc.

To collect all these information, various sensors with different characteristics are installed at different positions on the vehicle. For example, ultrasonic sensors with a range of about 5 m and very narrow directivity due to high frequency, are commonly used for parking assistant systems. The functionality of an ACC system mentioned above is usually based on the data collected by Radar (short for 'Radio Detection and Ranging') sensors. It has a range of about 200 m. Radar sensor is able to detect one or more traffic participants and measure the (relative) speed of these detected vehicles and their positions relative to ego-vehicle (distance and angle). One shortage of radar sensor's application in automobile is that, the measurement of lateral speed of a detected vehicle is quite difficult. This shortage can be made up by using Lidar (short for 'Light Detection and Ranging') sensor. Instead of microwave emitted by Radar emits Lidar ultraviolet, infra-red or visible light beams. It is highly accurate but the cost for production is very high.

Another sensor significant for the development of autonomous vehicle is camera. With camera the vehicle is able to identify driving lanes, understand the meaning of road signs, distinguish between different types of traffic participants. Each kind of sensor has its advantages and disadvantages, so that the collected information can be as complete and accurate as possible, application of sensors with different characteristics are necessary. However, alone sensor data is not enough for autonomous driving. In the future, with the development of telecommunication and 5G technology, the vehicle will be able to communicate with infrastructure (V2I), network (V2N), pedestrians (V2P), other vehicles (V2V), etc. known as vehicle-to-everything (V2X).

Before a vehicle with partial automation (or in the future higher levels of automation) can be put on the market, various tests need to be conducted to ensure the vehicle's performance in the real-world situation. The factors needed to be considered in the tests, cases needed to be covered, number of tests needed to be run, etc. are all aspects that ought to be included in the consideration. Various concepts are available to answer these questions. One most commonly used concept the called the "Test Matrix", where all dimensions are predefined. This concept is often applied in the field of software-testing and not necessarily appropriate for automated vehicles, since the latter are more intelligent and aimed for more complex and unpredictable situations. In the recent years, a concept named Naturalistic Field Operational Tests (N-FOT) is becoming more and more popular for testing vehicles with automatic functions, which is a combination of Naturalistic Driving Studies (NDS) and Field Operational Tests (FOT). In NDS, real world vehicle data is collected by different devices without the driver's awareness of their existence. FOT can be used during NDS for the testing of some certain functions (e.g. testing ACC-function when following a front vehicle). N-FOT has the advantage of reflecting real-world situation. However, since the large part of the daily driving is not challenging, this concept is not effective enough for the test of challenging and critical situations. The number of traffic situations to be tested is endless. Therefore, finding a effective way of testing can be very necessary. ZHAO ET AL.'s work [2] offers a possibility to accelerate this process.

In order to make the test process effective, efficient, repeatable and economical at the same time, this work aims to develop a method for a quantitative evaluation of driving environment for automatic vehicles on the highway with real-world traffic data, focusing on the behaviour of surrounding traffic participants, so that the most representative and compact test cases can be designed.

1.3 Goal and structure of the work

Goal of this work is to develop a method to evaluate highway traffic situation for automated vehicles quantitatively with help of HighD Dataset. In the second chapter of this work, some relevant research will be introduced and discussed. Based on the results of literature research, the consideration for the topic of this work will be introduced and elaborated, which includes the derivation of influence factors of complexity and quantitative interpretations of these factors, several important definitions will also be clarified in this chapter as well. In the third chapter, each derivate factor will be implemented with help of Matlab. It will be explained in detail, how the influence is quantified and how quantified influence of different factors are normalized in order to calculate complexity. The method according to the implementation in chapter 3 will be applied for the evaluation with HighD Dataset. The results of calculation will be analysed in chapter 4. The unusual values or phenomenon will be discussed in the first part of this chapter. In the second part, scenes and scenarios with different complexities according to the evaluation with this method will be compared with each other. It will be investigated in detail, what are the reasons, or which factors leads to the high complexity of some scene or scenario. In the last chapter, the shortages and disadvantages of this method will be discussed and some possibility for improved are offered. Some potential extensions of this work will be discussed as well.

2 State of the art

For the evaluation of traffic environment, factors taken into consideration can be different regarding the subject of the study, whether the ego-vehicle is a human driving vehicle or an automated vehicle. Two major differences make this distinction necessary. Firstly, human perception is subjective, which differs from person to person and fluctuate through the day depending on the condition of the driver. Secondly, human perception is qualitative. The driver can only estimate, for example, distance to front vehicle, speed of surrounding vehicles, etc. This perception is not sensitive to small changes or fluctuation of parameters and therefore inaccurate, which may lead to false judgement of the driver. An automated vehicle can measure these parameters quite accurate with the help of various sensors and devices. The performance will also remain persistent and stable without fluctuation like humans do. The subjective of this thesis is automated vehicle, the evaluation of the environment around the ego-vehicle will be conducted quantitatively.

In the first part of this chapter, two concepts are introduced for the description of the scenario. In the second part, study about complexity is presented, also some research about the qualitative and quantitative ways to evaluate the traffic situations, including the factors taken into account and the algorithm applied to deal with these factors in order to obtain a final result of complexity of a scenario. In the third part, the data being used for this thesis, namely the HighD-data is introduced. Last but not least, combining the experience from other research and the data available. A list of influence factors is generated for the evaluation of environment complexity for highway traffic.

2.1 Scenario description

For a comprehensive analysis of the environment the automated vehicle is in, a hierarchical and description of the traffic situation is necessary. From the perspective of a human driver, FASTENMEIER [3, pp. 44-50] has divided all features into three categories: road type, road course and traffic flow, each with 2 to 7 attributes (Figure 2.1).

Similar work can be done for automated vehicles. MAURER ET AL. [4, pp. 25-28] develop 9 features for the description of defined use-cases (Table 2.1). These features include the properties of an automated vehicle and the traffic situation the vehicle can be in. Among them feature D, F and E are relevant for the environment analysis, which has the following attributes. Attributes with bold font are the ones related to the topic of this thesis, which will be elaborated in detail in the following text.

These classifications or features offer a concise overview of the different aspects a traffic situation may contain. However, in order to find or define indicators for quantitative analysis of the environment, this information is not enough.

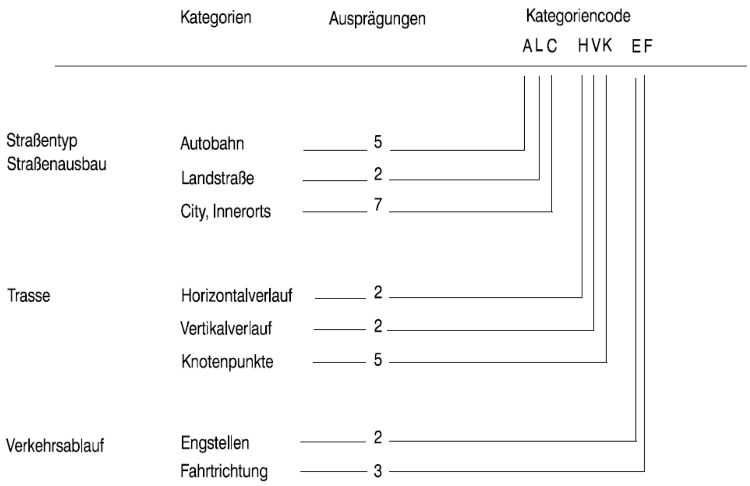


Figure 2.1: Classification of traffic situations by Fastenmeier [3, pp. 44-50]

Table 2.1: Features for description of use-cases

	Feature
A	Type pf promotion
B	Maximal permissible total mass
C	Maximal permissible velocity
D	Scenery
E	Dynamic elements
F	Information flow between automated vehicles and other traffic participants
G	Availability concept
H	Extension concept
I	Possibility of intervention

Table 2.2: Attributes of environment-relevant features

Feature	Attributes
Scenery	Terrain, agricultural road, parking lot or oarking garage, build-on main road, main road without construction, **highway**, country road, special areas
Dynamic elements	**Only motor vehicles**, **only autonomous vehicles**, all possible traffic participants (e.g. pedestrians, bike-riders, animals etc.)
Information flow	Optimization of navigation, optimization of track guidance, optimization of controlling, **environmental information**, update of automatic system, monitoring of autonomous vehicle, passenger surveillance, passenger-emergency call

2.2 Traffic situation analysis

The focus of the thesis is complexity of the environment around ego-vehicle. In the first part of this section, the objects of environment analysis will be clarified, and some important definitions are explained. In the second part, the concept complexity will be decomposed and analysed. In the last two parts, some research relevant to complexity analysis from the perspective of human and automated vehicles will be introduced respectively.

2.2.1 Objects of situation analysis

In order to organize all information and elements contained in a traffic situation, BAGSCHIK ET AL. [5] propose a five-layer-model (Figure 2.2), which is based on the work of SCHULDT [6]. Considering that the information contained in HighD Dataset in regard with infrastructure is only the lane markings, and the information about natural environment e.g. weather and lighting is not available, the emphasis of highway traffic situation analysis in this thesis will be placed on the analysis of dynamic elements in a defined region around ego-vehicle, corresponding to the fourth layer in five-layer-model.

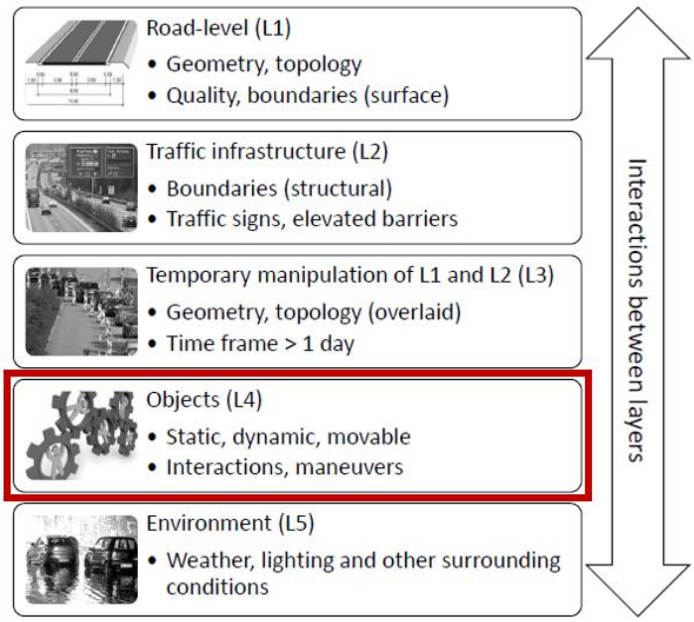


Figure 2.2: Five-layer-model for scene representation

Before a region of interest (ROI) around ego-vehicle can be defined, it is necessary to firstly distinguish the definitions of three terms: scenery, scene and scenario. ULBRICH ET AL. [7] have conducted a literature research and proposed their own definitions based on the result of the research. According to their study scene is a snapshot of the environment, which consists of three parts: dynamic elements (e.g. traffic elements), scenery (e.g. infrastructure, static elements like traffic signs and traffic lights, weather and light conditions), self-representation of actors and observers (e.g. driving skills, states of the driver, etc.). It is noticeable, that scenery is a part of scene. In the third part of each recording of HighD Dataset, where detailed information of all frames of each vehicle is stored, the information of each frame is corresponding to a scene. However, for HighD Dataset except lane markings, only information about dynamic elements in a scene is available. A scene is a snapshot at a time a time point, a scenario is then a sequence of temporally consecutive scenes. It can be specified by the actions taken in this time period, e.g. lane change, overtake, etc. Figure 2.3 shows a good visualization of this relationship, where each dot represents a scene, four marked dots connected by a dashed line from left to right make up a scenario. The relationship between these three terms is presented in Figure 2.4.

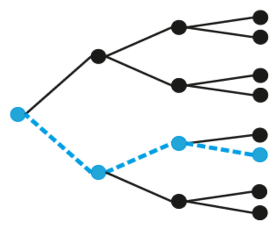


Figure 2.3: relationship between a scene and a scenario [7]

Complexity in this thesis is concept in regard with a scenario of individual vehicles. Therefore, it is a result extracted from a sequence of scene, or “frames” in case of HighD Dataset. The highway section recorded is about 420 meters long, assuming a vehicle drives with a speed of 30 m/s, then it takes the vehicle maximal roughly 14 seconds to pass the entire section. Since not all vehicles are recorded once they reach the left or right edge of the highway section, and some frames, in which a valid region of interest cannot be defined, must be cast away. The actual time period used for the evaluation is usually within 10 seconds, which is sufficient for an action like lane change and not long enough for the vehicle to take several actions. Therefore, a scenario is defined as a sequence of all valid frames of each vehicle in this thesis. The validation of a frame will be elaborated in the first section of chapter **Fehler! Verweisquelle konnte nicht gefunden werden.**.

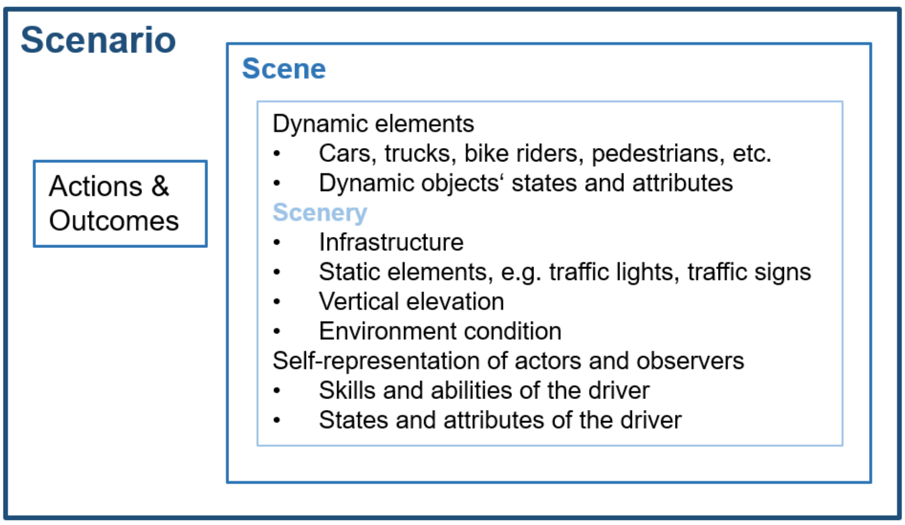


Figure 2.4: Scenario, scene and scenery [7]

2.2.2 General definition of complexity

SCHAUB [8] derives the following features of a situation in his work, in which people find difficulties and would characterize it as “complex”:

- Variables, which significant influence have and need to be considered.

- Connectivity, which describes mutual influence the variables might have on each other.
- Self-dynamic, which indicates the self-changing of the system with no outside intervention and is usually a result of internal connectivity.
- Non-transparency, which indicates the components of the system not visible or not known by the decision-maker.
- Polytelie, which describes the necessity to balance different objectives, which are not always compatible with each other.
- Indistinction of the target situation.
- Novelty, indicating the part of the system, which is new to us.

2.2.3 Complexity from perspective of human

Based on the seven dimensions of complexity above, SCHULDT [6, pp. 29-36] extends it with one more dimension

- Number of states per element,

and conducts a qualitative evaluation of complexity of different scenarios with the help of these dimensions. The evaluation is conducted with the help of a Kiviat-Diagram, where each axis represents one of the eight dimensions. Each axis of the diagram is provided with an ordinal scalar, ranging from 1 to 5, which indicate the levels of corresponding dimensions, with 1 = very low, 2 = low, 3 = middle, 4 = high, 5 = very high (Figure 2.5).

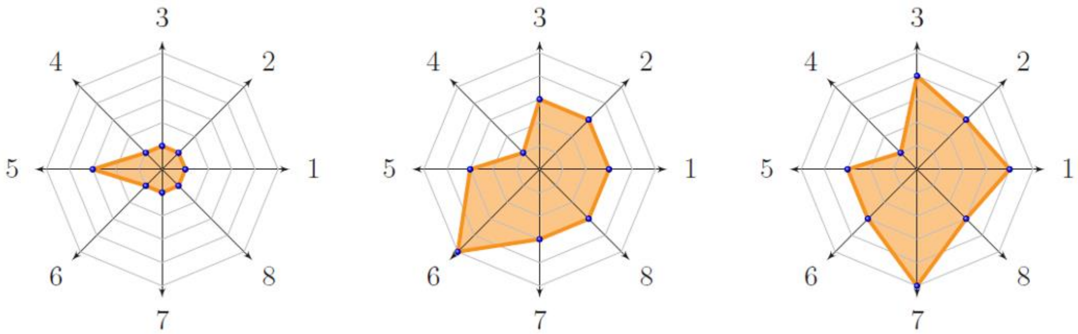


Figure 2.5: Qualitative evaluation of complexity with Kiviat-Diagram (Legend: 1: Non-transparency, 2: Self-dynamic, 3: Connectivity, 4: Novelty, 5: Number of elements per element, 6: Number of elements, 7: Indistinction of the target situation, 8: Polytelie) [6, pp. 29-36]

Figure 2.5 shows an example of complexity evaluation of different scenarios on the highway. Taking dimension 7, number of elements (number of traffic participants in scenario) as an example. For highway section with less traffic (Kiviat-Diagram on the left), the corresponding axis is assigned with value 1, which indicates that the number of traffic participants is small in this scenario. For scenario highway junction (Kiviat-Diagram on the right) this dimension is assigned with value 5. It is assumed, that highway junction is where two highways join and therefore has the biggest number of elements. Through median and mean value of the scalars of eight dimensions, it is a concise method to make a relative comparison of complexity of different scenarios. However, an absolute value of complexity cannot be obtained with this method from the perspective of the author. Another limitation of this method is that, the ordinal scalars are assigned intuitively, and the evaluation is subjective, which may lead to different results if different persons apply this method.

In the work of SCHWEIGERT [9, pp. 63-64], which focuses on the study of the driver's eye movement, an evaluation of visual complexity is conducted for several different road sections; described with the classification method developed by FASTENMEIER [3, pp. 44-50]. The following four influence factors are chosen to be the complexity-index:

- Curves
- Junctions
- Oncoming vehicles
- Preceding vehicles

For curves and junctions, the number of these two elements will be counted. For oncoming vehicles, the mean number of detected vehicles is collected. For preceding vehicles, the average time proportion is calculated, in which the driver takes a glance at the preceding vehicles. The values of these indicators are then converted into an index, 0, 1 or 2, indicating the three categories or levels of the factor, with 0 = low, 1 = middle, 2 = high. Adding up the indexes results in [9, pp. 63-64] with a maximal value of 8 for corresponding road section (Figure 2.6).

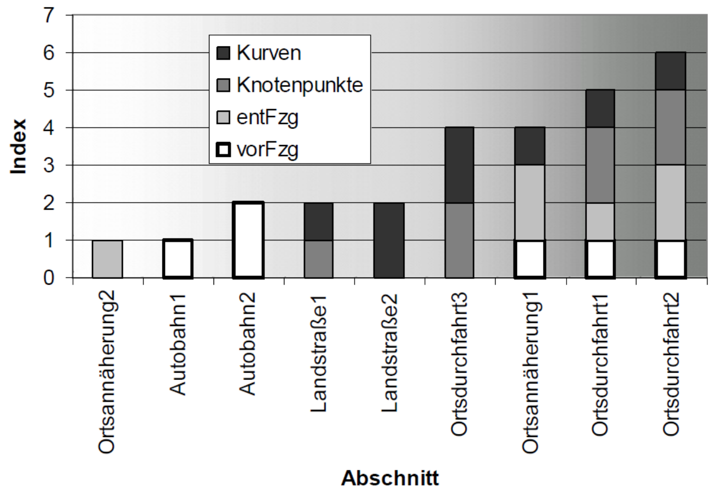


Figure 2.6: Composition of indicators' indexes for individual road section [9, pp. 63-64]

Compared to Kiviat-Diagram, this method has the advantage of taking the condition of infrastructure into consideration. However, since all factors in SCHWEIGERT's method [9, pp. 63-64] are equally weighted and the index-range is quite small, it is not obvious to discover the factor influencing the complexity most like Kiviat-Diagram does. These two methods also have several similarities. First, they both select some influence factors as indicators for complexity. Second, they both assign each indicator an index indicating the levels of this factor. Third, they are both qualitative evaluation method. Finally, they both offer a good visualization of the result.

2.2.4 Complexity from perspective of AV

There is much research about the evaluation of traffic environment available. In this part, four relevant research will be introduced. The first two research are for general environment analysis and can be adapted for different sceneries, e.g. city road, rural area, highway etc. The last two research are specific for highway traffic.

With the aim of automatic generation of test cases, which are effective, economical and at the same time cover as many factors as possible, XIA ET AL. [10] develop a test case generation algorithm with the help of analytic hierarchy process (AHP). An index C, which has a value between 0 and 1, is introduced as a measurement of the complexity of scenario. Higher value of this index indicates higher complexity of the scenario. Test cases will then be obtained by clustering the scenarios with high level of complexity. In this work the influence factors are selected and arranged in a hierarchical structure by means of AHP (Figure 2.7). All influence factors are categorized into different layers. S_{ij} represents the j-th factor in the i-th layer, which furthermore is influenced by the sub-factors in the next layer. F_{ij} corresponds to the importance degree of factor S_{ij}, which is also a value between 0 and 1. The higher this value is, the bigger is the influence of this factor. The determination of importance degrees is based on Delphi method [11, pp. 3-12]. It is a result of the sum of importance degrees of the sub-factors. For example, S_{11} as the first factor in the first layer, is at the same time influenced by factor S_{21} and S_{22} with importance degree F_{21} and F_{22}. F_{11} is the importance degree of factor S_{11}, which is the sum of F_{21} and F_{22} and indicates how strong is the influence of S_{11} on the final complexity of the scenario.

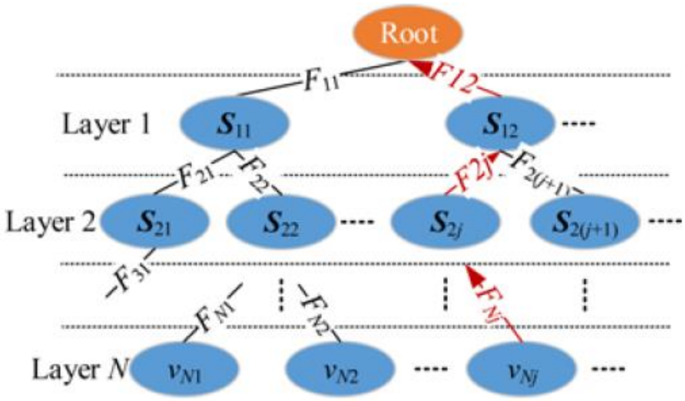


Figure 2.7: Hierarchical Model with influence factors and importance degrees [10]

In the work of WANG ET AL. [12], an evaluation of scenario complexity has also been conducted to classify massive traffic data, with the aim of accelerating the process of testing autonomous vehicles. Same as XIA ET AL.'s work [10], an index C is introduced to measure the complexity of the scenario. However, instead of structuring the influence factors hierarchically, complexity in this work is consisted of two parts (Eq.(*2.1)*). The first part is called road semantic complexity, corresponding to C_R in the formula. The second part is traffic element complexity, corresponding to C_E.

$$C = \lambda_1 C_R + \lambda_2 C_E \qquad (2.1)$$

λ_1 and λ_2 are the corresponding weighting factors of two parts. The part road semantic furthermore consists of three levels: i. Road type, e.g. urban area, highway, rural areas etc. ii. Scene type, e.g. normal driving, intersection, up/down viaduct, tunnel, bridge, etc. iii. Challenging conditions, e.g. overtaking, avoiding pedestrians, blurred lane lines, driving at night, etc. Assuming there are n road types and m scene types, these two levels are described with a n- or m-dimensional vector respectively. The element of the vector will be assigned 1 if the corresponding type is met, otherwise the value will be set to 0. Assuming there are o types of challenging conditions, this level will be described with an o-dimensional vector. 0, 0.2, 0.4, 0.6, 0.8 or 1 will be assigned to each element of vector according to the challenging degree of the condition. An M-dimensional ($M = n + m + o$) matrix can be obtained, which is defined as the semantic descriptor.

The second part traffic elements complexity refers to the influence of the movement of vehicles around ego-vehicle, which is very similar to the topic of this thesis. Since not all of surrounding vehicles contribute to the scenario complexity, therefore in this work only vehicles at 8-nearest positions are taken into account. A $Nx2$ matrix is defined to describe the traffic elements, with N corresponding to the number of traffic elements around ego-vehicle. First column of the matrix corresponds to the distance between traffic element and ego-vehicle while the second column include the angles of the traffic element relative to ego-vehicle from ego-vehicle's point of view.

A value between 0 and 1 for complexity index C can be obtained by combining the effects of these two parts. The interval of C is categorized into three levels. Scenarios with complexity in interval (0,1/3) are labelled with simple, in [1/3, 2/3) are labelled with medium, in [2/3,1) are considered as complex. Figure 2.8 provides an overview of the entire algorithm.

