1 Modelling and calibrating situation adaptive lane changing and merging behavior on Chinese elevated roads

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1.1 Abstract

This paper describes the extension and the calibration of a driver model in SUMO that enables a situation adaptive driver behavior for lane changing and merging processes. The extensions are tailored to improve the representation of Chinese traffic dynamics but are expected to yield improvements for other regions of the world as well. To design and calibrate the model extensions FOT (field operational test) Data is used to analyze which influence critical traffic situations have on driving behavior. The results are discussed and findings for driver models, as well as for piloted driving systems are derived. To this end a detailed evaluation of merging and lane change behavior, with respect to different traffic situations, is conducted. Subsequently the model extensions of *emotion-memory* and *lateral encroachment* are explained and it's implementation and calibration discussed. Finally the resulting driver model is validated by using real world data from Chinese elevated road interchanges and merging areas.

Keywords: Heterogeneous traffic, Driver Model, Testing ADAS

1.2 Introduction

1.2.1 Motivation

A new field of application for traffic simulation and driver modeling is continuously growing in importance, namely testing and developing driving functions. Currently a lot of real driving tests are carried out, when testing or improving assisted or piloted driving functions. Their precision is so far not reached with simulations. Nevertheless, with rising automation level of driving functions they become more complex and the testing process becomes not only more and more expensive but is also extremely time consuming. Consequently, time restrictions often render comprehensive real world tests cumbersome, which is why simulations are an indispensable part of the overall testing process.
Semrau et. al. [15] introduced a framework for this testing process, described some extensions of driver models and the first calibration methods for lateral dynamics in [15]. Based on findings

described in [15] further research was necessary in several aspects. With testing driving functions in a traffic simulation we choose a behavior based approach, meaning that the driver characteristics have a significant influence on the simulation. The behavior of human drivers is not constant but changing due to various conditions, like interactions with other drivers and surroundings. This is especially true for complex merging situations at highway intersections, since a lot of interactions happen here.
Section 1.3 describes the generation of the data basis for this research, as well as the processing of the new Velodyne lidar data. In section 1.4 the lane changing an merging behavior is analyzed. It starts with lane changes for merging and the concept of emotional memory and goes on with a detailed analysis of pushing behavior and virtual lane formation. After the implementation is described, section 1.5 presents the validation concept. Section 1.6 concludes this paper by discussing open points and limitations of the developed models.

1.2.2 Related work

The importance of driver emotions for the driving style is well known in the research community. Nevertheless there are not many findings about the concrete influence on driver to driver interactions. Cai et al. used a multiple simulator system with three human drivers to include emotion into their study in [1]. This enabled them to display high fidelity driver to driver interactions. They decided to replace simulated cars with human drivers due to the importance of emotions and the difficulties to measure this short term effect.
Kraus went one step further and analyzed the OCC (Ortony, Clore and Collins) emotion model [10] and selected the emotions with influences on traffic in [8]. In his work he modeled automated, situation adaptive lane changes and validated them in a study. To this end the participants were asked to evaluate the automated lane changes. Two big differences to our work are the use of an automated system and the questioning of the participants concerning the emotions. We will prove the existence of emotions without questioning the participants and with naturalistic driving data in section 1.4.2.
Leu et. al. also analyzed and described different emotion models and decided to use the five factors model model [5] in [9]. They used a classic car following and lane changing model and modified it with a short term emotional factor. In contrast to the research presented here, Leu et. al. only proved the influence of emotions by comparing macroscopic parameters like travel times. Therefore they only calibrated the influence on a macroscopic level, but not on the car to car interaction level.
The fka ("'Forschungsgesellschaft Kraftfahrwesen mbH Aachen"') discussed emotions with regard to lane change motivations in their whitepaper [4]. Without doubt this is one important point of emotions. The influences discussed are similar to the memory for lane changing motivations used in SUMO. However this work is dealing with the influence of emotions on the viability of lane changes, which is not discussed in [4].