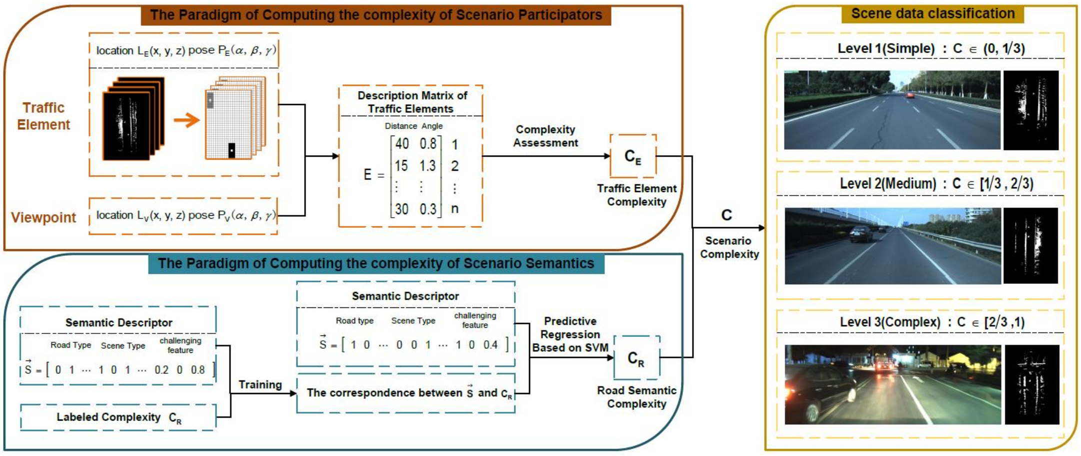


Figure 2.8: Overview of complexity-calculation-algorithm [12]

There is also much research focusing on the traffic situation on the highway. In DAVID ET AL.'s work [13] , they model each traffic participant as a Markov-Decision-Process in order to predict the movements of dynamic elements in the scenario as accurate as possible. The focus of the research is on the prediction of dynamic elements, which is an important part of complexity analysis on the highway. The cost function of each Markov-Decision-Process is a linear combination of weighting factors and features:

$$\boldsymbol{C}(s) = \boldsymbol{\theta} \cdot \boldsymbol{f}(s) \tag{2.2}$$

In the formula above, $\boldsymbol{\theta}$ is a vector including weighting factors of all features. $\boldsymbol{f}(s)$ is a vector of all features with respect to state s of the Markov-Decision-Process, which describes the state of ego-vehicle and its environment.

$$\boldsymbol{C}(s) = \boldsymbol{\theta_s} \cdot \boldsymbol{f_s}(s) + \boldsymbol{\theta_d} \cdot \boldsymbol{f_d}(s) \tag{2.3}$$

All features are divided into static features $\boldsymbol{f_s}$ and dynamic features $\boldsymbol{f_d}$. Static features are the ones, which do not change over time and model the preferences of the driver, e.g. driving with desired velocity. Following two features are selected as static features:

- Lane, to see if the driver prefers to drive on a particular lane
- Difference between actual velocity and desired velocity

Dynamic features change over time and are defined as “risk-aversive” behaviour of the driver. Following features are included:

- Time-headway to vehicle directly ahead of ego-vehicle
- Time-headway to vehicle directly behind ego-vehicle

The concept time-headway is the time period between the time point when the rear of leading vehicle passing one point and the time point when the front of direct following vehicle passing the same point.

Another research about traffic situation analysis on the highway is NOH ET AL.’s work [14]. The aim of this research is to evaluate the possibility of collision and then to determine a maneuver to reduce this possibility, namely two components, situation assessment component and strategy decision component. The assessment of the traffic situations takes place in a defined region around ego-vehicle: 170 meters forward, 50 meters backward, adjacent area on both sides of the vehicle are also included. Assuming a vehicle drives with about 100 km/h on the highway, a safety distance nearly half of velocity ought to be maintained during driving, which is about 50 meters. Although this distance cannot usually be kept in the reality (Based on the observation in HighD Dataset, this distance can sometimes only be within 30 m and it depends on the driver’s willingness). However, it is reasonable to use this value to define a region for environment analysis. It is noticeable, that the area forwards for the assessment much longer than backwards. It is also reasonable, since the area in front of vehicle is much more important. The entire region is divided into six local parts: left lane rear/front, current lane rear/front, right lane rear/front (Figure 2.9). The assessment is firstly conducted on a local region level and then taken to the entire region level.

For each local region, “threat measure” will be calculated for each vehicle in this region, which is defined to evaluate the possibility of collision between ego-vehicle and the respective local region vehicle. For the area in front of ego-vehicle, three values are selected as “threat measures”:

- Time-to-collision (TTC)
- Distance between two vehicles to be kept ensuring minimum safety (MSM)
- In case of sudden brake from vehicle in front of ego-vehicle, the remaining time until an emergency brake is taken to avoid collision (TTB).

For region behind ego-vehicle, since the sudden halt of vehicle behind ego-vehicle won’t have any influence, therefore only TTC and MSM are chosen as “threat measures” for regions behind ego-vehicle. The result of “threat measure” is categorized into three different “threat levels” respectively according to two defined thresholds x^A and x^D: dangerous, attentive and safe, which are based on international standards for safety (Table 2.3).

Thus, each vehicle in each local region is assigned with a “threat level”. Vehicles with highest level of threat will then be reported to the situation assessment component, which means that the vehicles with high possibility to collide with ego-vehicle will be taken into consideration. Based on these results, a “threat level” on lane-level can be obtained. Furthermore, the maneuvers ought to be executed to reduce complexity or potential of collision can be determined.

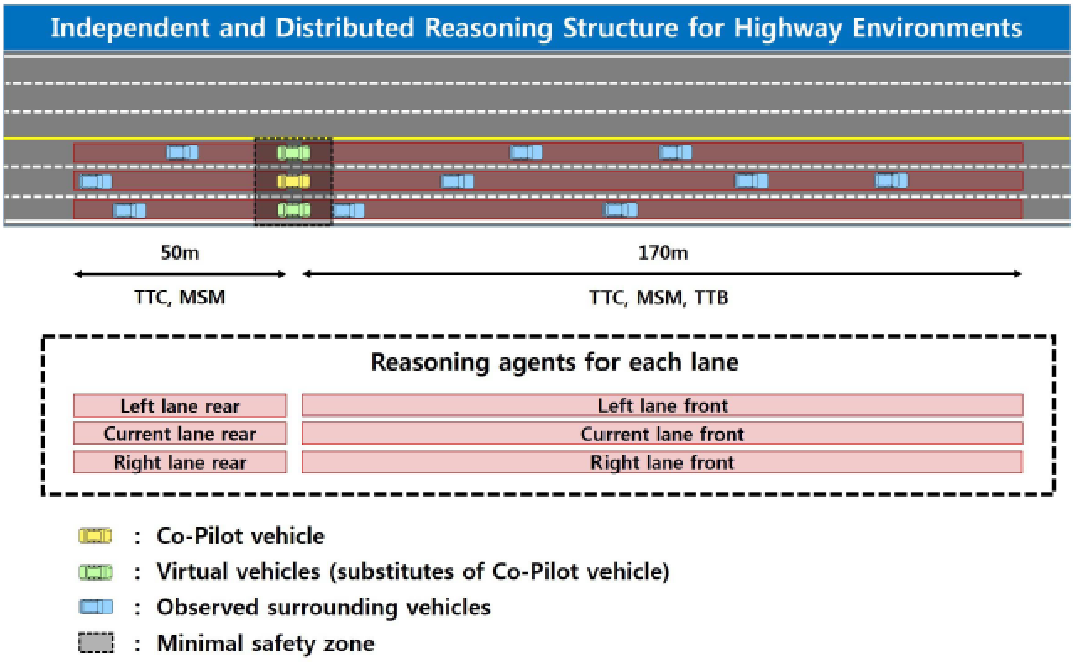


Figure 2.9: Region of interest for environment assessment

Table 2.3: Threat measure & threat level

Threat measure s		Threat level
	$x < x^A$	Safe
TTC, MSM, TTB	$x^A < x < x^D$	Attentive
	$x > x^D$	Dangerous

2.3 HighD Dataset

The research from the last subchapter offer many good ideas and experiences with respect to the factors ought to be taken into consideration for evaluation of different environments with different purposes, also the algorithms to deal with these factors to obtain a conclusive result. However, the information from background research is not enough for the selection of influence factors, since the availability is at the same time restricted by the data being used. Therefore, before concrete influence factors are derived, it is necessary to look into the available dataset.

The dataset being used in this thesis is HighD Dataset (short for “The Highway Drone Dataset”). It is a naturalistic dataset containing 110500 vehicles’ trajectories. Vehicles passing a highway section of 420 meters long are recorded by a drone (Figure 2.10). The recording takes place on the highways at six different locations in Germany, which is 44500 driven kilometres land 147 driven hours in total.

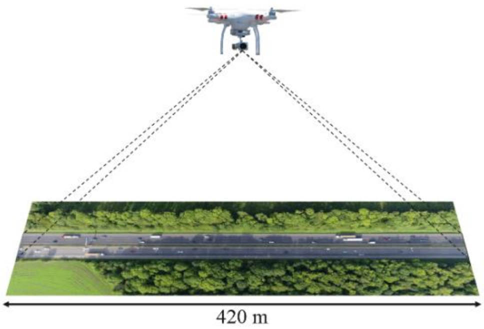


Figure 2.10: Highway section recorded by drone [15]

Each recording consists of three part. The first part contains general information of the recording, e.g. recording day, frame rate and duration of the recording. Total driven distance, total driven time, total number of vehicles, cars and trucks recorded, etc. It is noticeable that HighD Datatset contains only two types of traffic participants: car and truck. The information necessary for the evaluation of environment is the positions of lane markings in each section:

Table 2.4: Positions of lane markings [16]

Name	Description
upperLaneMarkings	Vector of y-positions of upper lane markings (negative driving direction)
lowerLaneMarkings	Vector of y-positions of lower lane markings (positive direction)

The global coordinate system used to record the positions of lane markings and vehicle positions is shown in Figure 2.11, with upper left corner as origin, horizontal axis as x-axis and vertical axis as y-axis.

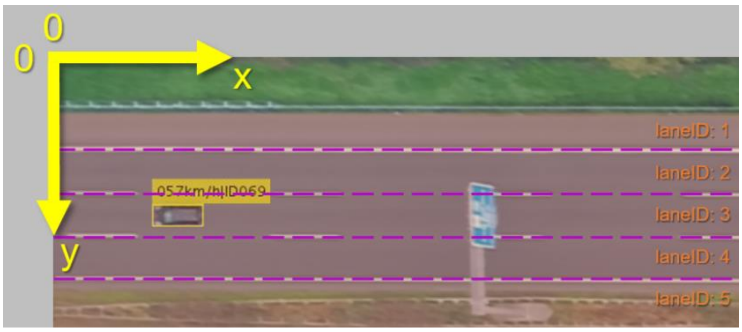


Figure 2.11: Global coordinate system

Each lane is assigned with an id number starting from 1 in ascending order in negative y-direction. The areas above the first lane, below the last lane and between lanes of two directions, which are not drivable, are also taken into account. In this thesis, only cases with two-lane or three-lane highway are used for the evaluation (Figure 2.12), which are the first 57 recordings of all 60 recordings. The last three recordings contain an extra lane for acceleration at highway junction. Because of limited time available for this work, the discussion of this situation will not be included in this thesis.

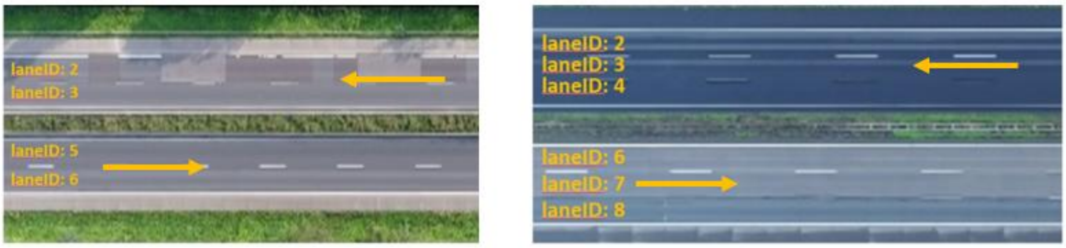


Figure 2.12: Lane-IDs of two-lane and three-lane highways

The second part of data for each recording contains the general information of each vehicle captured by the camera, including id, type, length and width (corresponding to width and height in data), driving direction (1 = positive direction, 2 = negative direction), the frame number when vehicle enters and leaves the camera, number of frames, detected number of lane changes, maximal and minimal velocity over all frames. Furthermore, the average velocity of each vehicle, minimal distance headway, minimal time headway, minimal time-to-collision are also included through calculation.

In the third part, detailed information of each vehicle in each individual frame is available, which includes position of the vehicle (corresponding to the coordinates of upper left corner of the vehicle's bounding box), velocity and acceleration in both longitudinal (x-direction) and lateral (y-direction) direction, ID of the lane, in which the vehicle is currently in. It is notable that, if the vehicle drives in positive direction (direction = 2), the value of acceleration will be positive if the vehicle accelerates and negative when decelerating. However, it is the other way around if the vehicle drives in negative direction (direction = 1). The value of acceleration will be negative if the vehicle accelerates and positive when decelerating, since the velocity in this case is negative.

3 Method

In this chapter, the factors influencing the complexity of environment will be derived based on the result of literature research from last chapter. In the next step these factors are implemented with Matlab respectively, so that the influence of each factor can be quantified. Finally, the quantified values of influence factors will be normalized for the calculation of complexity.

3.1 Influence factors for complexity evaluation

Before the complexity of a scenario can be obtained, complexity of each frame will be calculated, the average value of all frames results in the final complexity of the scenario. This step of calculation is presented with the following formula:

$$C = \frac{1}{m}\sum_{j=1}^{m} \boldsymbol{f}_j^T \cdot \boldsymbol{w}, \quad \sum_{\boldsymbol{i}}^{\boldsymbol{n}} w_i = 1 \tag{3.1}$$

In the formula above, C is the complexity of the scenario from the perspective of ego-vehicle. m represents the total number of valid frames of the observed vehicle. $\boldsymbol{f}$ is a vector with normalized values representing the influence of each factor in the j-th frame. $\boldsymbol{w}$ is a vector containing weighting factors of corresponding influence factors and n is the total number of influence factors.

In order that the influence factors complexity of the environment around ego-vehicle reflects, the derivation will be based on the the work of SCHAUB [8] by interpreting the characteristics in highway traffic situation and concretizing the adaptable ones for a quantitative evaluation:

- Variables: for variables with significant influence on system, in SCHULDT's work it is interpreted as the number of elements, more exactly it can be interpreted as the number of traffic participants within defined ROI.
- Connectivity, it describes the mutual influence between variables, which can be understood as the interactions between different traffic participants within ROI. Seeing each traffic participant as a point and drawing a line through two points, this line can be defined as a connection. Therefore, this characteristic can be concretized as the number of connections within ROI.
- Self-dynamic: as this characteristic is usually a result of internal connectivity according to the interpretation of the author, which is to say, the movement of ego-vehicle is influenced by the behaviours of surrounding vehicles. For example, from the perspective of ego-vehicle, if there are no other vehicles around, ego-vehicle is able to take any action as desired. If there is a vehicle ahead, which is within a safety distance to ego-vehicle and moves as fast as or a bit slowly as ego vehicle, then ego-vehicle would better not accelerate in this case for reasons of safety. It is also the same for surrounding vehicles when considering each surrounding

vehicle as ego-vehicle. Therefore, this characteristic can be interpreted with the following two factors:

  - number of possible actions of ego-vehicle
  - total number of possible actions of surrounding vehicles.

- Non-transparency: it indicates the information unknown to the decision maker. For an automated vehicle in highway traffic, this will be the area not reachable by various sensors installed in ego-vehicle, namely the blind spot of ego-vehicle.

For the remaining two characteristics “Polyteile” and “Indistinction of the target situation”, the interpretation may have similar meanings to “Self-dynamic”. For instance, if ego-vehicle plans to change to the left lane, however, at the same time, a vehicle behind ego-vehicle in the left lane is coming up with a much faster speed, which conflicts with the goal of ego-vehicle. This situation can also be interpreted as, that the number of possible actions of ego-vehicle is one less. The indistinction of target situation is also another word for the interpretation of factor “Self-dynamic”, since the result is open and can therefore have more than one possibility.

The characteristics above are derived when considering the system as a whole. The behaviour of each individual vehicle should also be taken into consideration. First is the dynamic of vehicles around ego-vehicle, namely the velocity and acceleration in both longitudinal and lateral direction. Vehicles at different positions relative to ego-vehicle with different actions or behaviours have different influence on ego-vehicle. For instance, assuming a vehicle moving in front of ego-vehicle, in longitudinal direction the influence of this vehicle has on ego-vehicle will be larger when decelerating and smaller when accelerating. Therefore, the dynamic of surrounding vehicles should be weighted differently to obtain a reasonable result of general dynamic of the environment. Another factor in regard with dynamic can be considered is the difference of these dynamical parameters of vehicles within ROI. Taking acceleration in lateral direction as an example, if the difference between the maximal lateral acceleration and the minimal value is small or nearly zero, it means that the surrounding vehicles in ROI drive with similar lateral acceleration and the situation will not be very complex in this aspect. If this difference is large, it indicates the possibility of one or more vehicles trying to change the lane, since without the intention of lane-changing, the lateral acceleration will remain zero.

Many vehicles with automated functions are able to track and predict the behaviours of surrounding vehicles in order to reduce the possibility of involving into a difficult or critical situation. If the final state of a surrounding vehicle is close to the result of prediction, then the automated vehicle will be able to react to the behaviour of this vehicle appropriately. However, if the final state of surrounding vehicle has great difference to the predicted state, the automate vehicle may have trouble having a right response or responding on time, which may lead to a critical situation. Therefore, the quality of prediction should also be included.

In many researcs mentioned in chapter 2.2, infrastructure is also considered as an influence factor. In information available in HighD Dataset in regard with infrastructure is the number of lanes in each driving direction, which can be considered as a factor, since with more lanes in each driving direction, the situation can be more complicated. However, this influence can be reflected by other factors, for example, the number of vehicles, number of connections, etc. Since with more lanes in each driving direction, there can be more vehicles and more connections in ROI. Therefore, the influence of infrastructure will not be discussed in this thesis.

In the work of NOH ET AL [14], three indicators are introduced to describe the critical degree of the situation. It is necessary to distinguish between these two concepts. A critical situation must not be complex, an accident can happen due to the driver's mistake even when there is no other vehicle around. Vice versa, a complex situation also must not be a critical situation. The indicators time-to-collision, time-to-brake and minimal safety margin are more appropriate for the evaluation of critical situations. In this thesis for complex situation time-headway is chosen as an indicator reflecting the distance between surrounding vehicles and ego-vehicle. Because is case of a small time headway, ego-vehicle needs to execute the actions more precisely.

Last but not least, it makes sense to be aware of the types of traffic participants within ROI, since different types of participants usually have different behaviours. For example, trucks in general have a much lower speed compared with cars and will not change the lane very frequently. Compared with cars, trucks in adjacent lanes or ahead of ego-vehicle can cause a much larger blind spot for ego-vehicle. The behaviours of motorcycles will not be included in the discussion of this thesis, which can be a good extension if there is information available.

As a summary of all consideration above, Table 3.1 lists all the influence factors used in this thesis to evaluate the complexity of highway traffic with HighD Dataset:

Table 3.1: influence factors for evaluation of highway traffic environment

	Description
1	Number of surrounding vehicles
2	Types of surrounding vehicles
3	Dynamic of surrounding vehicles
4	Variation of dynamical parameters of surrounding vehicles
5	Connections within ROI
6	Deviation of surrounding vehicles from predicted state
7	Time-gap between ego-vehicle and surrounding vehicles
8	Possible actions of surrounding vehicles
9	Possible actions of ego-vehicle
10	Ratio of blind spot to ROI

3.2 Number and types of surrounding vehicles within ROI

A ROI based on the velocity in longitudinal direction of ego-vehicle will be defined in the first part. In the second part, vehicles within defined ROI will be identified.

3.2.1 Definition of ROI

Each frame contains information about dozens of vehicles appearing in this frame in both directions. The recorded highway section is 420 meters long. For vehicles, for instance, about 200 m to 300 m away from ego-vehicle, will barely have any influence on the behaviour of ego-vehicle.

Therefore, it is necessary to define a region of interest around ego-vehicle. Only traffic participants in this area will be observed and analysed.

Figure 2.9 from Noh et al.'s work [14] shows an example of ROI on the highway, which ranges from 50 meters behind ego-vehicle to 170 meters in front of ego-vehicle. It is notable that the observed area in front of ego-vehicle is over twice longer than the area behind it. It is reasonable to have this setting, since the behaviours of vehicles in front of ego-vehicle are more important and have more influence on the decision-making of ego-vehicle. However, this setting cannot be applied in this thesis directly. The recorded data include different situations on the highway. There is situation where vehicles move with velocity over 80 km/h, there is also situation where the vehicles are stuck in traffic jam and move very slowly. For the latter situation, it will not be necessary to observe an area 170 meters long in front of ego-vehicle, a much shorter distance can be enough. Therefore, a ROI will be defined according to the actual longitudinal velocity of ego-vehicle.

Assuming ego-vehicle moves with a velocity of 30 m/s, which is 108 km/h. A safety distance is usually defined as half of velocity (km/h), which in this case is 54 m. It means that, theoretically the vehicle behind ego-vehicle should keep a safety distance of 54 m to ego-vehicle, which is also the same for ego-vehicle to the vehicle in front of it. This distance is close to the length of area behind ego-vehicle in Figure 2.9. For the region in front of ego-vehicle, in this thesis a distance twice of the safety distance is determined (Eq. (3.3)). Eq. (3.2) shows the calculation of safety distance given the velocity of ego-vehicle in longitudinal direction (in HighD Dataset $v_{ego,x}$ is given in m/s, the calculation has no unit, the result of it will be assigned with unit meter). In lateral direction, if ego-vehicle is in the middle of a three-lane highway, ROI will have a width of three lanes. If ego-vehicle is in the left lane or right lane of a three-lane highway, or driving in either lane of a two-lane highway, ROI will have a width of two lanes (Figure 3.1). For vehicles driving in negative driving, the left- and right-side of ROI will remain left- and right-side from the perspective of ego-vehicle. The start position of ROI will be the one close to the origin of global coordinate system, i.e. in front of ego-vehicle.

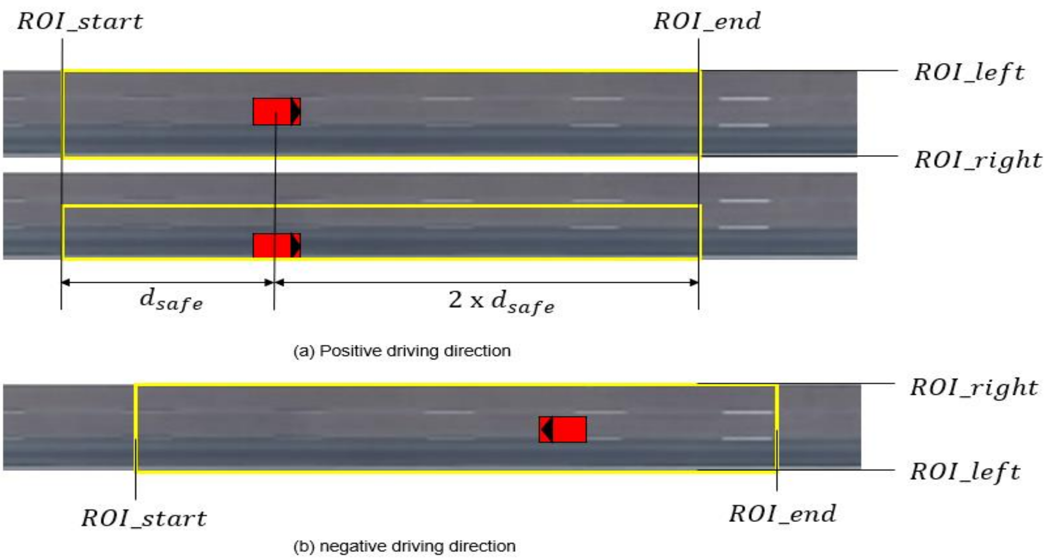


Figure 3.1: Region of Interest

$$d_{safe} = v_{ego,x} \cdot 3.6/2 \tag{3.2}$$

$$d_{front} = f_d \cdot d_{safe}, \;\; f_d = 2 \tag{3.3}$$

Theoretically based on the definition of ROI, environment analysis can be started within this area for each frame. However, for vehicles just enter or are about to leave the highway section in camera frame on both ends, ROI may exceed the boundaries of highway section (Figure 3.2). Since the area beyond camera frame is not known to ego-vehicle, this can cause the reduction of traffic participants within ROI, which furthermore will influence the results of other factors. Therefore, to ensure the accuracy of the evaluation, frames running into this situation will be cast away.

Figure 2.9:

Region of interest for environment assessment

Figure 3.2: ROI exceeding the boundary of highway section

3.2.2 Identification of vehicles within ROI

After a valid frame from a vehicle with defined ROI is determined, next step is to identify the vehicles appearing around ego-vehicle within ROI in this frame.

Detailed information including parameters in each frame of all detected vehicles passing the highway section is saved in a csv-file named “track” for each recording. The data in this file will be read and sorted in two ways. First, the read data will be grouped according to the ids of vehicles, each element contains parameters of all frames of respective vehicle. Second, the read data will be grouped according to the frame number, each element contains information about all vehicles appearing in this frame, e.g. their geometries, driving directions, velocities, accelerations, etc. Basic idea of identifying vehicles within ROI is to firstly find out the vehicles in the frame, which ego-vehicle is currently in.

Since each frame contains dynamic elements in the entire highway section, therefore next step is to sort out the vehicles within ROI. Vehicles satisfying the following conditions are determined to be qualified: i. vehicle has the same driving direction as ego vehicle. ii. vehicle lies between the start and end position of ROI in longitudinal direction. iii. vehicle lies between the left and right boundaries of ROI. Figure 3.4 shows the code structure of this screening process. For condition ii, a vehicle will be determined to be within ROI in longitudinal direction, when the x-coordinate of the right edge of its bounding-box not smaller than the x-coordinate of start position of ROI and the x-coordinate of the left edge of its bounding-box not larger than the x-coordinate of end position of ROI (Figure 3.3). For condition iii, the determination of a vehicle within ROI in lateral direction can be achieved with help of lane-ID assigned to each vehicle in each frame. For instance, if ego-vehicle is currently in the middle of a three-lane highway with lane-ID = 7 (positive direction, Figure 2.12), then the lane-IDs of vehicles within ROI can only be 6 (left adjacent lane), 7 and 8 (right adjacent lane), similar for two-lane highway and vehicles with negative driving direction.

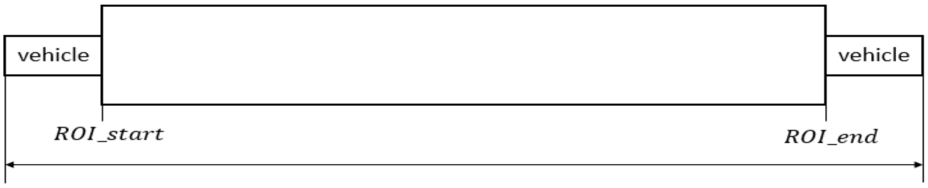


Figure 3.3: identification of vehicles within ROI in longitudinal direction

```
loop over all vehicles in the i-th frame
    if vehicle's id differs from egos'
        if vehicle has same driving direction as ego vehicle
            if vehicle lies within ROI in longitudinal direction
                if vehicle lies within ROI in lateral direction
                        vehicle_number + 1
                        note the type of vehicle
                        save the information and parameters of vehicle
                end
            end
        end
    end
end
```

Figure 3.4: Code structure for vehicle identification

In this section, the information and parameters of ego-vehicle and surrounding vehicles within ROI will be saved for the implementation and analysis of further influence factors.

3.3 Dynamic of surrounding vehicles

In the last section, a ROI in regard with ego-vehicle's longitudinal velocity is defined and the vehicles within ROI are identified. In this chapter the dynamic of these identified surrounding vehicles will be analysed. Since vehicles at different positions relative to ego-vehicle have different influence on the behaviour of ego-vehicle in longitudinal and lateral direction, therefore these surrounding vehicles will be at first classified according to their positions relative to ego-vehicle. Based on the result of classification, weighting factors will be assigned to the surrounding vehicle according to their acceleration and velocity in both longitudinal and lateral direction.

3.3.1 Classification of surrounding vehicles

In WANG ET AL.'s research [12] introduced in section **Fehler! Verweisquelle konnte nicht gefunden werden.**, considering the different contributions of surrounding vehicles, only vehicles at 8 nearest positions are taken into consideration. In this thesis, since the area in front of ego-vehicle is considered as more important than the area behind ego-vehicle, therefore, more vehicles in the front area will be observed and the 8-nearest-neighbour model is extended to a 11-nearest-neighbour model, which is used in the work of ANTONA-MAKOSHI ET AL. [4, pp. 25-28].

For vehicle direct in front of ego-vehicle, its dynamic in longitudinal direction has larger influence on ego-vehicle than in lateral direction. However, for vehicle, which is left in front of vehicle, its dynamic in lateral direction is more important, since it may change the lane and cuts into the lane, which ego-vehicle is currently in. From the perspective of ego-vehicle, if ego-vehicle intends to change to the right adjacent lane, then the behaviours of vehicles on the right side need to be paid more attention to than the ones on the left side. Based on these considerations, it is necessary to classify the surrounding vehicles according to their positions relative to ego vehicle for a more reasonable and accurate evaluation of their dynamic.

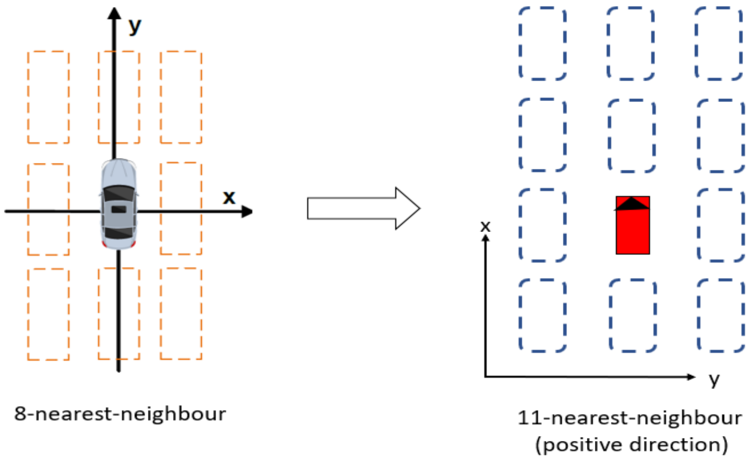


Figure 3.5: Extension of an 8-nearest-neighbour model to an 11-nearest-neighbour model

The ROI will be divided into 4 sections with help of three points ($S1, S2$ and $S3$) in longitudinal direction and 3 strips in lateral direction. The entire region is then separated into 12 sectors in total. Taking ego-vehicle with positive driving direction as an example, the x-coordinates of point $S2$ and $S3$ can be determined first, which are 5 meters in front of and behind ego-vehicle respectively ($d_{along} = 5$). $S1$ is the middle point of $S0$ and $S2$ (Eq. (3.4) to Eq. (3.7)). It is notable for the calculation, that the x- and y-coordinate of vehicles offered in HighD Dataset corresponds to the position of left-upper corner of the vehicle's bounding-box in global coordinate system. For ego-vehicle with negative driving direction the positions of these points will be the other way around along x-axis. The area between $S0$ and $S1$ will be referred to as the 1st section of ROI for the convenience of explanation in the following text, and the area between $S1$ and $S2$ is the 2nd section, between $S2$ and $S3$ the 3rd section, between $S3$ and $S4$ the 4th section.

$$x_{S4} = ROI_{start}, \qquad x_{S0} = ROI_{end} \tag{3.4}$$

$$x_{S3} = x_{ego} - 5m \tag{3.5}$$

$$x_{S2} = x_{ego} + width_{ego} + 5m \tag{3.6}$$

$$x_{S1} = (x_{S0} + x_{S2})/2 \tag{3.7}$$

Each surrounding vehicle will be assigned to one of the 12 sectors according to their x- and y-coordinates. In longitudinal direction for the area in front of ego vehicle, namely the 1st and 2nd section, the surrounding vehicle will be assigned to respective section, once vehicle rear enters each section, i.e. when the x-coordinate of surrounding vehicle larger than x_{S2} or x_{S1}. For the area along and behind ego vehicle, namely the 3rd and 4th section, the assignment takes place when vehicle front just enters respective section. In summary, the assignment for area in front of ego-vehicle is decided by the position of surrounding vehicle's front and for area behind ego-vehicle is decided by the position of surrounding vehicle's rear. It is reasonable for the assignment in the 3rd section. Assuming ego-vehicle is a car with a length of roughly five meters, on the left adjacent lane along ego-vehicle there is a truck with a length of about 15 meters, if the truck is assigned to the 2nd section once its front exceeds point $S2$, the majority part of the truck is still remaining in the 3rd section, which is very unreasonable. A visualization of this assignment is shown in Figure 3.6.

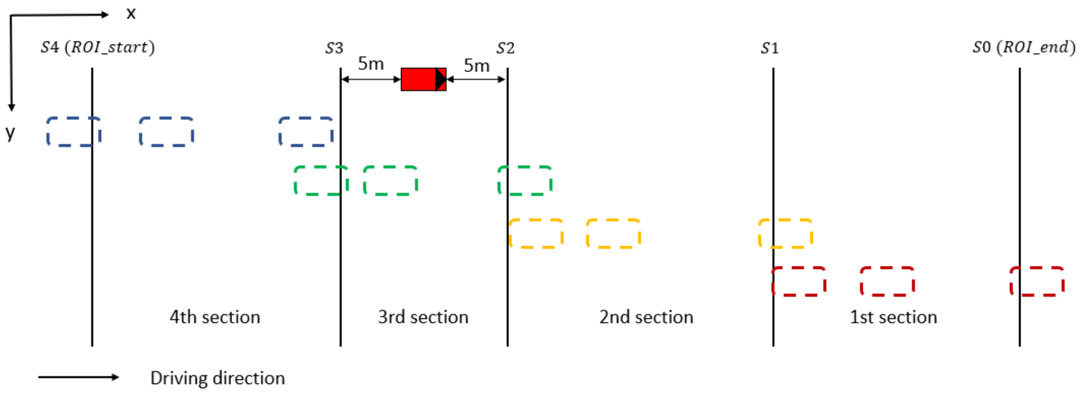


Figure 3.6: Assignment of vehicles in longitudinal direction

The assignment in lateral direction is carried out according to the lane-IDs of surrounding vehicles compared with that of ego-vehicle. If a surrounding vehicle has the same lane-ID as ego-vehicle, then it is in the same lane as ego-vehicle. If the lane-ID is one smaller than ego-vehicle's, then the surrounding vehicle is in the left adjacent lane for positive driving direction and right adjacent lane for negative driving direction. If the lane-ID is one larger than ego-vehicle's, then surrounding vehicle is in the right adjacent lane for positive driving direction and left adjacent lane for negative driving direction. After combining the assignment in both directions, the ascription of each surrounding vehicle to one of the 12 sectors is determined. Vehicles in respective sectors are assigned with a label describing their positions relative to ego-vehicle for the convenience of explanation in the following text. At the same time, a 4x3 matrix named "$neighbour\_ego$" is defined indicating the occupation state of each sector, i.e. whether the sector is occupied and the number of vehicles currently in this sector. The table on the left in Figure 3.7 shows the labels of surrounding vehicles in respective sectors from the perspective of ego vehicle and their corresponding matrix index. The table on the right shows an example of matrix "$neighbour\_ego$". The element in the 3rd row and the 2nd column has a minimal value of 1, which indicates, that this sector is always at least occupied by ego-vehicle. In this example ego-vehicle is surrounded by 4 vehicles in total, which include the one directly in front of ego-vehicle with label "middlepre", the one on the right side behind ego-vehicle with label "rightfollow" and two vehicles on the left side in front of ego-vehicle with label "leftpre". Thus, all surrounding vehicles are classified and can be used for further exploration.

(1,1) "leftleading"	(1,2) "middleleading"	(1,3) "rightleading"
(2,1) "leftpre"	(2,2) "middlepre"	(2,3) "rightpre"
(3,1) "leftalong"	(3,2) "egopos"	(3,3) "rightalong"
(4,1) "leftfollow"	(4,2) "middlefollow"	(4,3) "rightfollow"

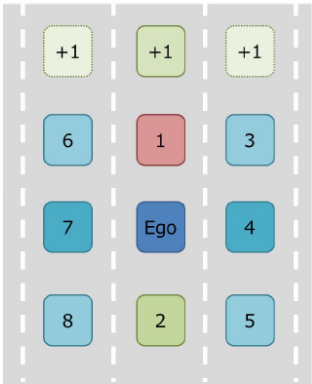
0	0	0
2	1	0
0	1	0
0	0	1

Driving direction

Figure 3.7: labels of surrounding vehicles in each sector with corresponding matrix index

3.3.2 Calculation of dynamic

Based on the result of classification, weighting factors can be assigned to each surrounding vehicle with respect to dynamic according to their labels. The general dynamic of the environment around ego-vehicle will be analysed in regard with four aspects: acceleration in longitudinal and lateral direction, velocity in longitudinal and lateral direction. In order to assign the weighting factors as objective as possible, it is necessary to analyse the possible movements of each surrounding vehicle and their influence on ego-vehicle's behaviour. In a research of ANTONA-MAKOSHI, et al. [17, pp. 9-10], all possible movements of vehicles at 8 nearest positions are divided into five categories (Figure 3.8), which offers an argumentation for the assignment of weighting factors.



Surrounding vehicle location	Surrounding vehicle motion: Cut in	Cut out	Accel.	Decel.	Sync
1.Lead		○		○	
2.Follow			○		
3.Parallel	○			○	
4. Parallel	○				○
EGO vehicle					
5. Parallel	○		○		
6. Parallel	○			○	
7. Parallel	○				○
8. Parallel	○		○		

'O' indicates a combination of surrounding vehicle location and motion that may become obstructive to the ego-vehicle

Figure 3.8: Possible movements of surrounding vehicle at 8 nearest positions [17, pp. 9-10]

In longitudinal direction in case of acceleration of a surrounding vehicle, for vehicles in front of ego-vehicle, their distance to ego-vehicle will become larger and larger and therefore have a descending effect on ego-vehicle, hence these vehicles are assigned with 0 as weighting factor in regard with acceleration. For vehicles along ego vehicle (with label "leftalong" and "rightalong"), the acceleration can be related to a cut-in movement in front of ego-vehicle, which then will influence the behaviour of ego-vehicle in longitudinal direction, hence these vehicles are assigned with 1 as weighting factors. For vehicles behind ego-vehicle, the acceleration of vehicle with label "middlefollow" may shorten the distance between itself and ego-vehicle, which will then influence ego-vehicle in longitudinal direction. Acceleration of "leftfollow" and "rightfollow" can be followed by a cut-in movement behind ego-vehicle, which will also influence ego-vehicle in longitudinal direction. Since the area behind ego-vehicle are not very well visible for ego-vehicle, there for these vehicles are assigned with 2 as weighting factor.

In longitudinal direction in case of deceleration of a surrounding vehicle, opposite to the case of acceleration, vehicles in front of ego-vehicle need to be paid more attention to, vehicles behind ego-vehicle will have a descending effect and therefore assigned with 0 as weighting factor. Vehicle labelled “middlepre” has direct and biggest influence on the behaviour of ego-vehicle and therefore is assigned with 3 as weighting factor. Vehicle labelled “leftpre” and “rightpre” have the possibility to cut in in front of ego-vehicle, thereby influencing ego-vehicle, hence they are assigned 2 as weighting factor. Vehicle “middleleading” is quite far away from ego-vehicle. It can influence ego-vehicle indirectly by influencing “middlepre”, therefore it is also assigned with 2 as weighting factor. Vehicle “leftleading” and “rightleading” have similar possible actions to “leftpre” and “rightpre”. Since they are farther away from ego-vehicle, thereby their influence is also indirect. Therefore, weighting factors of these two is one less compared to the pre-vehicles, namely 1.

A special case for vehicles labelled with “egopos”. It is possible to have another vehicle in sector (3,2). This happens when distance between the front of ego-vehicle and the rear of front vehicle, or the rear of ego-vehicle and the front of following vehicle is smaller as 5 meters. Since HighD Dataset include conditions from traffic flow with common highway velocities to traffic jam, where vehicles move very slowly and keep a much shorter distance to the front vehicle. Therefore, the assignment of weighting factors for vehicle labelled “egopos” needs to be done according to the traffic situation. A variable named $v_{limit} = 10\ km/h$ is chosen to be a threshold. If ego-vehicle has a velocity not larger than v_{limit}, it indicates that, the vehicle is probably in a traffic jam, vehicle “egopos” will be assigned with 3 as weighting factor. However, if the velocity of ego-vehicle Is larger than v_{limit}, a distance smaller as 5 m between a surrounding vehicle and ego-vehicle can lead to a very critical situation. In this situation, vehicle “egopos” will be assigned with 5 as weighting factor.

For velocity in longitudinal direction, the consideration for vehicles, which have a longitudinal velocity larger than that of ego-vehicle, is similar to the case of acceleration. Therefore, the assignment of weighting factors to surrounding vehicles in this case can be directly adopted from the case of acceleration. Analogously, the assignment of weighting factors to vehicles with a longitudinal velocity smaller than that of ego-vehicle can be adopted from the case of deceleration (Figure 3.9).

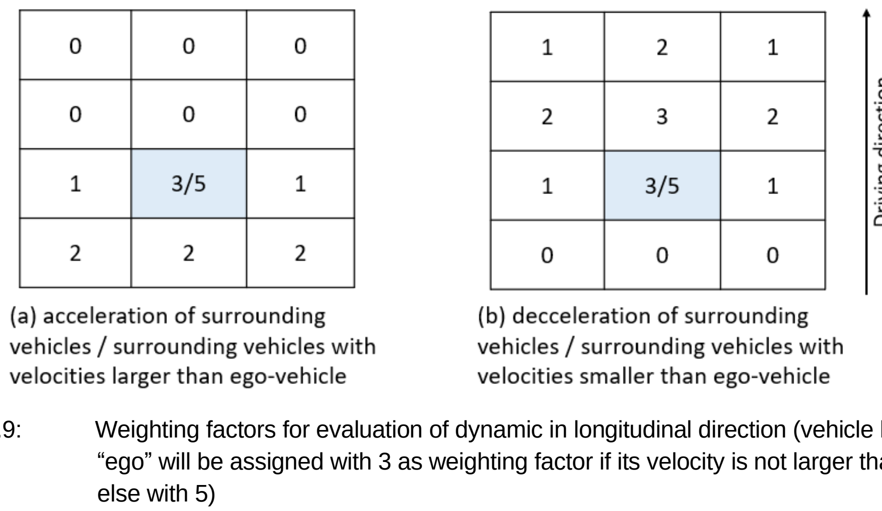
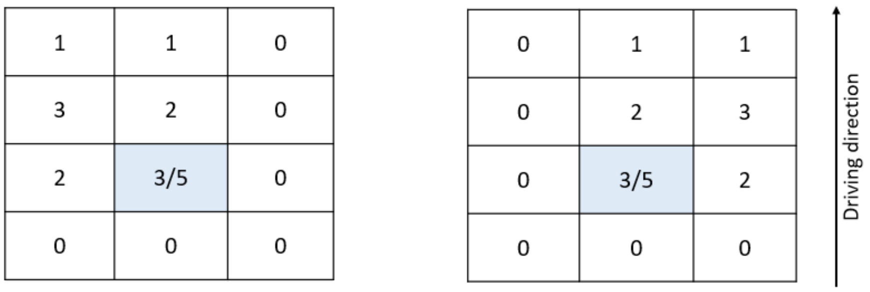


Figure 3.9: Weighting factors for evaluation of dynamic in longitudinal direction (vehicle labelled “ego” will be assigned with 3 as weighting factor if its velocity is not larger than v_{limit}, else with 5)

In lateral direction, taking positive driving direction as an example, assuming a surrounding vehicle with a lateral acceleration in positive direction, i.e. the vehicle intends to move to the right; if this vehicle is on the right side of ego vehicle, it will barely have any influence on ego-vehicle in lateral direction. However, if this vehicle is on the left side of ego-vehicle, then it has the possibility to change to the lane, which ego-vehicle is currently in. Therefore, vehicles on the right side of ego-vehicle are assigned with 0 as weighting factor, which include “rightleading”, “rightpre”, ”rightalong” and “rightfollow”. Although vehicle “leftalong” is very close to ego-vehicle in lateral direction, however, in the reality it is very unlikely for vehicles at this position to move towards ego-vehicle. Therefore, vehicle “leftalong” will be assigned with 1 as weighting factor. Vehicle “middlepre” has the possibility to cut out, which makes it possible for ego-vehicle to accelerate, thereby it is assigned with 2 as weighting factor. Vehicle ”leftpre” has the possibility to cut in in front of vehicle, which has a larger influence compared with cut-out of “middlepre”, thereby it is assigned with 3 as weighting factor. Vehicle “leftleading” and “middleleading” has indirect influence on the behaviour of ego-vehicle and are therefore assigned with 1 as weighting factor. For vehicles with a lateral acceleration in negative direction, the assignment is then the other way around.

For vehicles labelled “egopos”, the consideration is the same as the situation in longitudinal direction, i.e. these vehicles will be assigned with 3 as weighting factor when ego-vehicle has a velocity below 10 km/h and with 5 if ego-vehicle’s velocity is larger than 10 km/h.

In regard with velocity in lateral direction, if a surrounding vehicle has a lateral velocity in positive direction, the consideration is similar as the case of positive lateral acceleration, the assignment of weighting factors can be directly adopted from the consideration above. If a surrounding vehicle moves in negative lateral direction, the consideration is similar as the case of negative lateral acceleration and the assignment of weighting factors can directly be adopted.



(a) surrounding vehicles with positive lateral accelerations and velocities

(b) surrounding vehicles with negative lateral accelerations and velocities

Figure 3.10: Weighting factors of evaluation of dynamic in lateral direction (positive driving direction, vehicle labelled “ego” will be assigned with 3 as weighting factor if its velocity is not larger than v_{limit}, else with 5)

Based on the weighting factors of surrounding vehicles at different positions, the weighted average dynamic of the environment can be obtained with the following formulas:

Dynamic in an arbitrary frame j with respect to acceleration in longitudinal direction:

$$dynamic_{ax} = \sum_{i=1}^{n} \left(a_{x,i} \cdot \frac{w_{ax,i}}{\sum_{i=1}^{n} w_{ax,i}} \right) \tag{3.8}$$

n is the total number of surrounding vehicles within ROI detected in a particular frame of ego-vehicle, $a_{x,i}$ is the acceleration of vehicle i in longitudinal direction, $w_{ax,i}$ is the weighting factor assigned to vehicle i in regard with acceleration in longitudinal direction.

Analogously for dynamic with respect to acceleration in lateral direction:

$$dynamic_{ay} = \sum_{i=1}^{n} \left(a_{y,i} \cdot \frac{w_{ay,i}}{\sum_{i=1}^{n} w_{ay,i}} \right) \tag{3.9}$$

Dynamic with respect to velocity in longitudinal direction:

$$dynamic_{vx} = \sum_{i=1}^{n} \left(v_{x,i} \cdot \frac{w_{vx,i}}{\sum_{i=1}^{n} w_{vx,i}} \right) \tag{3.10}$$

Dynamic with respect to velocity in lateral direction:

$$dynamic_{vy} = \sum_{i=1}^{n} \left(v_{y,i} \cdot \frac{w_{vy,i}}{\sum_{i=1}^{n} w_{vy,i}} \right) \tag{3.11}$$

For the case, where there is no surrounding vehicle, the results of these equations will be 0.

3.4 Variation of dynamical parameters

Assuming all surrounding vehicles around ego-vehicle move with an identical velocity and acceleration, the distances between surrounding vehicles and ego-vehicle can better be kept, the behaviours of surrounding vehicles are also more predictable from the perspective of ego-vehicle. Environment in this situation is quite monotonous and simple for ego-vehicle. If there are vehicles accelerating behind or beside ego-vehicle, at the same time there are vehicles changing to the left or the right lane, i.e. vehicles moving with very different dynamic in both directions, then environment will be very complicated and mutable for ego-vehicle, because ego-vehicle needs to pay attention to the different behaviours and intentions of these vehicles to ensure safety. This characteristic of the environment can be described by observing the difference between the maximal and minimal value of respective dynamical parameters.

In section 3.2.2, all vehicles within ROI of a particular frame of ego-vehicle has been extracted, the information of their dynamical parameters are also included, i.e. their accelerations and velocities in longitudinal and lateral direction, from which the variation of these parameters can be obtained with the following formulas:

Variation in an arbitrary frame j of dynamical parameters with respect to longitudinal acceleration:

$$variation_{ax} = \max(\boldsymbol{a_x}) - \min(\boldsymbol{a_x}) \tag{3.12}$$

$\boldsymbol{a_x}$ is a vector containing the longitudinal acceleration of all surrounding vehicles. $\max(\boldsymbol{a_x})$ and $\min(\boldsymbol{a_x})$ represent the maximal and minimal value within vector respectively.

Analogously for variation of dynamical parameters with respect to lateral acceleration:

$$variation_{ay} = \max(\boldsymbol{a_y}) - \min(\boldsymbol{a_y}) \tag{3.13}$$

Variation of dynamical parameters with respect to longitudinal velocity:

$$variation_{vx} = \max(\boldsymbol{v_x}) - \min(\boldsymbol{v_x}) \quad (3.14)$$

Variation of dynamical parameters with respect to lateral velocity:

$$variation_{vx} = \max(\boldsymbol{v_y}) - \min(\boldsymbol{v_y}) \quad (3.15)$$

For the case, where there is no surrounding vehicle, the results of these equations will be 0.

This influence factor offers a different perspective of a system's complexity compared with the factor implemented in section 3.3.2. Although they have the similarity by both taking the dynamic of surrounding vehicles into consideration. One difference is, that the factor in section 3.3.2 analyses the influence of each surrounding vehicle very detailedly, the contribution of each vehicle to the final result is weighted differently according to their degrees of importance. While the variation takes only the two extreme cases into consideration. Another difference is, that the results of factor "dynamic of surrounding vehicles" shows the general dynamic of traffic flow around ego-vehicle, e.g. whether ego-vehicle is in a traffic flow where it can drive with a common velocity in the highway or it is stuck in a traffic jam. While the variation of dynamic observes the entire ROI as a whole and indicates the changeability of the system. For instance, large difference with respect to longitudinal or lateral acceleration indicate that, there are probably vehicles intending to change the lane or are currently changing the lane.

3.5 Connectivity

Connectivity indicates the mutual influence, i.e. the interactions between vehicles. With help of this influence factor, it will be able to see how much the traffic participants are (including ego-vehicle) connected with each other within ROI.

Connections between traffic participants is based on the existence of vehicles. System with low degree of connectivity must have a minimal number of vehicles. However, larger number of vehicles does not necessarily lead to high connectivity. An example is show in Figure 3.11.Both scenes contain same number of traffic participants (including ego-vehicle), which however are differently with each other connected. In the left scene, "leftleading" and "rightleading" (according to the classification algorithm in section 3.3.1) are a bit far from ego-vehicle and "leftfollow", therefore have weak connection with them. Since there is a lane between "leftleading" and "rightleading", the connection between these two is also very weak. Therefore, left scene has low degree of connectivity. In the right scene, the four vehicles are very close to each other, each vehicle's change in longitudinal and lateral direction can influence its neighbours beside it, in front of it or behind it. This scene has a higher degree of connectivity. Therefore, large number of vehicles is only a necessary but not sufficient condition for high connectivity.

This factor also differs from factor "variation of dynamical parameters". Scenes with high value of variation of dynamical parameters do not necessarily have high connectivity. For instance, in the left scene of Figure 3.12. "middleleading" and "leftfollow" intend to change to the adjacent lane following the red marked arrows. They have lateral velocities and eventually accelerations in different directions. Assuming ego-vehicle stays in the current lane, then the system will have a high variation of dynamic in lateral direction. However, connectivity of this scene remains poor, since these three vehicles are not directly next to each other. Vice versa, for a scene with high degree of connectivity, e.g. in the right scene of Figure 3.12, all sectors around ego-vehicle are occupied, each surrounding vehicle has thus very little freedom of movement, which will lead to monotonous behaviour of surrounding vehicles and small variation of dynamical parameters.