1.3 Driving studies (Data recording)

The data source used here consists of three consecutive studies, all executed in Shanghai. The first two studies have been described by the author in [15]. Their main purpose was to point out critical situations, typical for Chinese traffic, which could benefit from driver assistance systems. Moreover driver behavior was recorded during those situations and analyzed afterwards. Consequently this studies deliver the data used in section 1.4 to model lane changing behavior. Therefore a representative driver distribution was used here, so the behavior of the ego vehicle was used for analysis and calibration of the simulation. The two studies have a major limitation in sensor view, there is no object data alongside the ego vehicle.

To close this gap a consecutive study was planed. The focus were traffic jam situations on Chinese elevated roads, especially merging situation at motorway intersections. The Audi A7 test car was equipped with an additional Velodyne lidar on the rooftop. This makes object detection all around the vehicle possible.

1.3.1 ADAS Study

The ADAS study is a large-scaled study with the aim to investigate existing driver assistant systems (DAS) on the Chinese Market, respectively in Chinese traffic. As already described in [14, 15] the focus is the evaluation of availability and usability of DAS (including the recording of sensor data) as well as the subjective opinions of the participants. Therefore, it is possible to derive situations in Chinese traffic which cannot be handled by state-of-the-art DAS but assistance was demanded by the test persons. To get representative results the study was carried out with 40 Chinese drivers that where selected according to the typical Chinese driver distribution, concerning age, driving experience and gender. The surveys in this study took part in several phases of the test. The drivers were interviewed before, during and after the driving tests. Additionally, sensor data and data of the vehicle were recorded to make the analysis of the occurring situations possible. Especially congested situations are more common in China than in Germany and the complexity in congested situations is much higher, too. Details on this point will be shown in section 1.4.

1.3.2 Traffic jam study

The two previous studies had a major limitation in sensor view, there is no object data besides the vehicle. To close this gap a consecutive study was planed. The focus were traffic jam situations on Chinese elevated roads, especially merging situation at motorway intersections. The Audi A7 test car was equipped with an additional Velodyne lidar on the rooftop. This makes object detection all around the vehicle possible. The enhancement of sensor view is shown in figure 1.1. The solid areas

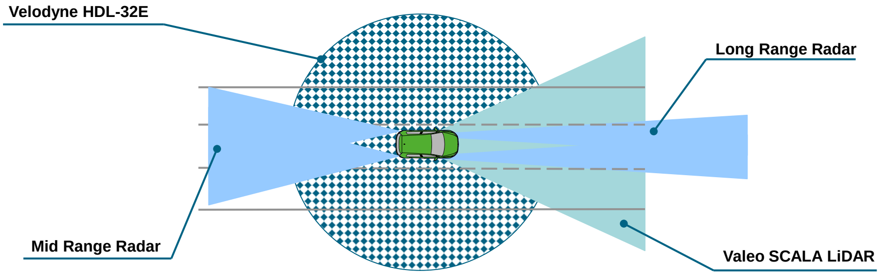


Figure 1.1: Sensorview

visualize the sensor view during the first two studies, area with diamonds represents the extension with the Velodyne lidar. The following paragraphs describe the details of the study, including route, sensor data processing and analysis. The focus were traffic jam situations on Chinese elevated roads, especially merging situation at motorway intersections. The driven route is shown in figure 1.2. It includes 1420 kilometers of Shanghai Inner City Elevated roads. For the scope of this paper we will mainly use the motorway intersection, including the marked access roads. For validation purpose traffic flow data for the whole area is available.