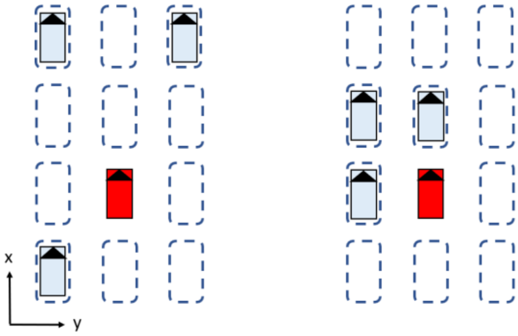


Figure 3.11: Relationship between number of vehicles and connectivity

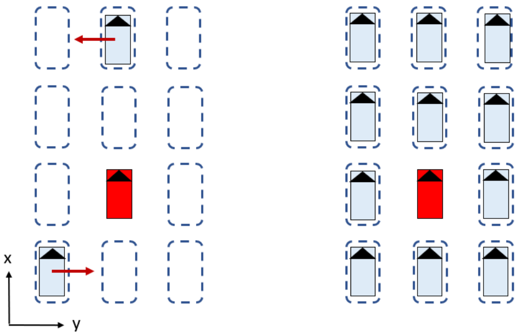
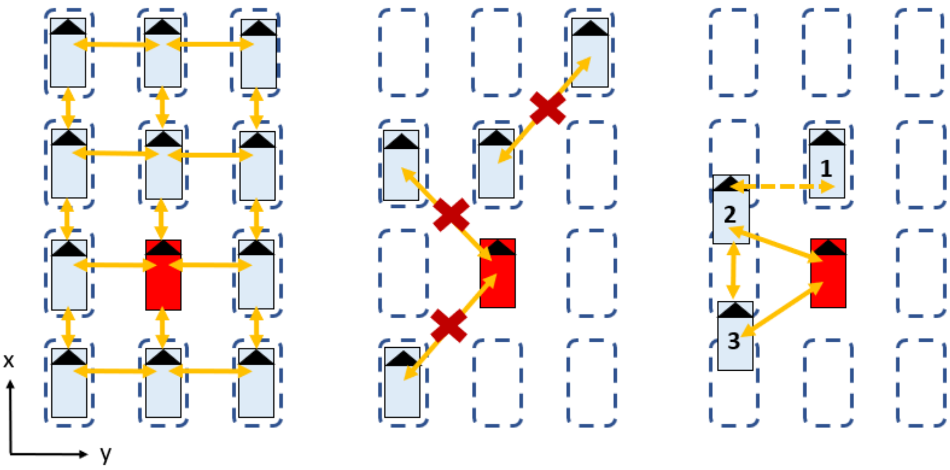


Figure 3.12: relationship between variation of dynamical parameters and connectivity

In this thesis, a connection will be counted if there are two traffic participants directly next to each other (left figure in Figure 3.13). If all sectors are occupied by exactly one vehicle, there will be 17 connections in total within ROI. However, during test of the program, this is not always the case. Occasionally, there are situations, in which one or more sectors is occupied by more than one vehicle (normally two, three will be very unlikely). This happens usually when a vehicle is almost leaving a sector and another vehicle is just entering this sector (right figure in Figure 3.13), which can lead to ambiguity and requires further exploration. In this case, connection will only be counted once assuming this sector is only occupied by one vehicle. For two vehicles in a diagonal (middle figure in Figure 3.13), the connection between them will not be included.

Because of the time limit of this work, a simple algorithm is adopted for the time being, namely, a connection will be counted as long as there are two occupied sectors next to each other. The result can be obtained with help of the matrix "*neighbour_ego*" defined in section 3.3.1. When implementing in Matlab, the existence of each one of the total 17 connections will be determined with a if-condition respectively. For instance, if elements with index (1.1) and (1.2) of matrix "*neighbour_ego*" are none-zero, then the connection between sector "leftleading" and "middleleading" exists. Some examples are shown in Figure 3.14.



(a) Maximal number of connections

(b) Exclusion of diagonal connections

(c) If a sector is occupied with 2 vehicles, connection will be calculated only once

Figure 3.13: maximal number of connections within ROI

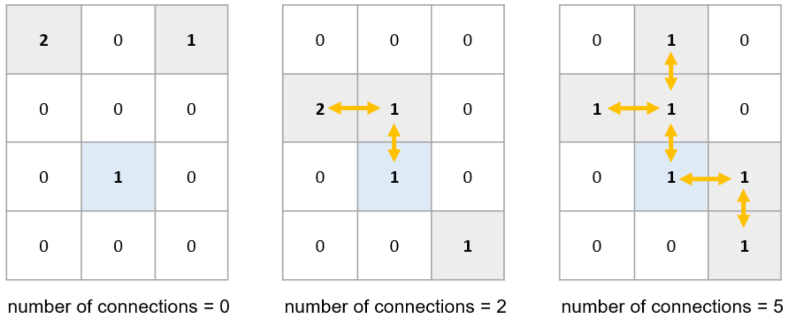


Figure 3.14: Examples of calculation of connection with help of matrix

3.6 Traffic prediction

Prediction of behaviours of vehicles in the surrounding environment is one of the most important functions for intelligent vehicles. An accurate prediction allows the automated vehicle to take actions in advance to avoid potential danger. If the state of a predicted surrounding vehicle deviates far from the result of prediction, the automated vehicle may have improper judgement about the surrounding environment and cannot respond appropriately.

In the first part of this section, the state of the art pf relevant work will be introduced, which introduce and compare the performance of different motion models for the prediction of surrounding vehicles' behaviours. In the second part, a motion model will be chosen based on the result of literature research and applied to the prediction of vehicles' states with HighD Dataset.

3.6.1 Relevant research

SCHUBERT et al. [18] classify all motion models into three categories according to their degrees of complexity. Models at lowest level are the linear motion models, which are Constant Velocity model (CV) and Constant Acceleration model (CA, which is the motion model applied in this thesis). The names are self-explanatory, the prediction is conducted assuming the predicted vehicle to move with a constant velocity or acceleration in the following defined time period. These models can easily be adopted. However, the rotation part of vehicles' movement is not taken into consideration, which are included in the models at the second level, which are curvilinear models. Most simple and commonly used ones are Constant Turn Rate and Velocity model (CTRV) and Constant Turn Rate and Acceleration model (CTRA). Although the motion models at this level have taken rotations of vehicle into account, the relationship between velocity and rotation is not considered. This shortage is compensated by models at the third level; Constant Steering Angle and Velocity model (CSAV) and Constant Curvature and Acceleration model (CCA). The performance of four of the mentioned models are evaluated and compared with each other with help of several test drives in urban areas and on the highway. Figure 3.15 shows the errors (root mean square) of different models in urban areas and on the highway. It is noticeable that models at higher levels (CTRV, CTRA and CCA) in general have a better performance than the simple CV model in both scenarios. Through comparison of the results of CV and CTRV, a conclusion can be obtained, that the prediction can be improved by taking rotation movement into consideration. By comparing CTRV and CTRA, it can be noticed that taking acceleration into consideration can improve the performance significantly. It is notable by comparing the result of CTRA and CCA, that although CCA is a motion model with high level of complexity, it does not ensure the accuracy of the prediction. Focusing on the results of tests on the highway, it can be seen that, the difference of the results between different models is smaller compared to that of urban areas. CTRA model offers the best performance, At the same time, the performance of the simple CV model is not necessarily much poorer than others. One explanation for this outcome can be that, compared with the variety of traffic participants and their behaviours in urban scenario, the traffic on the highway is more monotonous and predictable. Therefore, a very sophisticated model will not necessarily bring a much better performance. However, since the average velocity of traffic participants on the highway are much larger than that in urban scenario, which can lead to a larger deviation of prediction in a same time step. Therefore, the Euclidean distance of the errors on the highway is in general larger than that in urban areas.

			Model			
		RMS [m]	CV	CTRV	CTRA	CCA
Scenario	Urban	Euclidian	3.17	2.36	1.85	2.49
		Lateral	2.32	1.76	1.31	1.68
		Longitudinal	2.16	1.58	1.31	1.84
	Highway	Euclidian	3.89	3.98	3.35	3.36
		Lateral	1.67	1.52	1.35	1.35
		Longitudinal	3.52	3.68	3.07	3.08

Figure 3.15: Errors of different models in urban areas and on the highway [18]

Another research with respect to traffic prediction is DIEHL ET AL.'s work [13], in which the interaction between traffic participants has been taken into consideration as well and the prediction is done by means of Graph Neural Network (GNN) models. Four strategies are compared when constructing the connections between traffic participants:

- Self-connections: considering only ego-vehicle
- All-connections: taking connections between all traffic participants

- Preceding -connection: observing only the vehicle directly in front of ego-vehicle
- Close vehicles: considering only the vehicles at eight nearest positions

Figure 3.16 shows the errors (displacement of prediction from ground truth in a time period of 5 seconds) applying different connection strategies with Graph Attention Network (GAT). A conclusion can be drawn from the figure, that strategy Neighbour Connections offers the best results.

	Mean Displ. $[m]$	Displ. @5s $[m]$
GCN Adaptations		
Default	2.50 ± 0.07	4.68 ± 0.15
no ff output	2.52 ± 0.06	4.66 ± 0.11
with weighted edges	2.60 ± 0.08	4.91 ± 0.15
no residuals & weighted edges	2.87 ± 0.04	5.19 ± 0.08
no residuals	3.74 ± 0.11	6.42 ± 0.10
GAT Adaptations		
Default	1.92 ± 0.04	3.45 ± 0.08
no ff output	1.93 ± 0.07	3.38 ± 0.16
no residuals	2.32 ± 0.02	3.96 ± 0.04
no edge features	2.40 ± 0.05	4.48 ± 0.09
Connection Strategy (GAT)		
Self-Connections	2.68 ± 0.05	5.08 ± 0.08
Preceding Connection	2.70 ± 0.04	5.11 ± 0.07
Neighbour Connection	1.93 ± 0.08	3.47 ± 0.13
All Connections ($\star$)	2.41 ± 0.02	4.42 ± 0.03

Figure 3.16: results of different strategies constructing connections [13]

Neighbour Connection strategy is then used to evaluate the performance of different GNN models, which include FF Model (model without taking interaction into consideration), GAT, GAT NEF (GAT without edge features) and GCN (Graph Convolutional Network). The evaluation is conducted on two datasets, i.e. NGSIM I-80 (Next Generation Simulation Interstate 80 Freeway Dataset, collected on eastbound in San Francisco Bay, CA, USA) and HighD Dataset. The result of this evaluation is shown in Figure 3.17. It is noticeable, that for NGSIM Dataset, the three GNN models give better results than the model without taking interaction between traffic participants into consideration. However, for HighD Dataset the performance of different models is very similar, which might be related to little interaction between the vehicles. Figure 3.18 shows a comparison of results between different GNN models and two model-based static approaches, Constant Velocity model (CV) and Intelligent Driver Model (IDM).

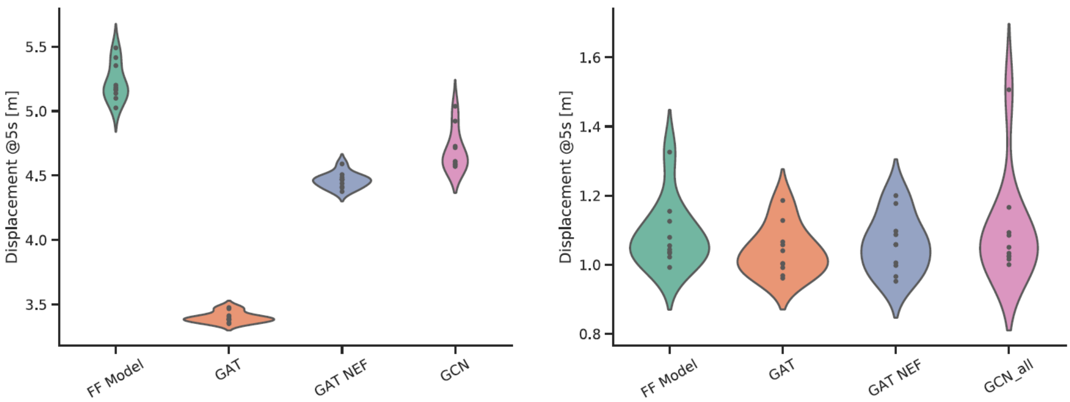


Figure 3.17: Performance on NGSIM Dataset (left) and HighD Dataset (right) [13]

	Mean Displ. $[m]$	Displ. @5s $[m]$
GAT	1.89 ± 0.02	3.40 ± 0.04
GAT NEF	2.39 ± 0.03	4.46 ± 0.06
GCN	2.51 ± 0.07	4.69 ± 0.12
FF	2.78 ± 0.08	5.22 ± 0.14
CVM	2.58	5.00
IDM	3.10	6.60

	Mean Displ. $[m]$	Displ. @5s $[m]$
GAT	0.47 ± 0.04	1.04 ± 0.07
GAT NEF	0.49 ± 0.07	1.06 ± 0.08
GCN	0.47 ± 0.08	1.10 ± 0.14
FF	0.45 ± 0.06	1.09 ± 0.09
CVM	1.09	2.66
IDM	1.12	2.66

Figure 3.18: Comparison of GNN models and static models on NGSIM Dataset (left) and HighD Dataset (right) [13]

Based on the knowledge from the research above and the information available, following conclusions can be obtained: i. influence of interaction is neglectable for traffic prediction with HighD Dataset. ii. errors can be reduced when taking acceleration into consideration. iii. vehicles at eight nearest positions around ego-vehicle should be taken into consideration. iv. compared with sophisticated models the results of simple models are not much poorer when predicting traffic on the highway. Therefore, Constant Acceleration (CA) model will be chosen in this thesis for the prediction of vehicles around ego-vehicle.

3.6.2 Trajectories prediction for surrounding vehicles

Applying “Close vehicles” from the connection strategy mentioned in DIEHL ET AL.’s work [13], namely, all surrounding vehicles except the ones with labels “leftleading”, “middleleading” and “rightleading” will be taken into consideration.

Goal is to calculate the displacement of a surrounding vehicle’s position with prediction from the position in ground truth after a certain time period, which is related to the current longitudinal velocity of ego-vehicle. The recording of HighD Dataset has a frame rate of 0.04 s/frame. The time period for prediction is determined as the required time for ego-vehicle to come to a halt when taking an emergency brake at this moment (actual observed frame). An emergency brake of vehicles has an average value of 10 m/s^2 [19]. Therefore, the time period for prediction is obtained with following formula:

$$t\_period = |v_{ego,x}/10| \tag{3.16}$$

The corresponding number of frames nof contained in this time period is:

$$nof = round\left(\frac{t}{0.04}\right), nof \in N \tag{3.17}$$

There is a possibility, that the remaining number of frames of a surrounding vehicle before it leaves the camera frame is smaller than the value of nof, therefore, a case discrimination is necessary to solve this problem. If $i + nof \leq f_{end}$, with i the actual frame number of ego-vehicle and f_{end} the frame number of the last frame of a surrounding vehicle, then the prediction is for nof frames. If $i + nof > f_{end}$, namely the number of frames being predicted exceeds the upper boundary of vehicle v’s frame interval, then the prediction will only be conducted till the last frame of this surrounding vehicle. nof will be updated to:

$$nof = f_{end} - i, nof \in N \tag{3.18}$$

The actual trajectory of surrounding vehicle, i.e. its position in each frame, can directly be extracted from the HighD data, the x- and y-coordinates are respectively saved in a $(nof + 1)$ x 1 vector $\boldsymbol{v\_traj}_{actual,x}$ and $\boldsymbol{v\_traj}_{actual,y}$ (actual frame is included as the initial state of vehicle v).The predicted trajectory needs to be obtained through calculation. If the prediction is based on a CV model, then it will be assumed, that the surrounding vehicle will move with the lateral and longitudinal velocity from actual frame constantly in both directions in the following predefined time period. If the prediction is based on a CA model, the position, lateral and longitudinal velocity from actual frame will be the initial state of the vehicle. It will move with constant accelerations in both directions, which are the lateral and longitudinal acceleration in the actual frame. Vectors representing the actual trajectory can be obtained with the following formulas.

The duration t from the 1st frame to the f-th frame of total $nof + 1$ frames can be expressed with the following formula (frame rate = 25 fps):

$$t = (f - 1) \cdot 0.04s \tag{3.19}$$

x-coordinate of surrounding vehicle in the $(f + 1)$-th frame according to prediction with CA model:

$$v\_traj_{predict,x,f+1} = x_{v,0} + v_{v,x,0} \cdot t + \frac{1}{2} \cdot a_{v,x,0} \cdot t^2, f = 1,2, \dots, nof + 1 \tag{3.20}$$

$x_{v,0}$, $v_{v,x,0}$ and $a_{v,x.0}$ are the x-coordinate, longitudinal velocity and longitudinal acceleration of ego-vehicle in the current frame respectively, y-coordinate of surrounding vehicle in the $(f + 1)$-th frame of prediction with CA model:

$$v_{traj_{predict,y,f}} = y_{v,0} + v_{v,y,0} \cdot t + \frac{1}{2} \cdot a_{v,y,0} \cdot t^2, f = 1,2, \dots, nof + 1 \tag{3.21}$$

If with CV model, then the acceleration part of Eq. (3.20) and Eq. (3.21) will be cast away. Based on the actual and predicted trajectories, the displacement can easily be calculated.

Deviation from actual position of surrounding vehicle in the f-th frame of prediction ($nof + 1$ frames in total) in longitudinal direction is:

$$deviation_{longitudinal,f} = |v\_traj_{actual,x,f} \; - v\_traj_{predict,y,f}| \tag{3.22}$$

Deviation from actual position of surrounding vehicle in the f-th frame of prediction ($nof + 1$ frames in total) in lateral direction is:

$$deviation_{lateral,f} = |v\_traj_{actual,x,f} - v\_traj_{predict,x,f}| \tag{3.23}$$

Euclidean distance of deviation in the f-th frame can be derived from the results of Eq. (3.22) and Eq. (3.23):

$$deviation_{euclidean,f} = \sqrt{{deviation_{longitudinal,f}}^2 + {deviation_{lateral,f}}^2} \tag{3.24}$$

The result of Eq. (3.26) is the deviation of one surrounding vehicle in the f-th frame of predicted $nof + 1$ frames in total. The deviations of all $nof + 1$ frames will then be expressed with an $(nof + 1)x1$ vector $\boldsymbol{deviation}_{euclidean}$. An example of prediction with CV and CA model is shown in Figure 3.19, showing the development of deviations of all surrounding vehicles (except the “leading” vehicles in the 1st section of ROI) over the predicted frames. For instance, in frame with number 100, 4 surrounding vehicles are considered for prediction. The deviation corresponding to this frame is the sum of deviation of all 4 surrounding vehicles in their last predicted frame, namely the $(nof + 1)$-th frame. As can be seen from the diagram, that overall CA model has a better performance than CV model. However, the development of deviation in lateral direction of two models are almost identical. In detail this can be seen from Figure 3.20, where the development of deviation with CV and CA model of each individual surrounding vehicle appearing in the 25th frame of vehicle Nr.37 in the 48th recording. An explanation for this can be, that if no vehicle intends to change the lane, the acceleration in lateral direction is close to 0, in which case CA model has the same effect as CV model and therefore have very close results. The number of observed surrounding vehicles over all predicted frames is also plotted in the diagram (thick black short lines). It is noticeable, that this development corresponds to the development of Euclidean and longitudinal deviation. When observing the development of deviation of each vehicle respectively, as can be seen from Figure 3.20, that the deviation will become larger and larger as the number of frames being predicted becomes bigger and bigger. Since the surrounding vehicle is predicted to keep moving with a constant acceleration, but in reality, If the acceleration differs a lot from the one used for prediction. The more frames are predicted from current time point, the larger is the deviation in the last frame of prediction.

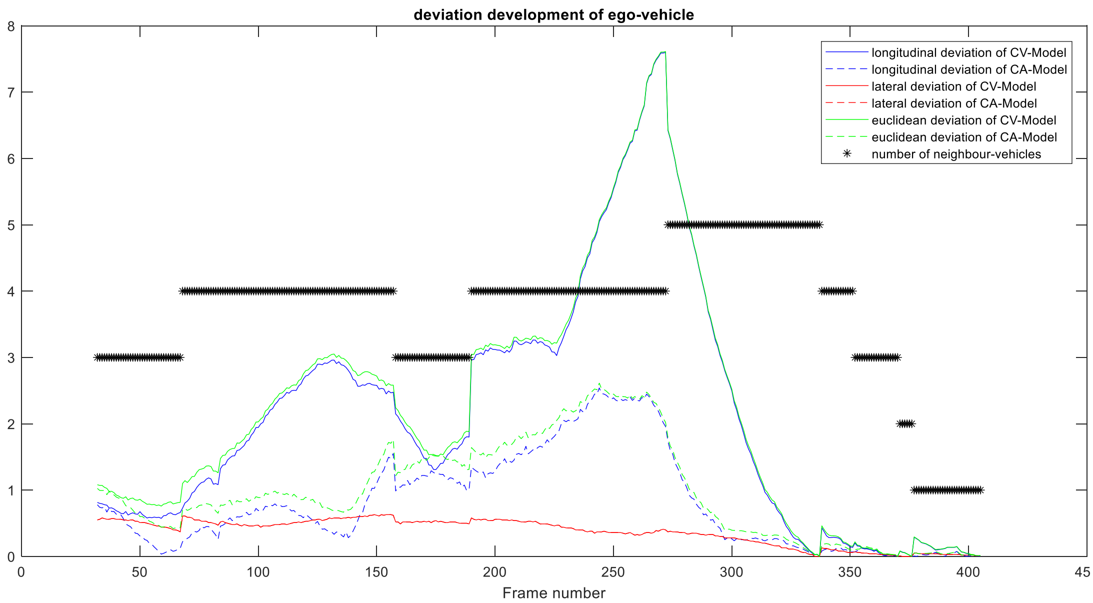


Figure 3.19: Development of deviation of vehicle Nr.37 from track Nr.48 over all predicted frames

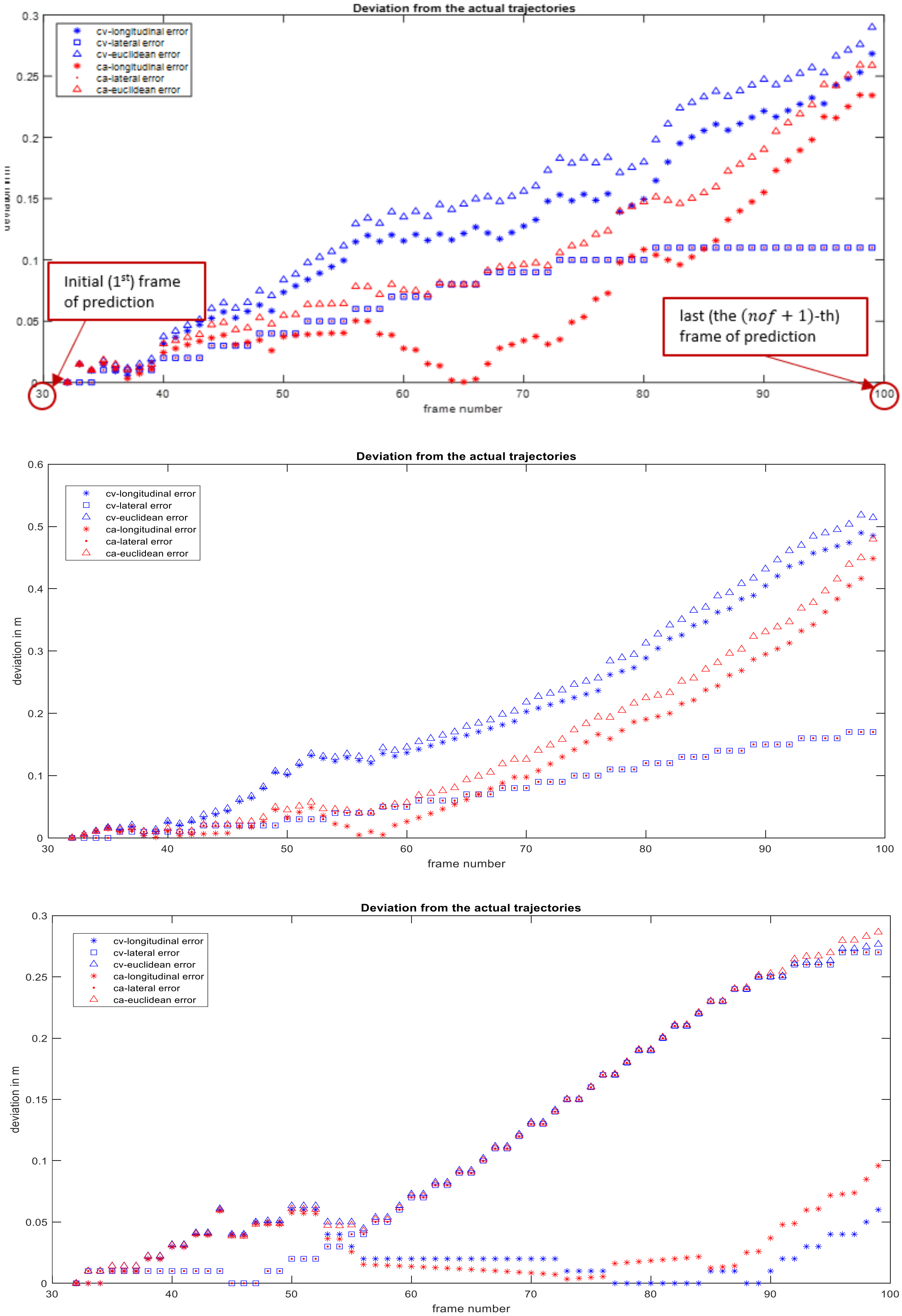


Figure 3.20: Development of deviation of 3 surrounding vehicles appearing in ROI in the 25th frame of vehicle Nr.37 from the 48th recording

3.7 Possible actions of ego-vehicle and surrounding vehicles

The possible actions for a vehicle are the actions, the vehicle is able to take at present time point considering the actual surrounding environment. This corresponds to the characteristic "indistinction of the target situation" of concept complexity from SCHAUB's work [8]. In other words, this factor gives answer to the question, from out the current traffic situation at current time point, how many possible states dose the end situation have after evolution over a time period.

The significance of this factor differs from that of factor "traffic prediction". Although they are both based on the situation, which a vehicle is currently in. However, factor "traffic prediction" assumes that the vehicle will keep moving with the dynamical parameters (CA) from current time point. For instance, a vehicle with a positive acceleration in longitudinal direction and no acceleration in lateral direction, will continue moving with the same acceleration in longitudinal direction and no lateral acceleration in the following defined time period. This behaviour is assumed to be kept in the following defined time period, irrelevant to the traffic situation around it and the vehicle itself's intention, for example, whether it might should decelerate, since the its distance to the front vehicle is too short or it can change the lane in order to take over. While factor "possible actions" takes the behaviours of surrounding vehicles into consideration, and the potential intentions of the vehicle are also included. Another difference is, that factor "traffic prediction" has only one output while factor "possible actions" may have more than one output.

Factor "possible actions" also differs from the factor "variation of dynamical parameters". The latter considers only the dynamical parameters of a vehicle at the current time point and indicates mainly the system's intention to change, while the former considers the evolution of traffic flow within ROI in a time period and describes the uncertainty of a system.

Compared with factor "traffic prediction" and "variation of dynamical parameters", the higher their values are, the more complex or complicated is the situation for ego-vehicle. Namely, when the result of prediction has a large deviation from the ground truth, or when the difference between maximal and minimal dynamical parameter is large, then the environment is probably complicated for ego-vehicle to a certain extent. However, for "possible actions", if a vehicle has a big number of possible actions, it does not lead to a conclusion, that the environment around this vehicle is complex. In an extreme case, when a vehicle has no vehicle around, theoretically it can take all actions as desired and the complex degree of the environment in this case is 0. On the other hand, assuming the vehicle is currently stuck in traffic jam, all sectors of its ROI are occupied, the vehicle has no other option except to move along. The surrounding environment in this case also has a low degree of complexity. The evaluation of factor "traffic prediction" and "variation of dynamical parameters" focus on the surrounding vehicles, while factor "possible actions" takes ego-vehicle into consideration as well. This factor can be seen as an extension and concretization of factor "connectivity".

In this thesis, the possible actions will be analysed for ego-vehicle and the surrounding vehicles at its eight nearest positions. For surrounding vehicles, the evaluation will be conducted in the area of its own ROI when considering it as ego-vehicle (vehicles with colour blue and ROI with colour green in Figure 3.21).

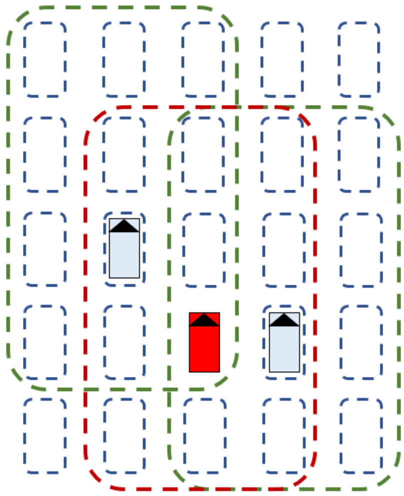


Figure 3.21: Possible actions of ego-vehicle and its surrounding vehicles

Since the evaluation is the same for ego-vehicle and its surrounding vehicles, the evaluation will be conducted with help of a general vehicle. For a forward moving vehicle, deceleration is always a possible action. If position “middlepre” regarding observed vehicle is empty, then acceleration is one more possible action. For lane change to the left side, firstly a lane must be available on the left side of ego vehicle. Secondly, position “leftalong” is not occupied if a lane is available. A lane change to the left should be given up if there is a vehicle in the left adjacent lane coming up from behind with a large velocity or acceleration. Therefore, the longitudinal velocity of “leftfollow” needs to be considered as well. This will be judged with help of TTC in longitudinal direction between “ego-vehicle” and “leftfollow” (Eq. (3.25)).The action will be considered possible if the value of TTC is larger than 2s. Following this action acceleration is possible if “leftpre” is vacant in the target lane and deceleration is possible if this position is occupied. The same analysis can be done for lane change to the right side.

$$ttc_{left} = \frac{|x_{leftfollow} - x_{ego}|}{|v_{leftfollow,x} - v_{ego,x}|}, \qquad |v_{leftfollow,x}| > |v_{ego,x}| \tag{3.25}$$

$$ttc_{right} = \frac{|x_{rightfollow} - x_{ego}|}{|v_{rightfollow,x} - v_{ego,x}|}, \qquad |v_{rightfollow,x}| > |v_{ego,x}| \tag{3.26}$$

An overview of all possible actions is shown in Table 3.2. As can be seen that, there are eight possible actions in total. It is distinguished here between ego-vehicle and surrounding vehicles. Since deceleration is always a possible action, therefore, this action will not be included for ego-vehicle. Which is to say, the maximal number of possible actions for ego-vehicle is 8-3 = 5.

Table 3.2: Possible actions of a vehicle

Possible action	Conditions to be met
Deceleration	Always possible when moving forward
Acceleration	Position “middlepre” is vacant
Lane change to the left	- Existence of a left lane - Position “leftalong” is vacant - $ttc_{left} \geq 2s$
Acceleration after lane change to the left	Position “leftpre” is vacant
Deceleration after lane change to the left	Position “leftpre” is occupied
Lane change to the right	- Existence of a right lane - Position “rightalong” is vacant - $ttc_{right} \geq 2s$
Acceleration after lane change to the right	Position “rightpre” is vacant
Deceleration after lane change to the right	Position “rightpre” is occupied

3.8 Time-gap

The possible actions derived from last subchapter are only the actions, which are theoretically possible. However, in the reality, many actions are restricted by the behaviours and positions of surrounding vehicle.

For instance, with the existence of a “middlepre” or a “middleleading”, to which level is ego-vehicle allowed to accelerate while still remaining in a safe state, or how big is the possibility for ego-vehicle to change the lane with existence of a vehicle behind ego-vehicle in the target lane, etc. Therefore, another indicator for the required precision of the action is required. In this thesis, time-gap between ego-vehicle and surrounding vehicle is used as such indicator. This indicator comes from the concept time-headway. For vehicles in front of ego-vehicle, time-gap is almost time-headway, only difference is that the following vehicle is not necessarily immediately behind ego-vehicle, it can also be in an adjacent lane, i.e. in this case time-gap is time-headway in longitudinal direction. For vehicles behind ego-vehicle, time-gap is the time period between the time point when the rear of ego-vehicle passing one point and the time point when the front of following vehicle passing a point with same x-coordinate with same longitudinal velocity as ego-vehicle.

Time-gap will be calculated for vehicles at five positions around ego-vehicle (Figure 3.22), namely, vehicles with label “leftpre”, “middlepre”, “rightpre”, “leftfollow” and “rightfollow”. Vehicle “leftalong” and “rightalong” are not included in consideration, since the length of this section in ROI is only 5 m ahead and behind ego-vehicle, and the length of a car is usually close to 5 m, therefore, the time-gap between these two vehicles and ego-vehicle in longitudinal direction is close to zero. These two vehicles barely have any influence on ego in longitudinal direction and their distances to ego-vehicle in longitudinal direction are not important.

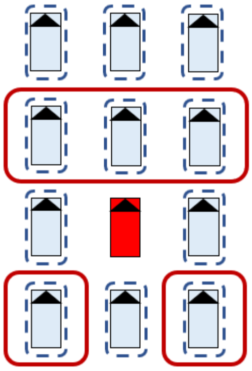


Figure 3.22: time-gap for vehicles around ego-vehicle

Time-gap of a surrounding vehicle can be obtained with the following formula:

$$time\_gap_{label} = \frac{|x_{label} - x_{ego}|}{v_{ego,x}} ,$$
$$label \in \{leftpre, middlepre, rightpre, leftfollow, rightfollow\} \quad (3.27)$$

3.9 Blind Spot

Blind spot is the area which are not visible to the driver if the vehicle is controlled by human. For an automated vehicle, this will be the area, which cannot be reached by different types of sensors combined. In the future, with the realization of V2V communication, the existence of vehicles in the blind spot of ego-vehicle may also be known by ego-vehicle and the influence of this factor on complexity may disappear. However, since this technology is currently not yet on the market, this factor will still be discussed. It corresponds to the characteristic “non-transparency” in SCHAUB’s work [8].

The concept “non-transparency” contains the meaning of uncertainty, which has been considered by analysing the possible actions of vehicle in subchapter 3.7. However, it is not equal to uncertainty, since the amount of information referred by “non-transparency” is zero. Facing uncertain situation or unknown situation, the latter may cause more severe consequences. For instance, there is a vehicle on the right adjacent lane in front of ego-vehicle, which has the possibility to change the lane to the left, its existence can be detected by the radars of ego-vehicle in normal conditions. Once it really moves to the left, it can quickly be noticed by ego-vehicle (upper figure in Figure 3.23). However, if the visibility of this vehicle is blocked because of the existence of a truck along ego-vehicle (lower figure in Figure 3.23). Ego-vehicle may not be able to respond in time and appropriately if this vehicle takes any actions. The smaller the blind spot, the better is ego-vehicle’s understanding about the environment.

In the first part of this subchapter, some adjustments are clarified to prepare for the calculation. In the second part, the implementation of the algorithm will be illustrated in detail.

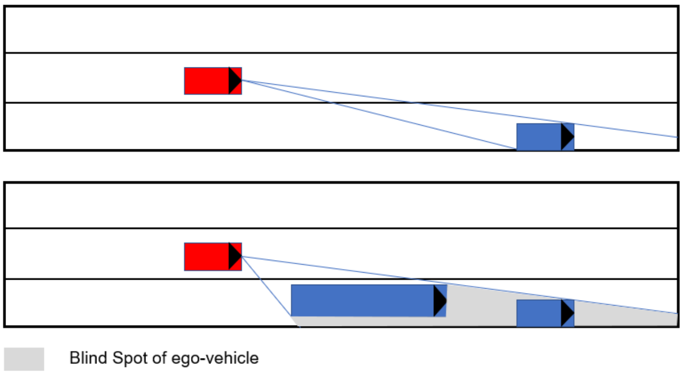


Figure 3.23: influence of blind spot on ego-vehicle

3.9.1 Preparations and adjustments

In this thesis blind spot is defined as the area not reachable by the sensors of ego-vehicle, which is caused by the existence of surrounding vehicles. The detecting range of the sensors is shown in Figure 3.24. For vehicles, whose centres (centre of the bounding box of each vehicle) are in front of the centre of ego-vehicle, are assumed to be detectable by the sensor installed at the middle position of ego-vehicle's front. For vehicles, whose centres are behind that of ego-vehicle, are assumed to be within the detecting range of the sensor at the middle position of ego-vehicle's rear.

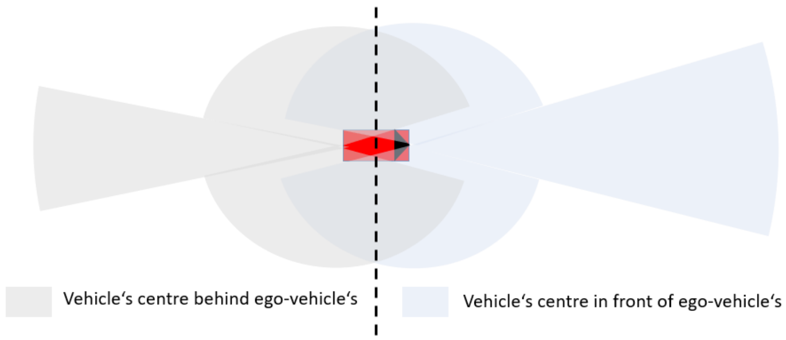


Figure 3.24: Detecting range of automated ego-vehicle

Because of limited time and knowledge, the obtained result of blind spot Is only an approximation of the actual value. In order to simplify the calculation to a certain extent, following adjustments are made:

- No blind spot caused by vehicles just entering or just about to leave ROI. In other words, if the bounding box of a surrounding vehicle is not completely within ROI yet, it will cause no blind spot of ego-vehicle
- If there are more than two vehicles in the area of each lane in front of ego-vehicle, only the blind spot caused by vehicle closer to ego-vehicle will be calculated
- For the area in front of ego-vehicle, the blind spot caused by vehicles in the second section ("leftpre", "middlepre", "rightpre") will be calculated first. If one or more sectors in this section contains more than one vehicle, usually two vehicles (three vehicles are very unlikely), the vehicle closer to ego-vehicle remain its "pre"-label, the other adjust its label to "leading", and the other "leading"-vehicles in this lane

will be ignored. For instance, in a scene of ego-vehicle, there are two vehicles labelled “leftpre” and one vehicle labelled “leftleading”, one vehicle labelled “leftpre” and farther away from ego-vehicle compared with the other will change its label to “leftleading”. The vehicle originally labelled “leftleading” will not be considered for the calculation.

- If a sector in the first section of ROI (“leftleading“, “middleleading”, “rightleading”) contains more than one vehicle, only the blind spot caused by the vehicle closer to ego-vehicle will be included. The argumentation for the last two adjustments is that, the “leading”-vehicles are already very close to the end of ROI, the blind spot caused by these vehicles are very limited and therefore neglectable. Furthermore, they can sometimes be within the blind spot caused by “pre”-vehicles, in which case no new blind spot will be created.
- For the area behind ego-vehicle, namely the fourth section of ROI, similar adjustment is made. If a sector (“leftfollow”, “middlefollow”, “rightfollow”) contains more than one vehicle, only the one closer to ego-vehicle will be considered.

The algorithms differ from each other for the area behind, beside and in front of ego-vehicle. One significant difference is that, the blind spots caused by vehicles behind and beside ego-vehicle is very unlikely to overlap with each other, even when there is, since the area behind ego-vehicle has only a length of roughly 50 meters, the overlap can be ignored. For the area beside ego-vehicle overlap is excluded. However, for the area in front of ego-vehicle, overlap can exist when a ”leading”-vehicle is partially located within the blind spot caused by a “pre”-vehicle, which needs extra consideration for the calculation.

3.9.2 Implementation of the calculation

The entire ROI is divided into three parts for the calculation (Figure 3.25). This division is only for the convenience of calculation and will not replace the classification in section 3.3.1. A vehicle belongs to the area behind ego-vehicle, after it enters ROI completely and before its front reaches the rear of ego-vehicle in longitudinal direction. A vehicle belongs to the area beside ego-vehicle, once its front reaches the rear of ego-vehicle and before its rear exceeds the front of ego-vehicle in longitudinal direction. A vehicle belongs to the area in front of ego-vehicle, after its rear exceeds the front of ego-vehicle and before its front leaves ROI in longitudinal direction. The calculation will be done with an example of positive driving direction.

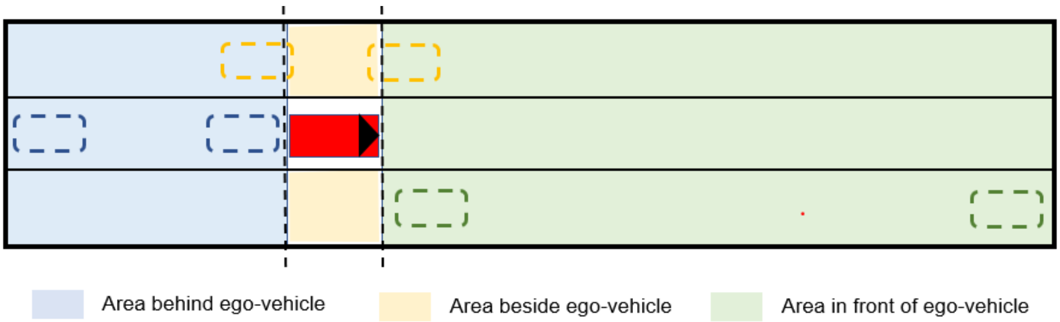


Figure 3.25: Division of ROI for the calculation

Area in front of ego-vehicle

Based on the consideration in the first part, the calculation of blind spot caused by “pre”-vehicles will be put in front of “leading”-vehicles (labels are the ones after adjustments in the first part). The existence of “leading”-vehicles will be checked first. The existence of each “leading”-vehicle will generate two “beams”, in total six beams are available if all sectors in the second section of ROI are occupied. The tangent value of the angles between these beams and symmetry axis of ego-vehicle can be used as auxiliary variables to judge the existence and position of a “pre”-vehicle. The four corners of the bounding box of “pre”- or “along”-vehicle is defined as in Figure 3.26, whose coordinates are already given and can be used for the calculation. The tangent value of the angle between connection of O and one corner of surrounding vehicle and the symmetry axis of ego-vehicle is expressed in Eq. (3.28).

Figure 3.26: markings of four corners of surrounding vehicle

$$\tan_p = -\frac{y_p - y_O}{x_p - x_O}, \qquad p \in \{a, b, c, d\} \tag{3.28}$$

Each beam is numbered as shown in Figure 3.27. For instance, if “leftpre” exists, then $tan\ \_1$ and $tan\ \_2$ will exist and have positive values. Furthermore, $tan\ \_3$ and $tan\ \_4$ correspond with the existence of “middlepre”, $tan\ \_5$ and $tan\ \_6$ then “rightpre”. A beam on the left side of ego-vehicle has a positive tangent value.

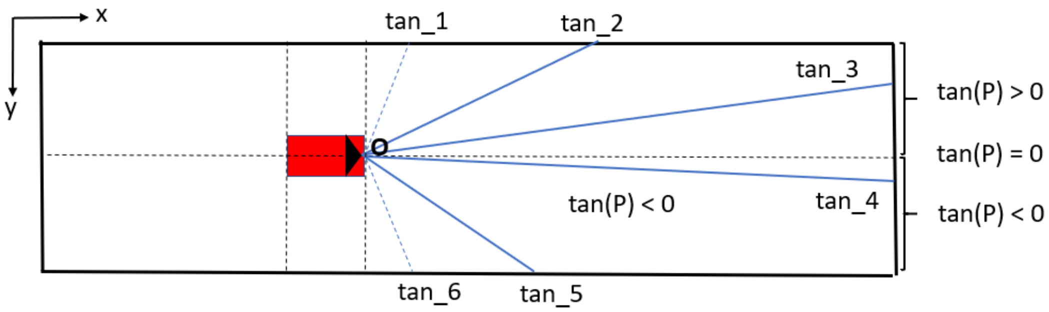


Figure 3.27: Beams generated by “pre“-vehicles

- **Basic function: BS_front**

For the area in front of ego-vehicle according to Figure 3.25. The function for the calculations of blind spot caused by “pre”-vehicles, “leading”-vehicles and occasionally “along”-vehicles are defined as the basic unit function: BS_front. According to the positions of these vehicles relative to the symmetry axis of ego-vehicle, several case discriminations are made for the calculation (Figure 3.28, Figure 3.29 and Figure 3.30, with S representing the corresponding area).

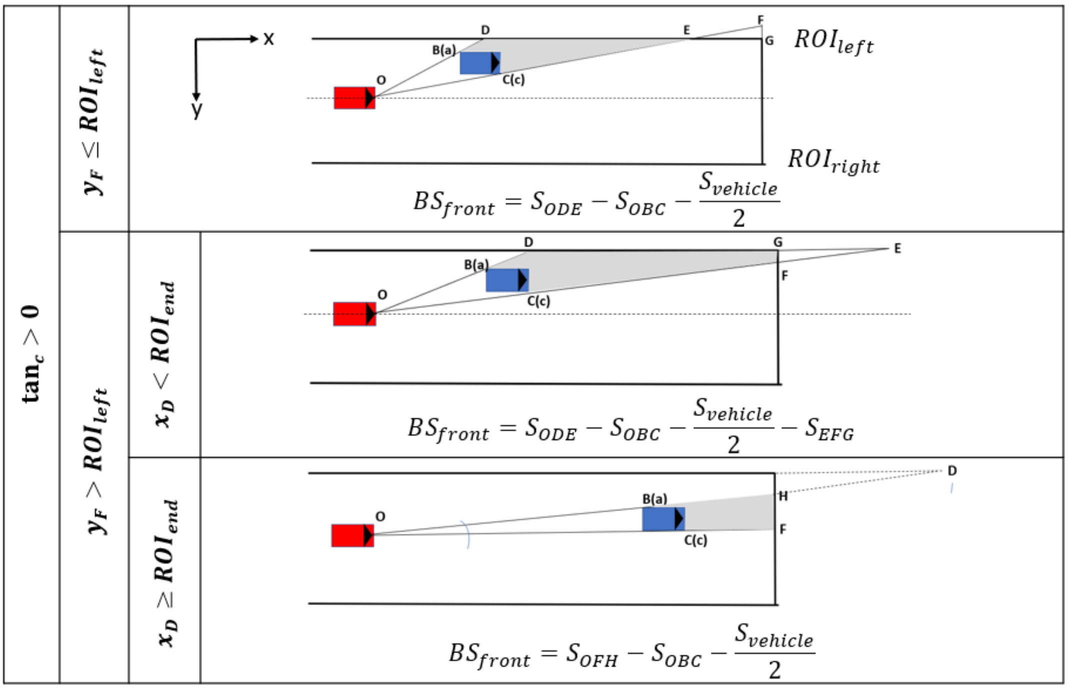


Figure 3.28: Blind spot caused by vehicle on the left side in front of ego-vehicle (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

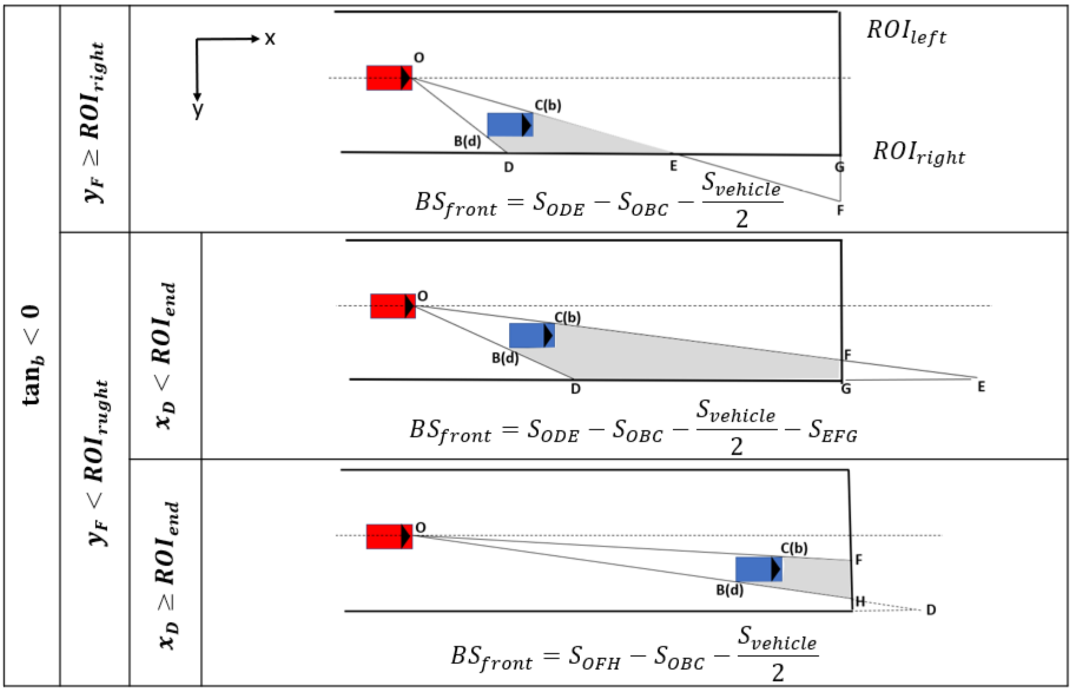


Figure 3.29: Blind spot caused by vehicle on the right side in front of ego-vehicle (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

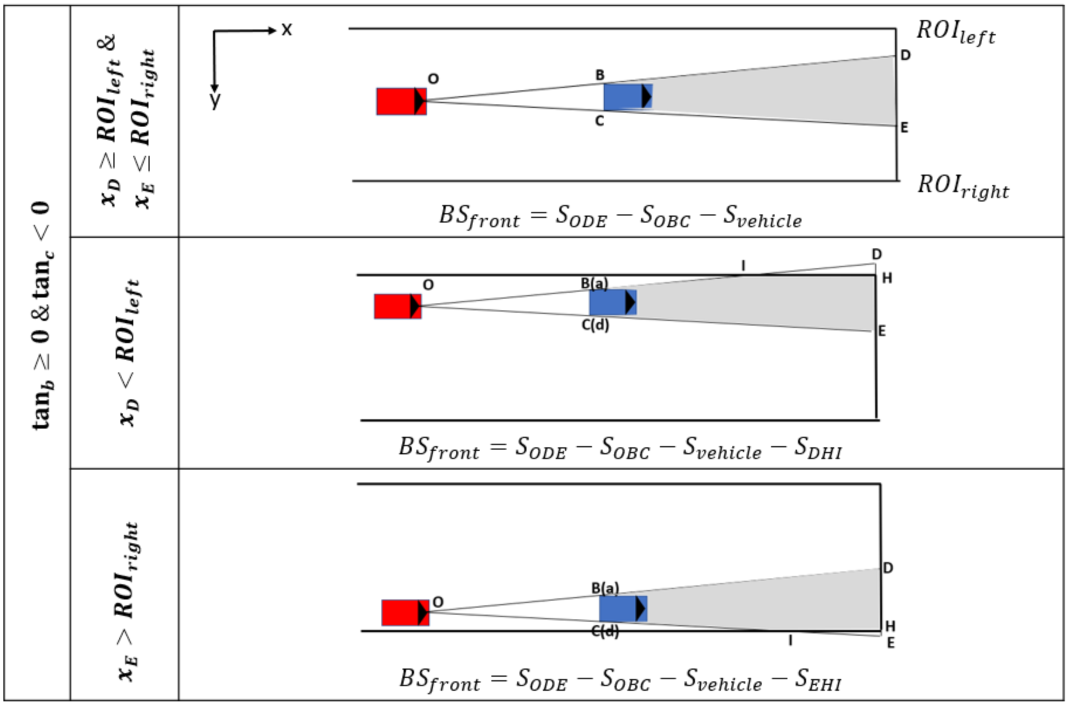


Figure 3.30: Blind spot caused by vehicles on the symmetry axis of ego-vehicle (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

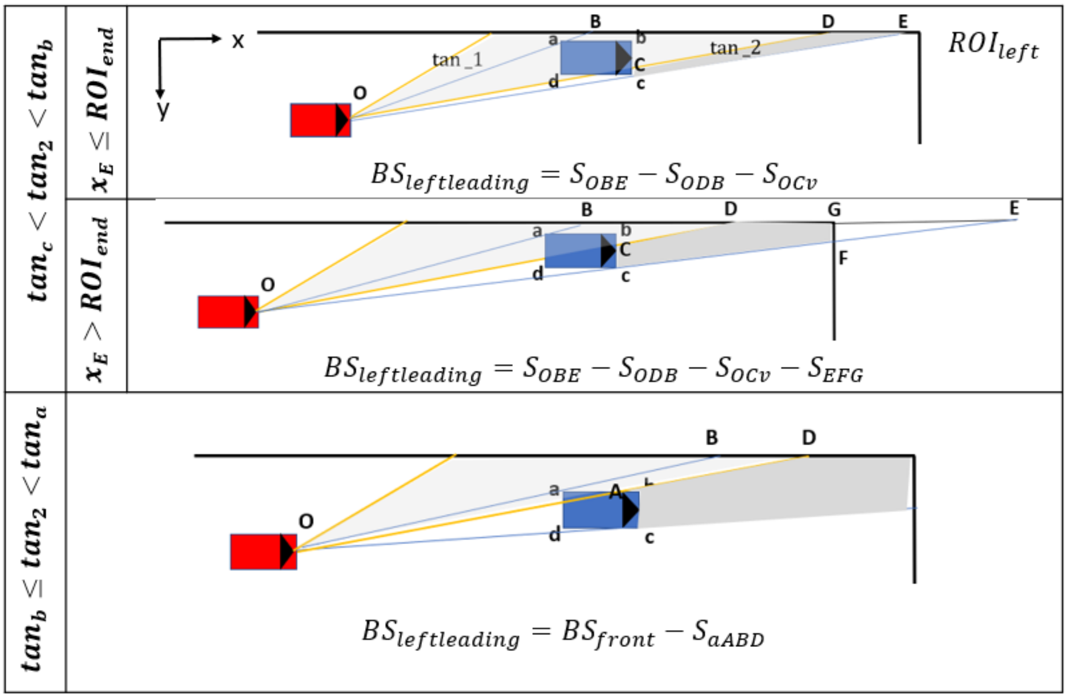


Figure 3.31: Blind spot caused by “leftleading” (overlap on the left) (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

- **Blind spot of “leftleading” and “rightleading”**

For “pre”-vehicles or “along”-vehicles in the front area of ego-vehicle, the blind spot can be calculated with the basic function “*BS_front*”. However, for “leading”-vehicles it is not exactly the same. Because there is a possibility, that the “leading”-vehicle is located in the blind spot of a “pre”-vehicle. Thus, the blind spot of the “pre”-vehicle partially overlaps with the one caused by “leading”-vehicle. Therefore, a case discrimination is necessary for the calculation. If this vehicle is not located in the blind spot of a “pre”-vehicle, the blind spot caused by “leading”-vehicle can still be calculated with the basic function “*BS_front*”. If this vehicle is partially in the blind spot of a “pre”-vehicle, then the area which has been calculated twice, needs to be identified and subtracted, or to calculate only the newly added part. If a “leading”-vehicle is completely in the blind spot of a “pre”-vehicle, then further calculation is no more necessary. For a vehicle labelled “leftleading”, overlap on the left side of “leftleading” can caused by “leftpre” or “middlepre”, the newly added blind spot by “leftleading” is shown in Figure 3.31.