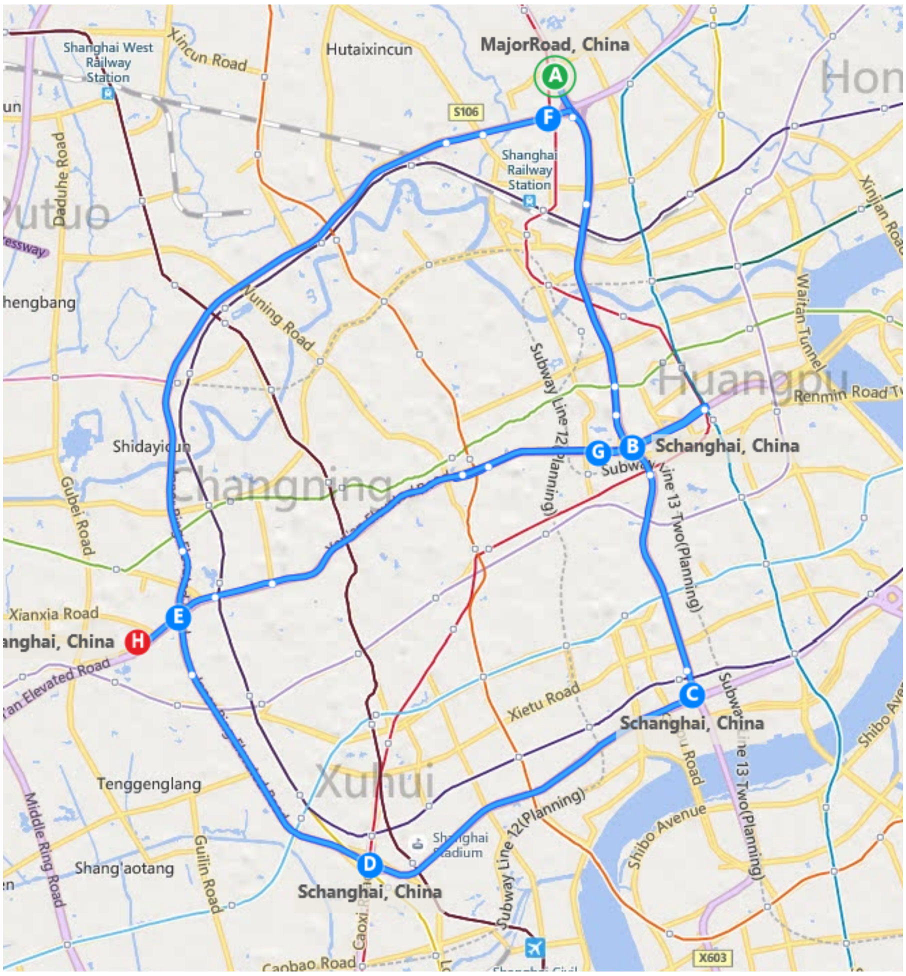
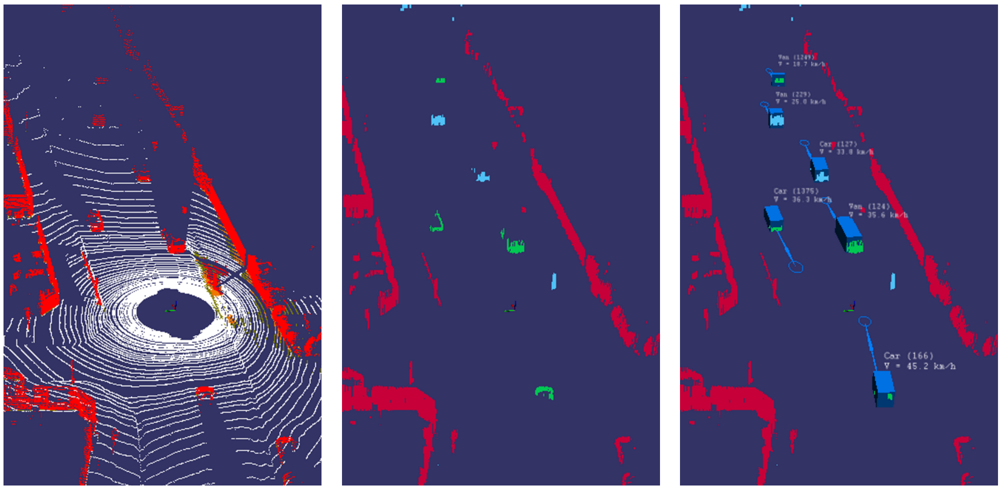