Based on the consideration above (blind spot with no overlap or overlap on the left side of “leftleading”), it is possible, that there is overlap on the right side of “leftleading”, which can only be caused by the existence of a “middlepre” (Figure 3.32). In this case the overlapped area needs to be subtracted from the previous result.

Consideration for “rightleading” follows the same principle as “leftleading”.

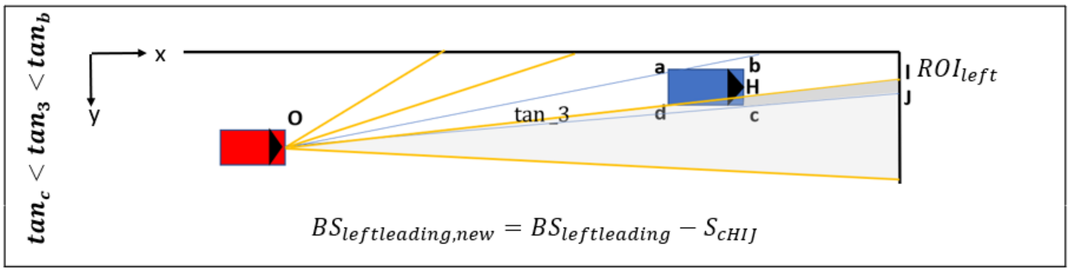


Figure 3.32: Blind spot caused by “leftleading” (overlap on the right) (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

- **Blind spot of “middleleading”**

Similarly, if “middleleading” is not in the blind spot of a “pre”-vehicle, then the blind spot caused by it can be calculated with the basic function “*BS_front*”. If it is completely in the blind spot of another vehicle, then no further calculation is required. If it is partially located in the blind spot of a “pre”-vehicle. Cases with overlapped blind spot are divided into two categories: namely whether the overlapped part is on the left or the right side of “middleleading”. If the overlapped area is on the left side of “middleleading”, it can be caused by “leftpre” or “middlepre” (Figure 3.33). If on the right side, then it can be caused by “middlepre” and “rightpre” (Figure 3.34).

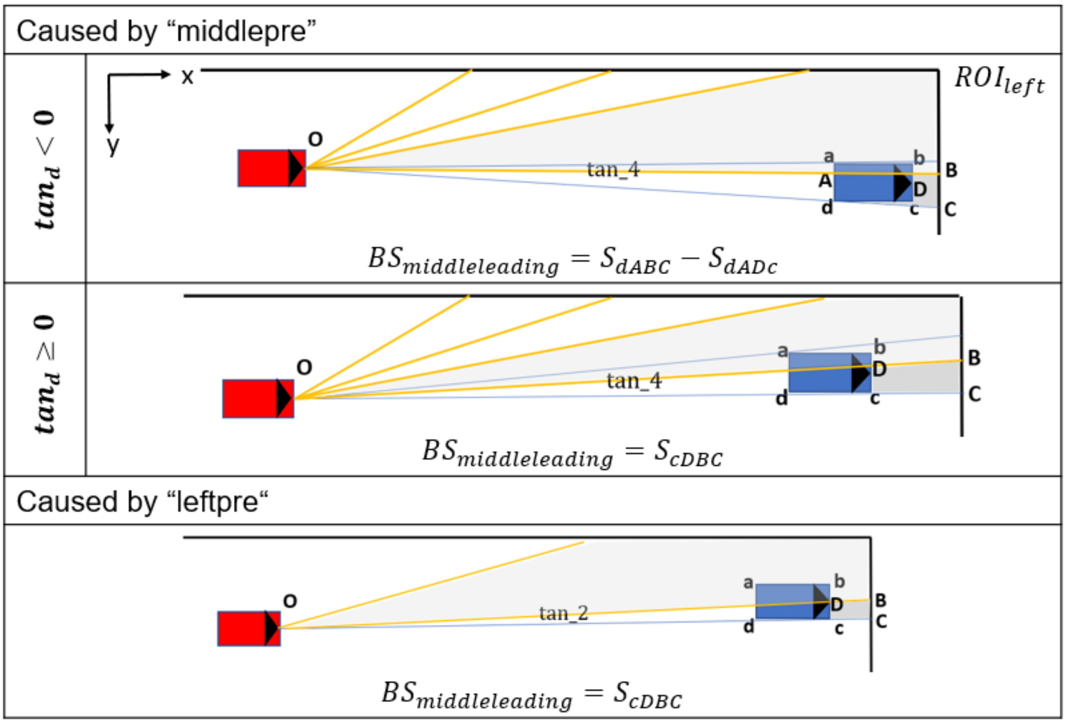


Figure 3.33: Overlap is on the left side of “middleleading” (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

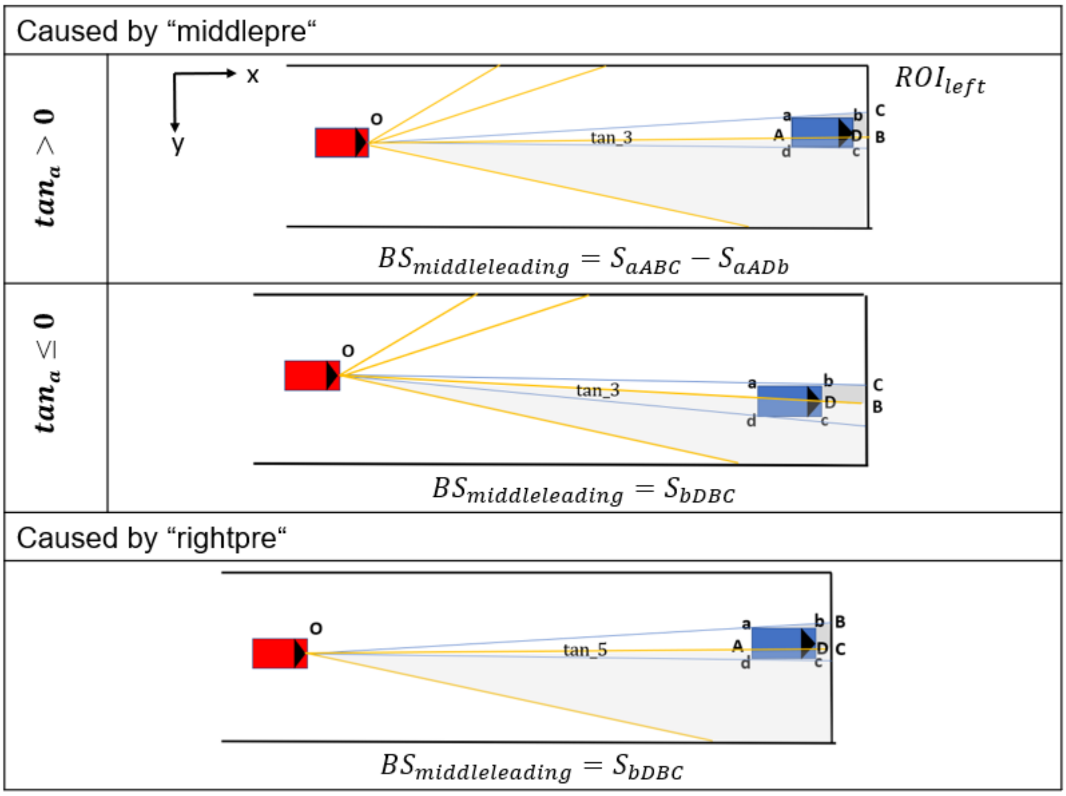


Figure 3.34: Overlap on the right side of “middleleading” (ROI_{left} corresponds to the y-coordinate of left boundary of ROI)

- **Blind spot caused by “follow”-vehicles**

For vehicles behind ego-vehicle according to Figure 3.25. The calculation follows the same principle as the basic function “*BS_front*”. Only that the detecting sensors are assumed to be installed in the middle of ego-vehicle’s rear. Since the length of the area behind ego-vehicle is only half of that in front of it, therefore, overlap of blind spot is very unlikely and does not need to be taken into consideration.

- **Blind spot caused by “along”-vehicles**

For the vehicles along ego-vehicle according to Figure 3.25, since the geometry of each bounding box (length, width, coordinates of four corners) is already known. The blind spot of “leftalong” or “rightalong” can easily be calculated using the principle of similar triangles (Figure 3.35).

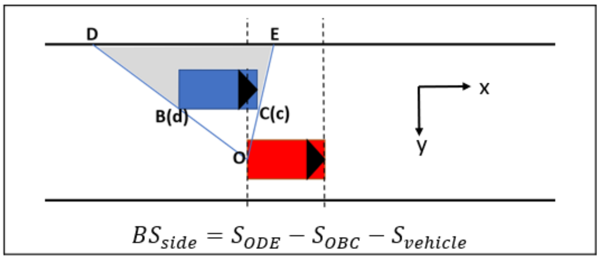


Figure 3.35: Blind spot caused by “along”-vehicles

The final blind spot of ego-vehicle can then be obtained by adding the blind spot caused by each individual surrounding-vehicle.

3.10 Complexity

From section 3.2 to section 3.9 the contribution of each influence factor to the complexity been interpreted, quantified and implemented. In order to indicate the complexity of surrounding environment with a single value, the influence of different factors need to be combined. However, the quantified results of influence factors have different ranges and different units. For instance, there are two types of surrounding vehicles within ROI, the number of surrounding vehicles is 5, the average deviation of surrounding vehicles from predicted trajectories is 1,3 m, the blind spot of ego-vehicle is 100 m^2, etc. These results cannot be directly used for the calculation. Therefore, a normalization of these values is necessary. The basic idea of normalization is to bring the result of each factor into a value between 0 and 1, with 0 indicating the lowest level of influence and 1 the highest level of influence. Complexity can then be calculated after binging the quantified influence to the same standard.

In the first part of this subchapter, the normalization of the results obtained from section 3.2 to section 3.9 will be conducted. In the second part, complexity of environment around ego-vehicle (ROI) will be calculated with help of normalized results.

3.10.1 Normalization

Since the range, significance of each influence factor is different, therefore, the strategy applied for normalization also differs from each other, which will be elaborated in the following text.

Types of surrounding vehicles

In HighD Dataset only two types of vehicles are included: car and truck. Assuming the number of types of surrounding vehicles is $type_{num}$, this value will be normalized with Eq. (3.29).

$$type_{norm} = \frac{type_{num}}{2} \tag{3.29}$$

"2" indicates two types in total. The value of $type_{num}$ can be 0, 1 and 2. Therefore, $type_{normed}$ can be 0, 0.5 and 1, with 0 indicating the simplest situation (no surrounding vehicles) and 1 the most complicated situation (both cars and trucks are included).

Number of surrounding vehicles

According to the definition in Figure 3.5, theoretically there can be maximal 11 surrounding vehicles within ROI, if each sector is occupied by exactly one vehicle. However, since it is possible, that a sector contains two vehicles, so the maximal number of surrounding vehicles can be larger than 11. If assuming 22 as the maximal number and using it as the reference value for normalization, then most cases are categorized into simple situations, since 22 is very unlikely in the reality. Therefore, 11 is chosen to be the reference value. The principle of normalization is similar as factor "types of surrounding vehicles". The result will be 0 if there is no surrounding vehicle and larger than 1, if all sectors of ROI are occupied and at least one sector is occupied with more than one vehicle.

$$vehicle_{norm} = \frac{vehicle_{num}}{11} \tag{3.30}$$

Dynamic of surrounding vehicles

Dynamic of surrounding vehicles consists of four aspects: velocity and acceleration in both longitudinal and lateral direction. The results in section 3.3 are weighted average values of respective aspect. A normalized result can be obtained by dividing a reference value, which is also a "maximal" value. This reference value cannot be endless large to cover all results but needs to be larger than the majority of the results. In order to choose a reasonable value as reference value for normalization, calculations are conducted for each frame of each vehicle for the 48th recording, which includes data of over 2000 vehicles. A cumulative histogram is created for each aspect of dynamic (Figure 3.36). For instance, choosing 35 m/s as reference value in regard with velocity in longitudinal direction covers 98,77% of the results. Choosing 0.65 m/s as reference value in regard with velocity in lateral direction covers 99.03% of the results. Analogously, reference values of acceleration in longitudinal and lateral directions can be determined as well.

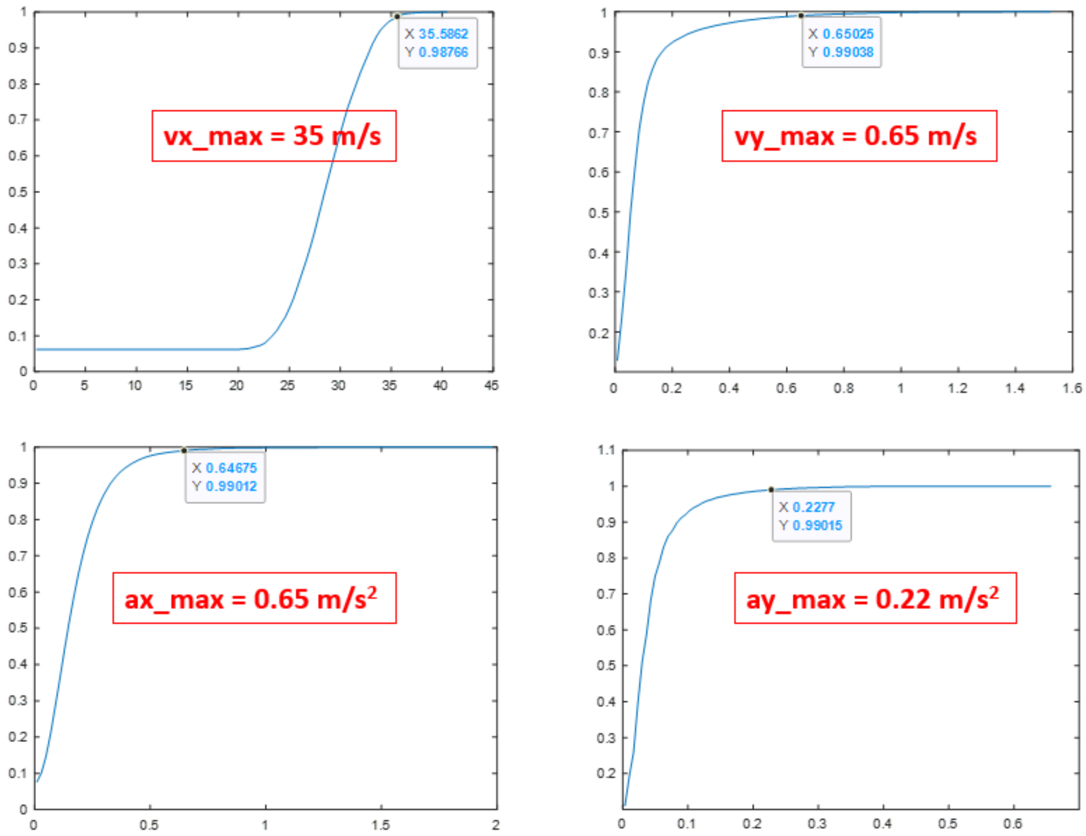


Figure 3.36: Reference values of dynamic

Normalized dynamic in regard with velocity in longitudinal direction:

$$dynamic_{norm,vx} = \frac{dynamic_{vx}}{vx_{max}} \tag{3.31}$$

Normalized dynamic in regard with velocity in lateral direction:

$$dynamic_{norm,vy} = \frac{dynamic_{vy}}{vy_{max}} \tag{3.32}$$

Normalized dynamic in regard with acceleration in longitudinal direction:

$$dynamic_{norm,ax} = \frac{dynamic_{ax}}{ax_{max}} \tag{3.33}$$

Normalized dynamic in regard with acceleration in lateral direction:

$$dynamic_{norm,ay} = \frac{dynamic_{ay}}{ay_{max}} \tag{3.34}$$

In order to represent the influence of factor dynamic with only one value, the four aspects of dynamic need to be combined. Figure 3.37 shows the distribution of result in form of histograms with different weighting factors of four aspects. It is noticeable, that whether accelerations or velocities are more weighted does not have much influence on the distribution. Therefore, the four aspects are equally weighted. The final expression to obtain a normalized value representing the influence of dynamic is shown in Eq. (3.35).

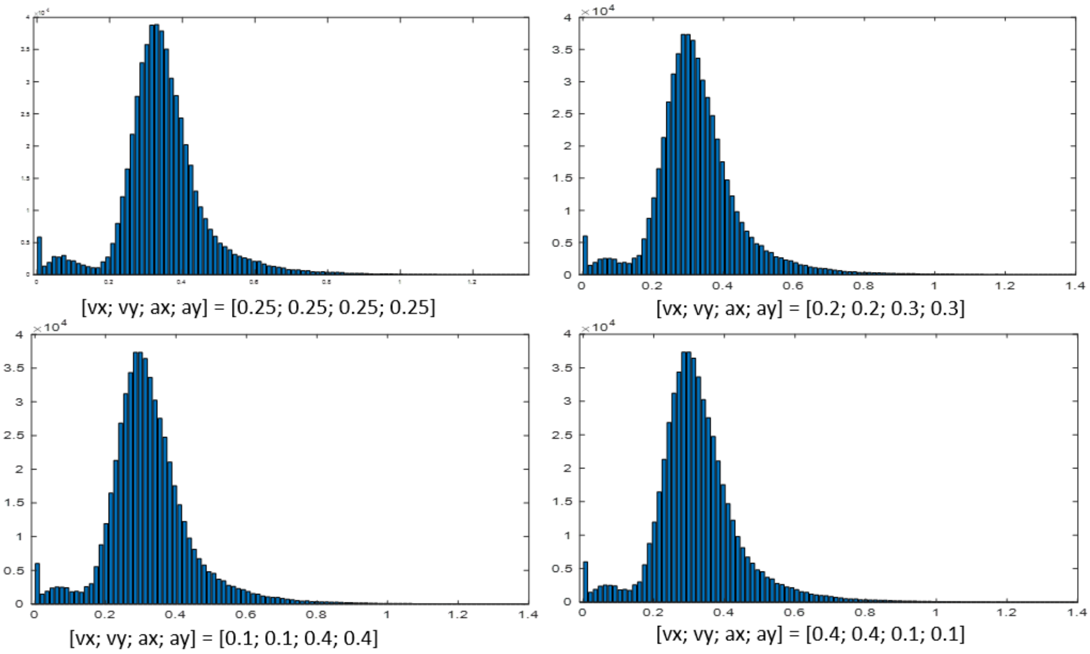


Figure 3.37: Weighting factors of four aspects of dynamic

$$dynamic_{norm} = \frac{dynamic_{norm,vx}}{4} + \frac{dynamic_{norm,vy}}{4} + \frac{dynamic_{norm,ax}}{4} + \frac{dynamic_{norm,ay}}{4} \tag{3.35}$$

Variation of dynamical parameters

Normalization of this factor is similar as factor "dynamic of surrounding vehicles". The reference values are determined with help of the results of the 48th recording (Figure 3.38).

Normalized variation in regard with velocity in longitudinal direction:

$$variation_{norm,vx} = \frac{variation_{vx}}{delta_{vx}} \tag{3.36}$$

Normalized variation in regard with velocity in lateral direction:

$$variation_{norm,vy} = \frac{variation_{vy}}{delta_{vy}} \tag{3.37}$$

Normalized variation in regard with acceleration in longitudinal direction:

$$variation_{norm,ax} = \frac{variation_{ax}}{delta_{ax}} \tag{3.38}$$

Normalized variation in regard with acceleration in lateral direction:

$$variation_{norm,ay} = \frac{variation_{ay}}{delta_{ay}} \tag{3.39}$$

Figure 3.39 shows the distribution of results when four aspects of this factors are weighted with different proportions. Similar as factor “dynamic of surrounding vehicles”, whether accelerations or velocities are more weighted, does not have much influence on the distribution of the results. Therefore, the four aspects of this factor are also chosen to be equally weighted.

Thus, the final normalized value of variation of dynamical parameters is expressed as:

$$variation_{norm} = \frac{variation_{norm,vx}}{4} + \frac{variation_{norm,vy}}{4} + \frac{variation_{norm,ax}}{4} + \frac{variation_{norm,ay}}{4} \tag{3.40}$$

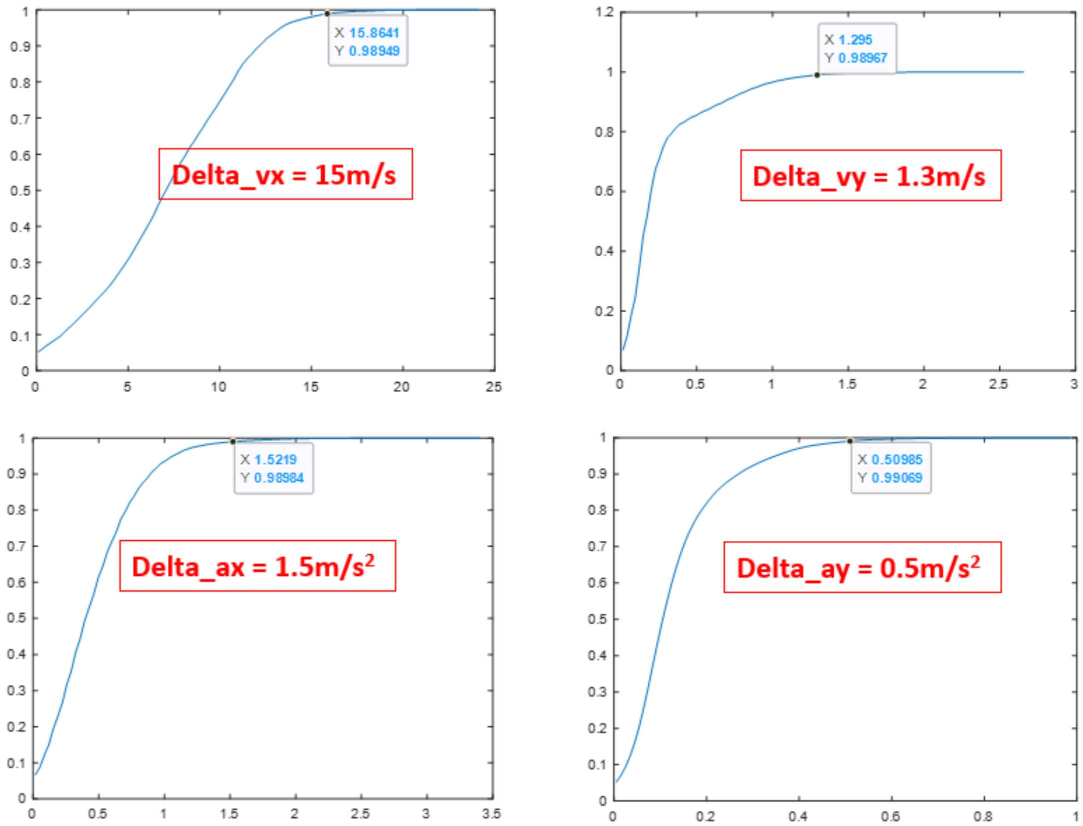


Figure 3.38: Reference value of variation of dynamical parameters

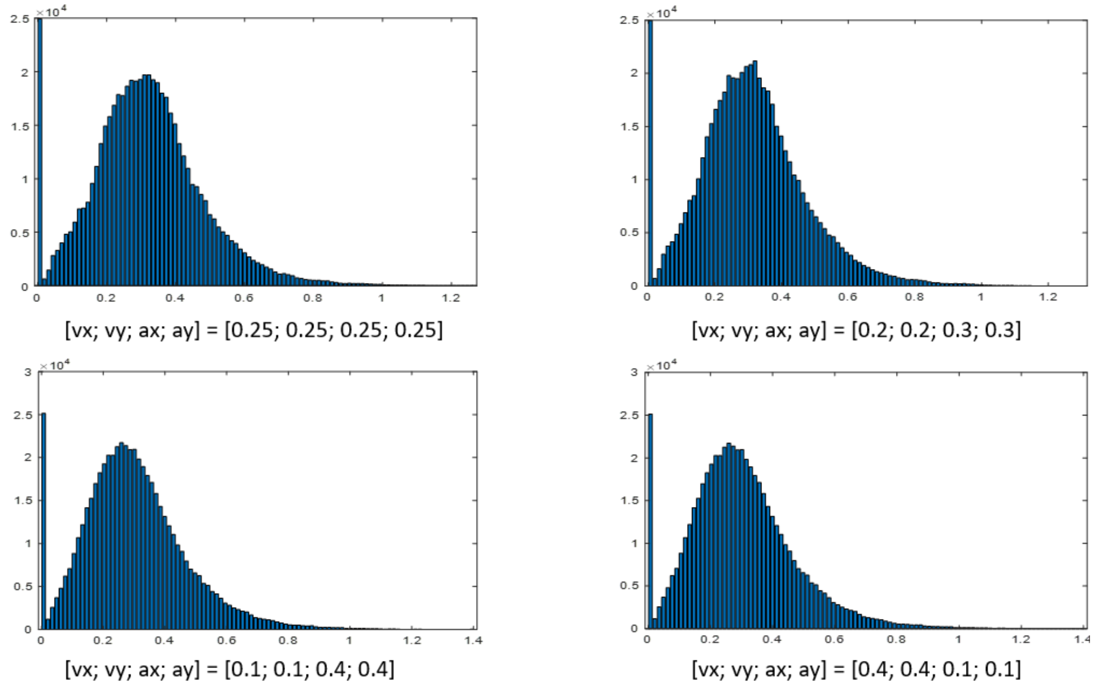


Figure 3.39: Weighting factors of four aspects of variation

Connectivity

Assuming the number of connections within ROI is $connection_{num}$, according to the definition in section 3.5, there can be maximal 17 connections within ROI if each sector is occupied by exactly one vehicle. Connectivity as a normalized result can be calculated with the following equation:

$$connectivity = \frac{connection_{num}}{17} \tag{3.41}$$

Traffic prediction

In section 3.6 $\boldsymbol{deviation}_{euclidean}$ is a vector containing the Euclidean distances of deviation of one surrounding vehicle in one frame of ego-vehicle for nof frames from the predicted positions. The deviation may have some changes in the development of nof frames. Taking the average value of this vector will ignore the cases, in which actual position of surrounding vehicle deviates a lot from predicted result. Therefore, the maximal value, namely the maximal deviation of this vehicle during prediction in a particular frame of ego-vehicle will be observed. If the trajectories of more than one vehicle are predicted, the average value of the maximal deviation of all surrounding vehicles in this frame is observed.

$$deviation_{euclidean} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{v}} \frac{max(\boldsymbol{deviation}_{euclidean,i})}{v} \tag{3.42}$$

v is the number of surrounding vehicles considered for prediction, $max(\boldsymbol{deviation}_{euclidean,i})$ is the maximal deviation of vehicle i from prediction in one frame of ego-vehicle.