Figure 1.2: driven route on bing maps

1.3.3 Velodyne raw data processing

The environment perception and modeling is accomplished using a Velodyne HDL-32 Lidar sensor. The sensor is mounted on the vehicle's roof. It is thus able to provide a 360 degree view around the ego vehicle, capturing the road surface as well as elevated elements.
For proper processing, point measurements of each full rotation are collected into a single scan. As measurements of the road surface itself are irrelevant to the object tracking algorithm, they are classified and excluded from further processing. This is done by a grid-based algorithm (cf. [12], see results in Figure 1.3a). This approach also provides an estimation of the ground surface, which allows for a ground-relative height estimation of elevated elements. The remaining measurements are considered as originated from elevated targets. They are converted into a 2.5D Stixel representation by projecting them into a polar grid and grouping them based on their polar position. Stixels are then clustered into segments by making use of their spacial distance properties, which result from the channel-based acquisition principle of the sensor.
In order to separate moving from non-moving elements, a consistency-based grid model is utilized to classify clusters based on their spatio-temporal consistency. The classification results are shown in Figure 1.3b. A box fitting algorithm is then applied for moving and potentially movable clusters. This algorithm classifies the shape of the outer contour and provides a bounding box estimation for each cluster. A more detailed description of the processing algorithms is given in [13].
An Extended Kalman Filter-based approach is finally applied to perform the tracking task. Each object hypothesis is represented by a separate filter instance. Based on a constant-acceleration model, dynamic states are estimated from subsequent associated box hypotheses, along with object's



(a) Ground points (b) Stixel dynamics (c) Object hypotheses

Figure 1.3: Processing steps of the Velodyne processing algorithms. Fig. 1.3a shows the result of the ground classification algorithm. Ground points are colored in white, elevated targets in red. Fig. 1.3b illustrates Stixel generation and dynamic classification. Stationary clusters are colored in red, stable moving clusters are colored in green. Potentially movable clusters are blue. The final object hypotheses are shown in Fig. 1.3c.

dimensions and most probable class. During the tracking process, timing effects resulting from the scanning principle of the sensor are compensated, as described in [11]. As a result, the tracking module provides a time-consistent representation of all movable object hypotheses around the ego vehicle, as shown in Figure 1.3c.

1.3.4 Object fusion

Mostly the plausibility of the objects recognized by the Velodyne lidar is higher than the one of the integrated vehicle sensor objects, delivered by a separate object detection. Nevertheless we decided to use an object fusion on object level to get the best possible results. This is particularly useful for the detection of stationary objects. The object fusion is kept as simple as possible, since it is not the main focus of this research. The developed algorithm checks whether objects overlap and if necessary which sensor delivers to most reliable data. Subsequently a merged object is generated, based on the best available sensor data.

1.4 Lane changing and merging behavior

1.4.1 Lane changes for merging

The lane changing model in SUMO has been described in [2]. It distinguishes a hierarchy of change motivations with *strategic* lane changing as the most important reasons. A lane change is called strategic, when it is necessary for following the route. Less urgent reasons include overtaking slower vehicles or helping other drivers. Lane changes by drivers merging onto a motorway from an on-ramp are strategic since the on-ramp typically ends at some point and does not permit further driving without changing.

In a fashion, typical for other microscopic traffic simulations, SUMO re-uses the car-following model for determining the viability of lane-changing to ensure safe driving. This is done by evaluating the car-following model for the hypothetical situation that would result from a lane change for the

follower vehicle on the target lane as well as for the ego vehicle with respect to the leader on the target lane. The influence between lateral dynamics and longitudinal dynamics runs in both ways however. Not only does the car-following model put restrictions on lane-changing, the lane-changing model may pose additional constraints at vehicle speeds as well. In SUMO this is accomplished by determining speed changes that aim to create an acceptable gap for lane changing. In the context of strategic changes, cooperative speed adaptions by surrounding traffic may also be triggered.
The car-following model allows the calibration of acceleration and deceleration limits and the desired time headway as well as minimum physical gap.
In SUMO these parameters are attributes of each vehicle. To meet the characteristic driver distribution in Chinese traffic which comprises aggressive, moderate and conservative drivers, a representative distribution of parameters was used for calibration.
The overall characteristics of lane changes have been described several times, for example in [2, 6, 15, 17] and will only be summarized here. In general the previous data analysis in [15] shows that the lane changing behavior strongly depends on the traffic conditions and on the level of driving experience. The difference between novice and expert driver increases with rising complexity of the traffic situations. As a result it is necessary to distinguish between driver types and traffic conditions. The general assumption under all circumstances is safe driving, as described in [7].