Same as the factors before, a reference value is needed for normalization, which is again determined with help of the result of recording number 48. Following figure is a cumulative histogram of $deviation_{euclidean}$ calculated for each vehicle's each frame in recording number 48. As can be seen from the diagram, that 99.07% of the results is within 1.4092 m. Therefore, 1.4 m is chosen to be the reference value. A normalized result can be calculated with Eq. (3.43).

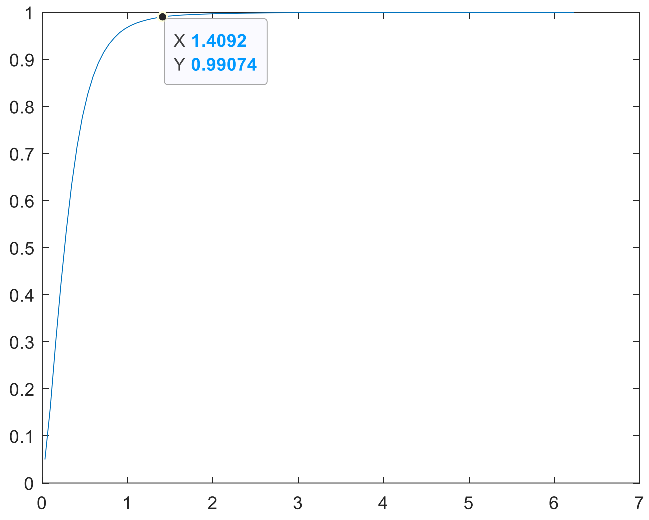


Figure 3.40: Reference value of deviation

$$deviation_{norm} = \frac{deviation_{average}}{1.4} \tag{3.43}$$

Possible actions of ego-vehicle and surrounding vehicles

For normalization of factor "possible actions" two extreme cases need to be considered first. One is that, if there is no other vehicle around, ego-vehicle have maximal number of possible actions and can do as desired. The environment in this case is very simple. The second case is that, if the vehicle is stuck in traffic jam, ego-vehicle has no other possibilities except move along with the traffic flow. The environment in this case is quite simple as well. Therefore, for this factor the highest level lies in the cases, in which a vehicle only has a particular number of possible actions. In this thesis, it is defined, that the influence of this factor has the highest level when a vehicle has only one possible action and lowest level when it has no or all possible actions. The maximal number of possible actions of ego-vehicle is 5. Possible actions of ego-vehicle can be normalized with the following equation:

$$pa_{norm,ego} = \begin{cases} 0 & pa_{ego} = 0 \\ \dfrac{-pa_{ego} + 5}{4} & pa_{ego} > 0 \end{cases} \tag{3.44}$$

The maximal number of possible actions of surrounding vehicle is 8. Possible actions of surrounding vehicles can be normalized with the following equation:

$$pa_{norm,nb} = \begin{cases} 0 & pa_{nb} = 0 \\ \dfrac{-pa_{nb} + 8}{7} & pa_{nb} > 0 \end{cases} \tag{3.45}$$

Time-gap

In section 3.8, time-gap is calculated for vehicles with label “leftpre”, “middlepre”, “rightpre”, “leftfollow” and “rightfollow”. Time-gap will not exist if corresponding sector is not occupied. Therefore, a default value for time-gap is necessary for a vacant sector. Since a “follow-vehicle does not exist, theoretically the value of time-gap between this vehicle and ego-vehicle can be endless large, therefore, a large value will be chosen to be the default value. Normalization will then be based on the average of time-gap of these five sectors.

$$time\_gap = \frac{\sum_1^5 time\_gap_i}{5} \tag{3.46}$$

The principle of normalization for this factor differs from the previous ones. If time-gap has a large value, which indicates, that the distance between ego-vehicle and surrounding vehicle is large enough, corresponding to a low level of influence. If time-gap has a very small value, it means that the distance between ego-vehicle and surrounding vehicle is too short, corresponding to a high level of influence. Therefore, this factor will be normalized with an exponential function.

$$time\_gap_{norm} = e^{-a \cdot time\_gap} \tag{3.47}$$

The choice of default value of time-gap and parameter a in Eq. (3.47) can influence the distribution of the results. Comparing the result shown in the following figures, 5 s is chosen to be default value of time-gap. Parameter a has the value 0.5.

By comparing the distributions from Figure 3.41 to Figure 3.44 it can be noticed, that when the default value of time-gap is equal to or larger than 5 s, five groups can be identified from the distribution in histogram. The reason for this phenomenon is that, vehicles at five positions are considered for the calculation of time-gap, for a position not occupied by a vehicle a default value of time-gap will be used for the calculation of an average value. Since this default value is much larger than the time-gap of an existing surrounding vehicle, it has larger influence on the result of average value. For instance, in case that default value is 10 s, if there is no surrounding vehicle, the average time-gap will be 10 s, if with one of the five surrounding vehicles (assuming time-gap of this vehicle is 2 s), then the average value will be 8.4 s, this calculation can go on for cases with two, three, four and five surrounding vehicle, and the average time-gap will be smaller and smaller. Since the average time-gap is normalized with an exponential function, whose output decreases with the increase of input, therefore, the larger the default value is, the smaller is the result after normalization for the case with no surrounding vehicle, which will lead to a more clearer distribution of five groups in histogram.

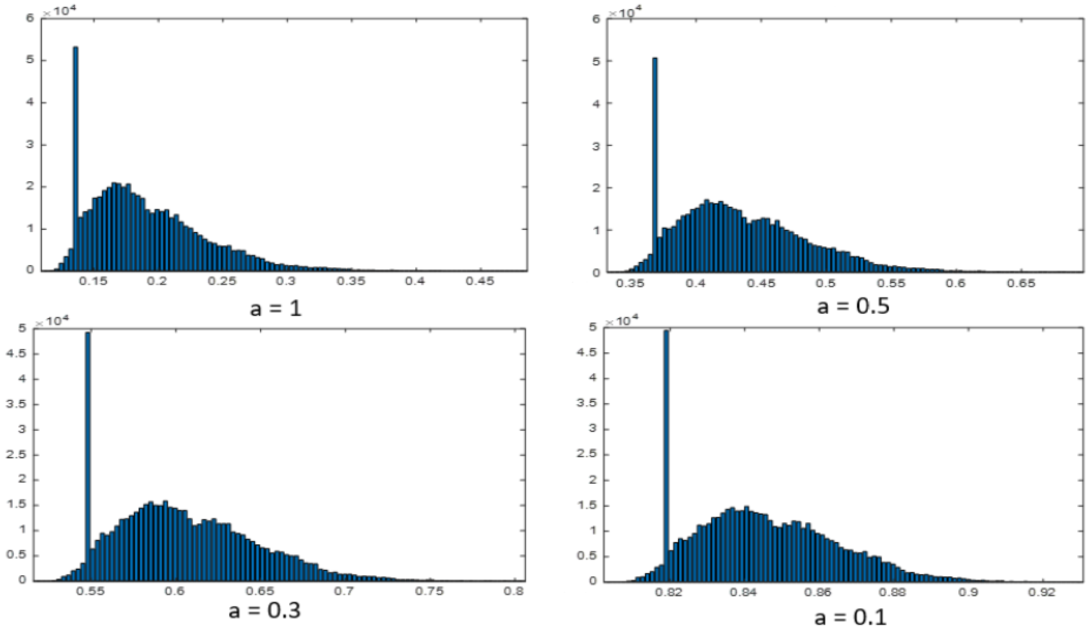


Figure 3.41: Default value of time-gap = 2 s

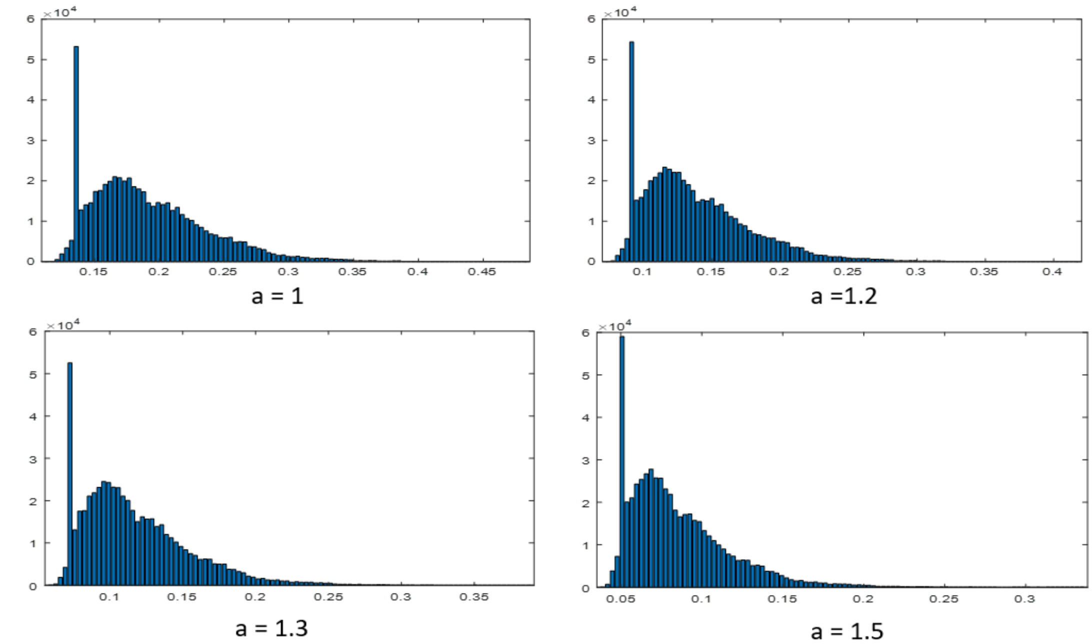


Figure 3.42: Default value of time-gap = 3 s

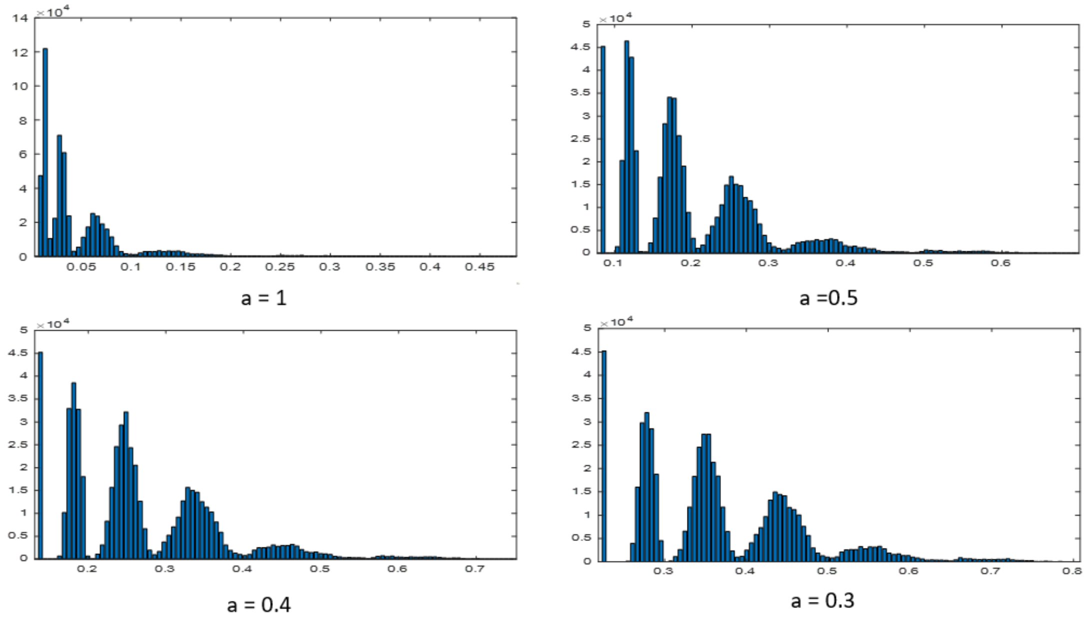


Figure 3.43: Default value of time-gap = 5 s

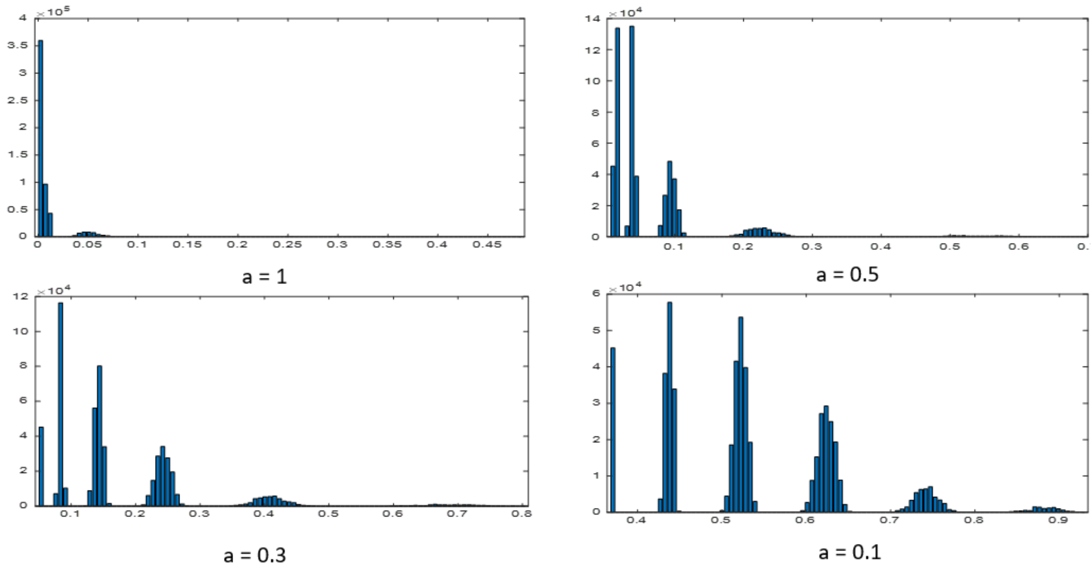


Figure 3.44: Default value of time-gap = 10 s

Blind spot

Normalization of this factor is obtained by dividing the blind spot of ego-vehicle to the area of ROI:

$$ratio = \frac{\sum_{i=1}^{v} BS_i}{S_{ROI}} \tag{3.48}$$

3.10.2 Calculation of complexity

The values of each factor have been brought to the same scale through normalization in the last section (section 3.10.1), scene complexity from the perspective of ego-vehicle can now be calculated with these normalized values with the following formula. In this thesis, all influence factors contribute equally to the complexity. There are ten influence factors, therefore, each factor is weighted with 0.1 ($\boldsymbol{w}$ is a 10x1 vector with all elements equal to 0.1).

$$C_{scene,m} = \boldsymbol{f}_m^T \cdot \boldsymbol{w}, \quad \sum_{i=1}^{n} w_i = 1 \tag{3.49}$$

m indicates one scene from a scenario, which consists of series of consecutive scenes. n is the total number of weighting factors, which is the total number of influence factors as well.

The complexity of a scenario from the perspective of ego-vehicle is then the average value of all scene complexities.

$$C_{scenario} = \frac{1}{m} \sum_{1}^{m} C_{scene} \tag{3.50}$$

4 Results and discussion

In this chapter, the results obtained through application of the introduced method in chapter 1 will be analysed. The first part will have an overview of the results and make explanations about some usual or obscure phenomenon. In the second part, a scenario with low and high complexity will be compared with each other and analysed respectively

4.1 Overview of the results

Computation of scenario complexity is conducted for 57 of 60 recordings. The last three recordings are not included because the infrastructure differs slightly from the previous ones: highway with junction (Figure 4.1), which has not yet taken into consideration and therefore is excluded for the discussion in this thesis.

Figure 4.1: Highway entrence

Figure 4.2 is a plot of maximal complexity of a scenario of all vehicles in 57 recordings (except the ones without valid frames for evaluation). Each colour band represent the results of one recording. X-axis is the numbering of all vehicles in an ascending order. Y-axis is the maximal complexity in of a scenario of each corresponding vehicle. The value of complexity is supposed to be within 0 and 1. However, it is notable, that the results of some vehicles have extreme large values. Furthermore, they all have the value 65535 (Figure 4.3).

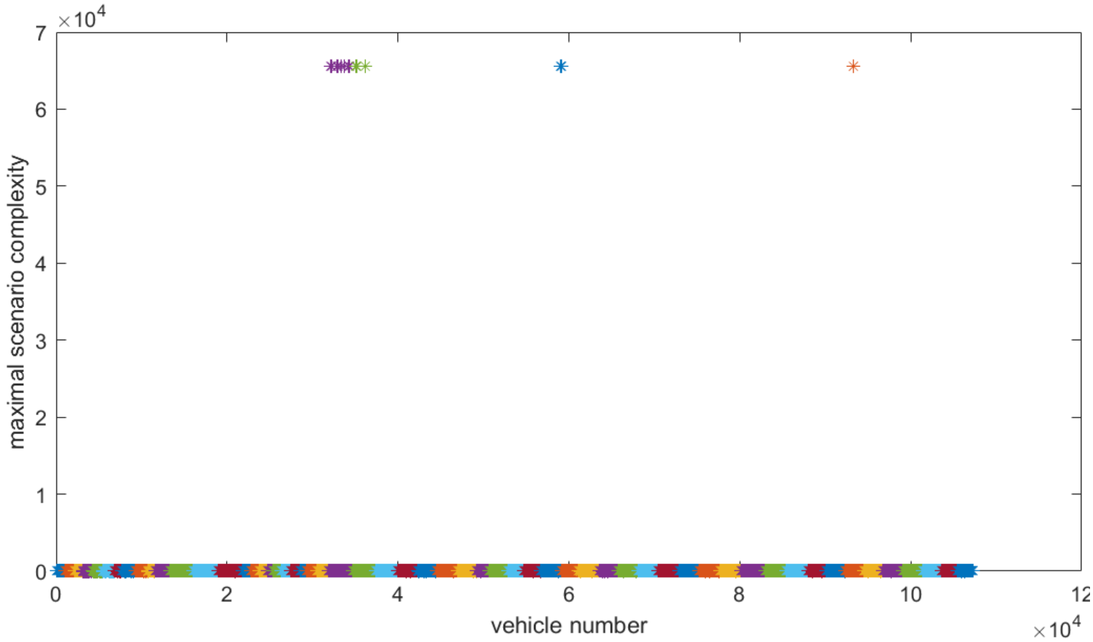


Figure 4.2: Scenario complexity of all vehicles

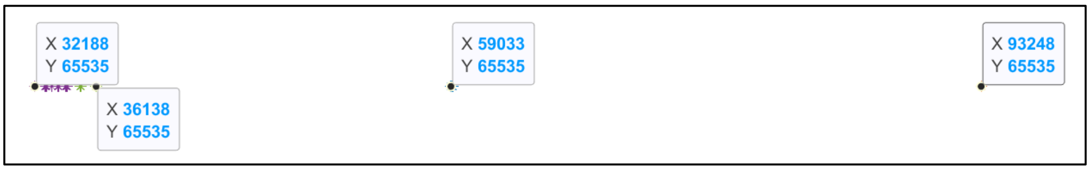


Figure 4.3: Usual value of complexity

Since each colour band represents each recording, it can be easily determined, that these usual values appear in the 25th, 26th, 36th and 51st recordings. This problem will be analysed taking the 36th recording as an example. There are several vehicles in the 36th recording with usually large complexity, vehicle Nr.2396 is one of these vehicles. Figure 4.4 shows the normalized values of each influence factor in several frames. As can be seen that, the large value of factor "ratio" result in the large value of complexity. "ratio" is defined as division of ROI by the area of blind spot. The area of ROI has in this case the value zero. Therefore, Matlab returns an infinite large number "Inf" as a result, which is 65535 in excel file. The reason for this value of ROI is that, according to the definition of ROI, its area is related to the longitudinal velocity of ego-vehicle. Ego-vehicle (vehicle Nr.2396) has in this case no longitudinal velocity, therefore the start position of ROI coincides with the end position, which leads to an ROI with 0 m^2.

id	frame_nr	nb_type	nb_num	connection	variation	dynamic	devi_eu	pa_nb	pa_ego	tg	ratio	C
2396	29944	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29945	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29946	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29947	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29948	0.5	0.090909091	0.058823529	0	0.169128372	0	0.428571429	0.5	0.082084999	65535	65535
2396	29949	0.5	0.090909091	0.058823529	0	0.169128372	0	0.428571429	0.5	0.082084999	65535	65535
2396	29950	0.5	0.090909091	0.058823529	0	0.157764735	0	0.428571429	0.5	0.082084999	65535	65535

Figure 4.4: Normalized values of influence factors of the 2396th vehicle of the 36th recording

By looking at the animation of this vehicle is these frames (Figure 4.5), it can be seen, that vehicle Nr.2396 seems to be stuck in its lane and cannot move forward. Since vehicles near Nr.2396 in this lane are all not able to keep moving, they should all sooner or later run into this situation. As mentioned before, that the maximal complexity several vehicles in this recording have this extreme large value: vehicle Nr. 2407, Nr.2417, Nr 2377, etc. Unsurprisingly, these vehicles are in the same lane as vehicle Nr.2396 (Figure 4.6). Figure 4.7 shows the normalized values of influence factors of these vehicles in several frames. It is noticeable, that although these vehicles have velocity close to zero, namely ROI with 0 m^2, however, some have a extreme large value for complexity, some have none in this column. The reason for this difference is that, the start position of ROI corresponds to the vehicle front and the end position to the vehicle rear, the existence of an “along”-vehicle and still be recognized and included for the calculation, which leads to a none-zero value of “ratio” and an “Inf” complexity. If there is no “along”-vehicle, then there will not be any surrounding vehicle in ROI at all. All normalized values will be 0, for instance vehicle Nr.2377 and vehicle Nr.2417. In this case Matlab gives a “NaN” as result. For the situation where vehicles barely move and have a velocity close to zero, a ROI should be extra defined not depending on the velocity of ego-vehicle.

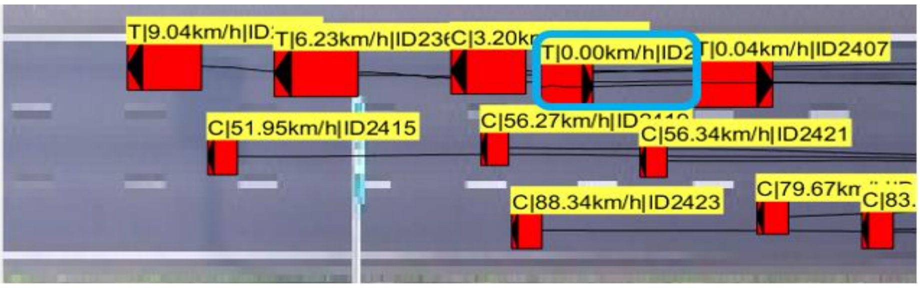


Figure 4.5: 29944th s frame in the 36th recording (all vehicles intend to move to the left side of the picture)

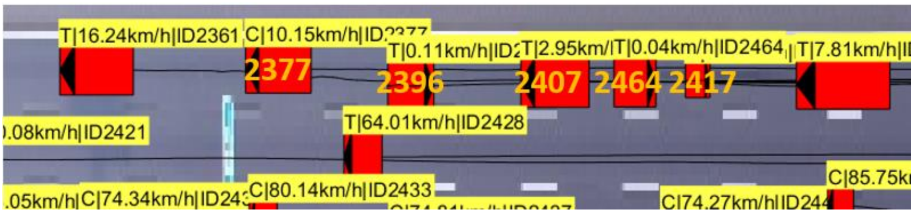


Figure 4.6: Vehicles with usually large complexity

id	frame_nr	nb_type	nb_num	connection	variation	dynamic	devi_eu	pa_nb	pa_ego	tg	ratio	C
2377	29812	0	0	0	0	0	0	0	0.5	0.082084999		
2377	29813	0	0	0	0	0	0	0	0.5	0.082084999		
2377	29814	0	0	0	0	0	0	0	0.5	0.082084999	NaN	NaN
2377	29815	0	0	0	0	0	0	0	0.5	0.082084999		
2377	29816	0	0	0	0	0	0	0	0.5	0.082084999		
2396	29944	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29945	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29946	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29947	0.5	0.090909091	0.058823529	0	0.169128372	0	0.714285714	0.5	0.082084999	65535	65535
2396	29948	0.5	0.090909091	0.058823529	0	0.169128372	0	0.428571429	0.5	0.082084999	65535	65535
2396	29949	0.5	0.090909091	0.058823529	0	0.169128372	0	0.428571429	0.5	0.082084999	65535	65535
2396	29950	0.5	0.090909091	0.058823529	0	0.157764735	0	0.428571429	0.5	0.082084999	65535	65535
2407	30024	0.5	0.090909091	0.058823529	0	0.295884615	0	0.285714286	0.5	0.082084999	65535	65535
2407	30025	0.5	0.090909091	0.058823529	0	0.291967033	0	0.285714286	0.5	0.082084999	65535	65535
2417	30175	0	0	0	0	0	0	0	0.5	0.082084999	NaN	NaN
2417	30176	0	0	0	0	0	0	0	0.5	0.082084999		
2417	30177	0.5	0.090909091	0.058823529	0	1.055027972	0	0.571428571	0.5	0.082084999	65535	65535
2417	30178	0.5	0.090909091	0.058823529	0	1.050538961	0	0.571428571	0.5	0.082084999	65535	65535
2417	30179	0.5	0.090909091	0.058823529	0	1.045978521	0	0.571428571	0.5	0.082084999	65535	65535

Figure 4.7: Normalized values of influence factors of vehicles with usually large complexity

Figure 4.2 contains the result of maximal complexity of 107343 vehicles, if exclude the ones, whose complexity is not within the interval [0,1], 107249 vehicles still remain, which is 99.94%

of all vehicles and will not influence the evaluation of the results. A histogram with scenario complexity in the valid interval is shown in Figure 4.8, which shows a normal distribution. However, there are two exceptions in interval [0,0.1]. The corresponding media of the two prominent bars are 0.0107 and 0.0599.

By looking at the vehicles with complexities around these values, it can be noticed that, these vehicles are in an environment, where there is no surrounding vehicle. Ideally, this corresponds to the simplest situation and ought to have complexity 0. However, there is no scenarios with complexity 0 after computation even for the situation without surrounding vehicles. One example of vehicle with complexity around 0.0082 is vehicle Nr.89 in the 5th recording. Figure 4.11shows the normalized values and concrete values of influence factors in several frames. As can be seen, that not all factors have value 0 when there is no surrounding vehicle. One is the possible action of ego-vehicle, which will have the maximal value 5, if ego-vehicle is in the middle lane of a three-lane-highway, but this value will become zero as well according to the strategy of normalization for this factor. The only value after normalization does not equal zero is factor time-gap. For a vehicle with no surrounding vehicle, time-gap of the surrounding vehicles have the default value 5 s, which result in 0.082 (Figure 4.12). This result contribution to one tenth of the complexity. Therefore, the value of complexity is 0.0082. If this vehicle is not in the middle lane of a three-lane-highway, the only thing changed is the number of possible actions, since actions in only one existing adjacent lane is allowed. The number of possible actions will be 3 in this case and 0.5 after normalization. The normalized value of factor “time-gap” remains the same, 0.082. They both contributes one tenth of the complexity, which lead to a result of 0.5/10 + 0.082/10 = 0.0582.

The reason for the existence of these two bars in histogram is that, for scenarios with existence of surrounding vehicles, the values of complexity will be different even when there is a very small difference in one or more factors. For cases with absolute no surrounding vehicles, the value of complexity is a fixed value and will not be a bit larger or a bit smaller, and therefore will not be distributed in several bars in histogram.

Same phenomenon can be seen in Figure 4.9, which is a histogram of average values of complexity for all vehicles. It can be noticed that, compared with the histogram of maximal values of complexity, in which the majority vehicles have a scenario complexity between 0.35 and 0.55, the interval shifted a small step to the left in histogram of average values, which is [0.3,0.5].

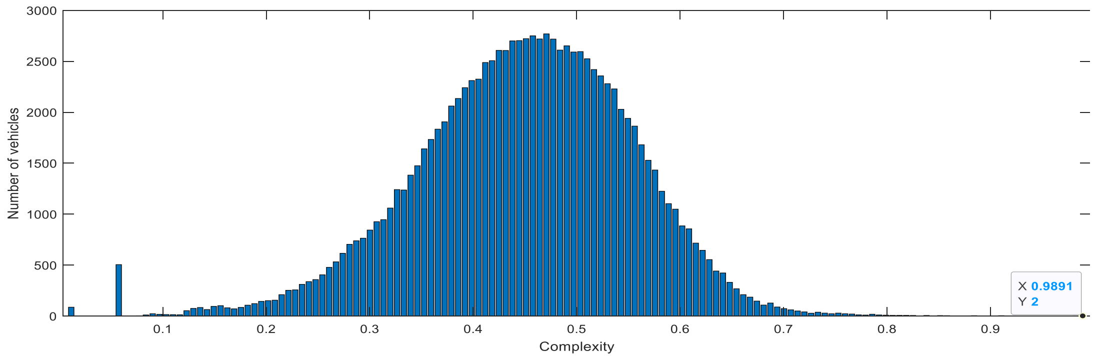


Figure 4.8: Distribution of scenarios’ maximal complexities of all vehicles (maximal scene complexity : 0.9891)

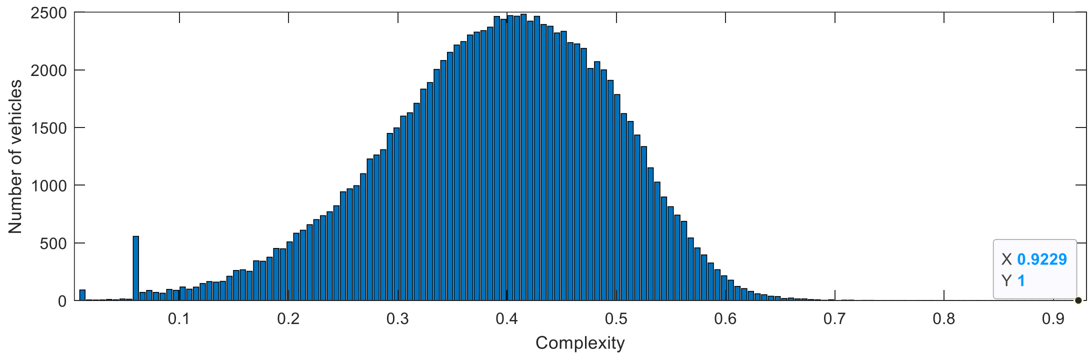


Figure 4.9: Distribution of scenarios complexities (average value of each vehicle's scene complexities) of all vehicles (maximal scenario complexity: 0.9229)

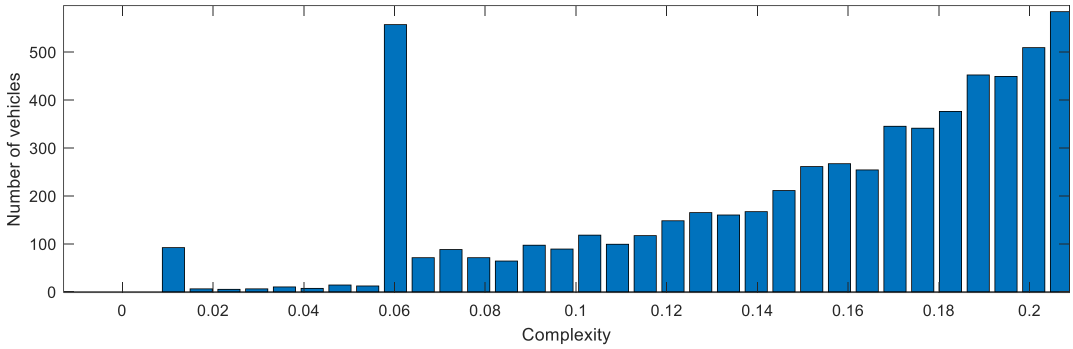


Figure 4.10: Exceptions in normal distribution

id	frame_nr	nb_type	nb_num	connection	variation	dynamic	devi_eu	pa_nb	pa_ego	tg	ratio	C
89	1761	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1762	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1763	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1764	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1765	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1766	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1767	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1768	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1769	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1770	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1771	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1772	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1773	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085
89	1774	0	0	0	0	0	0	0	0	0.082084999	0	0.0082085

devi_la	pa_nb	pa_ego	tg_leftfollow	tg_rightfollow	tg_leftpre	tg_middlepre	tg_rightpre	ratio
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0
0	0	5	5	5	5	5	5	0

Figure 4.11: Values of influence factors for vehicle Nr.89 in the 5th recording

id	frame_nr	nb_type	nb_num	connection	variation	dynamic	devi_eu	pa_nb	pa_ego	tg	ratio	C
1049	24322	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24323	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24324	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24325	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24326	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24327	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24328	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24329	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24330	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24331	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24332	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24333	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085
1049	24334	0	0	0	0	0	0	0	0.5	0.082084999	0	0.0582085

Figure 4.12: Values of influence factors for vehicle Nr.1049 in the 5th recording

4.2 Comparison of scenes and scenarios with different complexities

In order to find out the factors, which contribute to the high complexity of a scene or a scenario. Scenes and scenarios with different complexities will be compared with each other in this sub-chapter. The selected examples are from the 36th recording.

Complexity of a scene regarding ego-vehicle is a result based on all information only available in this scene (frame), while complexity of a scenario is an average value of the complexities of all scenes of a vehicle. Table 4.1 contains scenes with maximal complexity of respective scenarios in different levels. The normalized values of each influence factor contributing to respective scene complexities is shown in Figure 4.13. The representations of numbers in x-axis of this figure can be found in Table 4.2.

Table 4.1: Maximal scene complexity of respective scenarios

Complexity level	Vehicle Nr.	Frame Number	Scene complexity	Legend
0.1	836	9592	0.127579129	V1
0.2	1086	12683	0.205123322	V2
0.3	980	11670	0.303249507	V3
0.4	841	9605	0.406618806	V4
0.5	844	9671	0.506098264	V5
0.6	1008	11955	0.608617275	V6
0.7	398	4171	0.701762627	V7
0.8	327	3491	0.808823101	V8
0.9	2333	28410	0.91082928	V9

As can be seen from the diagram, that scenes with high complexity are usually the ones with more surrounding vehicles within ROI, which is consistent with the types of surrounding vehicles, connectivity within ROI, dynamic, variation of dynamical parameters and ratio. Vehicle V8 and V9 have complexities close to 1, which theoretically can be considered as very complex situations. From the diagram it can be easily seen that, the factor contributing the most to this result if the deviation of surrounding vehicles' trajectories from the predicted ones. For the normalization of this factor. 1,4 m has been chosen to be the reference value, which is based on the data from the 48th recording. In many cases, large deviation can be caused. For instance, if a vehicle has a negative acceleration in the actual frame, it will be predicted to continue moving with deceleration, while in reality it moves with a positive acceleration, which will lead to a large deviation. Or the average speed of the traffic flow in the 36th recording is larger than that in the 48th recording. Then the prediction for vehicles from the 48th frame will be predicted in general for a larger time period. Compared to scenarios with low speed, high speed can lead to larger deviation because of longer prediction horizon. One the other hand, for scenarios in traffic jam, in which vehicles move with a very low speed, the deviation after normalization will be in general smaller as 1. Therefore, further consideration of choice of this reference value is necessary.

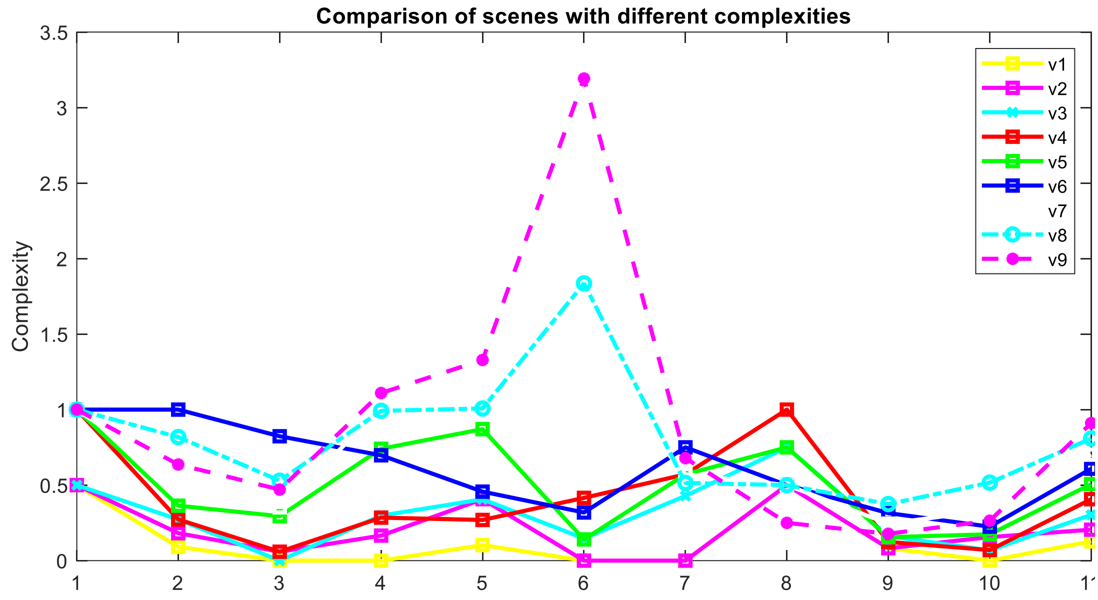


Figure 4.13: Comparison of scene complexities in different levels

Table 4.2: Representation of numbers in x-axis in Figure 4.13

Number	Description
1	Types of surrounding vehicles
2	Number of surrounding vehicles
3	Connectivity
4	Variation of dynamical parameters
5	Dynamic of surrounding vehicles
6	Deviation of surrounding vehicles from predicted trajectories
7	Possible actions of surrounding vehicles
8	Possible actions of ego-vehicle
9	Time-gap
10	Ratio (BS/ROI)
11	Complexity

The comparison is about complexity of a scene, namely complexity at a time point, which can vary over time. For complexity of a scenario, the development of complexity over all frames will be observed. Figure 4.14 shows an example of vehicle with high scenario complexity (vehicle Nr.349 in 36th recording) and an example of vehicle with low scenario complexity (vehicle Nr.386 in 36th recording). The figure contains a comparison of all factors over all frames of respective vehicles.

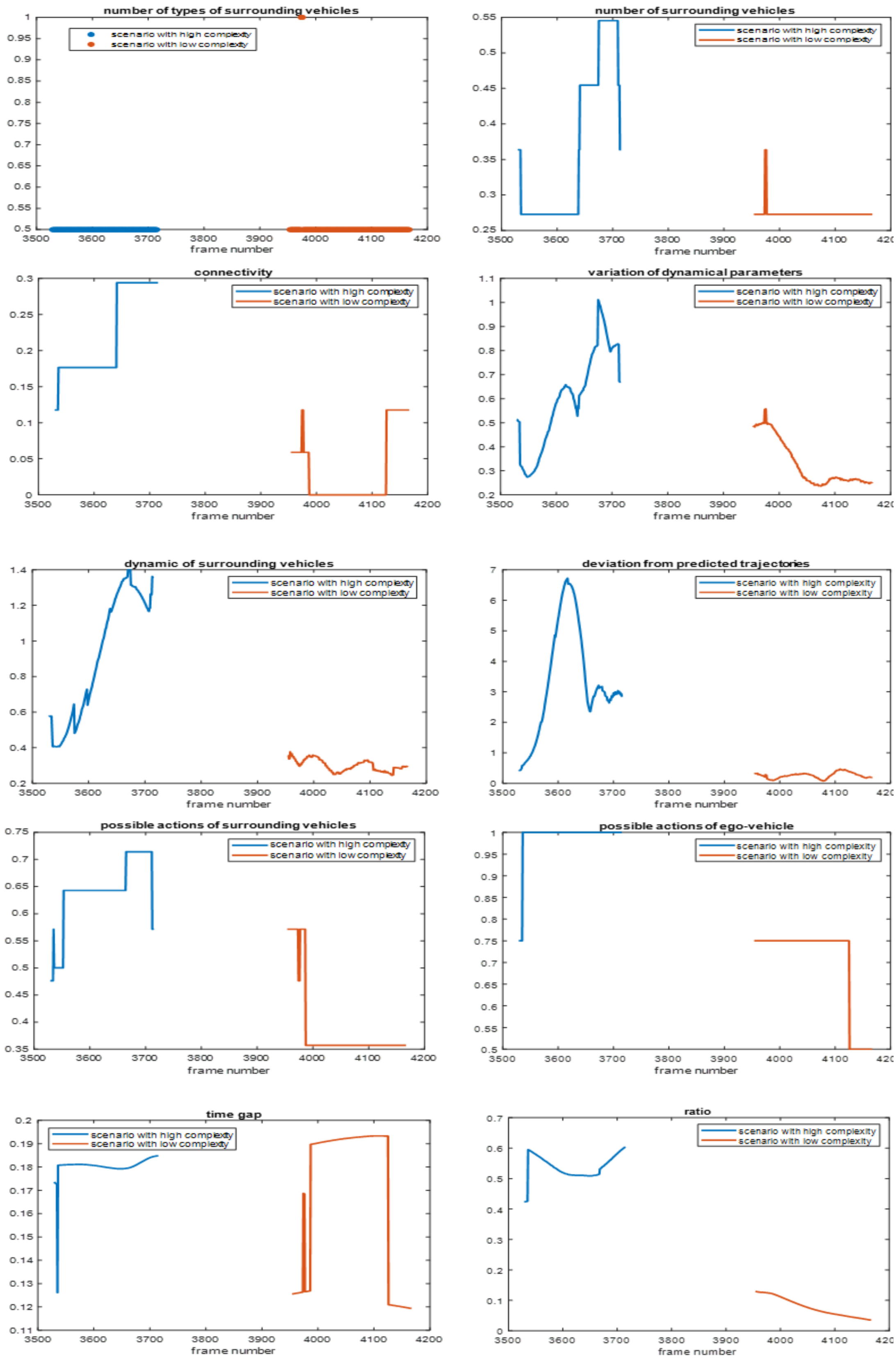


Figure 4.14: Comparison of scenario with high complexity and low complexity

From Figure 4.14, it can be seen that, except factor “types of surrounding vehicles” and factor “time gap”, the values of almost all the other factors of scenario with high complexity are larger than the ones of scenario with low complexity. The biggest difference lies in factor “deviation from predicted trajectories”. It is notable, that the development of this factor is similar to the development of factor “dynamic of surrounding vehicles”. The following animation shows the evolvements of situations of two vehicles. One difference can be noticed is that, the vehicles around vehicle Nr.349 (with high scenario complexity) has much higher velocities than the ones around vehicle Nr.386 (with low scenario complexity), which is correspond to the comparison of factor “dynamic of surrounding vehicles”. The other is that, the velocities of surrounding vehicles experience bigger changes for vehicle Nr.349. For instance, the two vehicles in front of vehicle Nr.349 have at the beginning a velocity roughly 120 km/h, which is only 80 km/h (vehicle Nr.342) after several seconds. This can lead to very large deviation from the predicted trajectories of these surrounding vehicles.

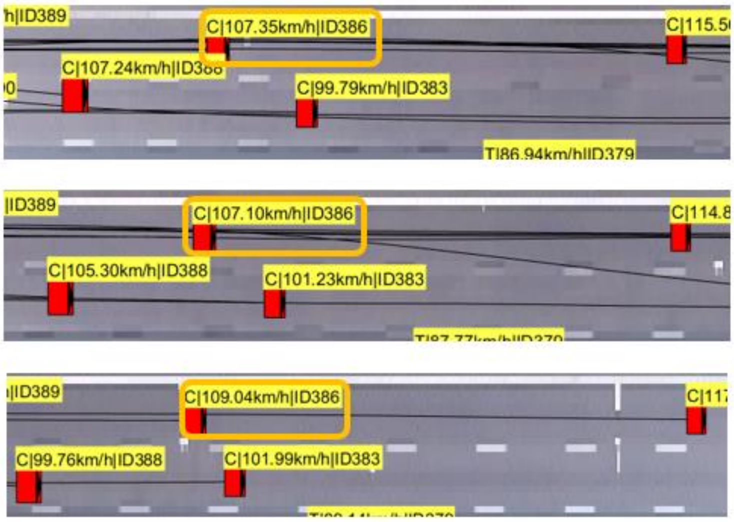


Figure 4.15: Evolvement of scenario with low complex

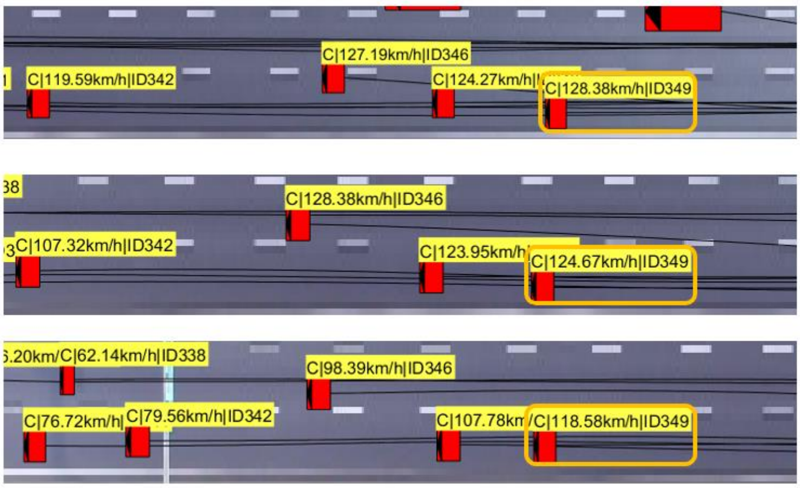


Figure 4.16: Evolvement of scenario with high complexity

5 Summary

In this chapter, the work of this thesis will firstly be summarized. In the second part, some possible extensions of this work will be discussed.

5.1 Summary and improvement

As a general summary of the evaluation method. The complexity of a scenario is an average value of complexities of all the vehicle's scenes. The complexity of each scene is then decided by ten factors, whose influence has been quantified and normalized for a objective and quantitative evaluation. During the analysis of the results obtained with application of the method implemented in this thesis, there are still some problems remain to be solved.

First, the area of ROI is related to the longitudinal direction of ego-vehicle. It is based on the assumption that ego-vehicle always has a positive longitudinal velocity. For cases with this velocity equal to 0, the area of ROI will become 0 as well. Therefore, for traffic jam, in which vehicles are not able to move at all, needs extra discussion. For instance, an ROI with fixed length and width can be defined and used, not depending on the longitudinal velocity of ego-vehicle anymore. Second, the calculation of connections is based on the assumption, that each sector of ROI is occupied by exactly one vehicle. For the situations, in which one sector has more than one vehicle, the definition of a connection needs to be altered or reconstructed. Third, the calculation of blind spot is not accurate. The implementation and calculation are very time-consuming. If there is a simpler way to implement this factor, further research is required. Four, it is clarified in this thesis, that a scene containing all static and dynamic elements is a state at a time point, and a scenario is a series of consecutive scenes. However, it is not defined, how many scenes ought to be contained in one scenario. The evaluated vehicles, some are about to leave the recorded highway section, have only 10 or 20 frames, while the vehicles just entering the highway section have over 200 frames. Scenario complexity is calculated no matter how many frames are included. About this problem, further argumentation is necessary. Finally, with respect to the calculation of complexity, the influence of each factor is equally weighted. For instance, from the analysis in last chapter, it is noticeable, that the value of factor "deviation from predicted trajectories of surrounding vehicles" have much influence on the value of complexity, while some factors have value varying in a small interval for different complex scenes or scenarios. On the one hand, the standard needs to be determined for the choice of reference value. On the other hand, the importance degree, namely the weighting factors of each influence factor needs to be arranged.

5.2 Outlook

Based on the completed work and things needed to be improved, there are many other topics, which can be extended from this work. First, the scenarios in this work are either two-lane-highway or three-lane-highway, while in reality highway sections with entrance and exit are also very often. They have more often lane changes, larger variation of dynamical parameters and in general more changeable situations., which should also be included in the discussion. Another factor can be included is the number of actions of both ego-vehicle and surrounding vehicle. In this thesis, the factor which has been discussed in the number of possible actions of ego-vehicle and surrounding vehicle. The latter indicates the indistinction of the movement, while the new added factor will count the actions of surrounding vehicles in the time period of scenario of ego-vehicle, the more actions are detected, the more changes are experienced in the traffic environment around ego-vehicle. These changes are neither the uncertainty, nor the intention of the system to change, but the movements that actually happen (one action can be understood as a change of driving state, for instance, from driving with constant velocity to driving with a constant acceleration).Another topic can be extended from this work is the sensitivity of each factor. Sensitivity of a factor means that how sensitive is complexity to the changes in this factor. The result of this analysis can be used for the determination of weighting factors.

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6 References

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