1.4.2 Emotional Memory

New research, presented in [15] proved that the assumption of safe driving is not true for all situations. Drivers undercut the safe gaps in several situations. The main focus of this paper is the change in behaviors of drivers due to emotions. To this end we analyzed the studies described before regarding critical traffic situations and driver's impatience. The main point was to prove the dependency of drivers aggressiveness and emotions caused by surrounding traffic. This assumption is supported by Kraus, who analyzed different emotions in traffic in [8].
The recorded situations suggest a continuous change between the focus of the two motivations: Reaching the destination safe against reaching it fast. Which is why we focus on these emotions here. We were able to empirically prove the dependency of these emotions from traffic situations experienced by the driver. To this end we compared characteristic values for the viability of lane changes shortly after the driver experienced critical situations with his average behavior. We define the *safety coefficient* as:

$$s = \frac{d}{d_{safe}} \tag{1.1}$$

With d being the actual gap and d_{safe} representing the minimal safe braking gap. The drivers reduce the safe gap, which was found to be important for evaluating the risk (cf. [15]). The data analysis showed, that the average safe coefficient is reduced by 24%, in case the driver experienced a critical situation during the last five seconds. We where only able to prove this effect for this small amount of time. This suggests that this emotion is rising instantaneously, but not lasting long. With the existing data we where not able to prove a permanent effect on the drivers behavior. This outcome is supported by the findings in [1] and [9], Consequently a well-founded statement on this point requires more research.
None of the so far used models considers an emotional memory to take account of this effect. Thus the impatience factor I is used to manipulate the safety criterion for lane changes with regard to the emotional memory. The implementation of this factor enables us to influence the lane changing behavior separately from the car following behavior. To this end we detect critical distances, including critical cut in situations, and increase the impatience factor by 24%. After five seconds the impatiences is decreased to the original value of the driver. Moreover we assume a dependency of aggressiveness when executing pushing maneuvers and the drivers emotions. Consequently we

analyzed pushing maneuvers and their impact on aggressiveness. Results are presented in the next section.

1.4.3 Pushing and virtual lane formation for merging

The second key aspect of this paper is the pushing behavior in Chinese traffic. We observe a behavior that we call *pushing* which leads to the formation of an additional temporary lane. The behavior is exhibited by some drivers when they are unable to find a safe gap for merging from a motorway on-ramp into the main flow. Instead of waiting for a gap to form, they encroach laterally on the vehicles in the main flow, thus *pushing* them aside. Another term to describe this effect is *forced cooperative lane changing* since the pushed vehicle cooperates with the merging vehicle rather than insisting on its right-of-way and risking an accident. This leads to a lateral compression of the road lanes and allows a virtual lane to form on which the merging vehicle may drive. The traffic jam study gives us the unique possibility to observe pushing behavior from surrounding traffic. This makes modeling of the complicated forced cooperative lane changes, that have been introduced in [15], possible. As we stated in [15] the principle of forced cooperation is working due to the lateral safety distance the vehicles try to keep and the so called *pushy* factor. The findings for emotional changes in 1.4.2 suggest that the level of aggressiveness is not constant but changing due to the experiences a driver made during his travel. The more aggressive the driver type is, the lower his pushy threshold will be. This results in an earlier pushing behavior with the resulting small lateral distances. The next section investigates if this is true for the pushing behavior as well. There are three possible conditions for pushing situations, giving the driver the choice between the given patters:

1. There is no blocking car and the vehicle can move away easily
   a) The driver could brake
   b) The driver could ignore the pushing car
   c) The driver could start moving lateral
2. There is a blocking car and the vehicle cannot move easily
   a) The driver could brake
   b) The driver could ignore the pushing car
   c) The driver could start pushing himself to move lateral
3. There is a static obstacle and it is not possible to move away lateral
   a) The driver could brake
   b) The driver could ignore the pushing car

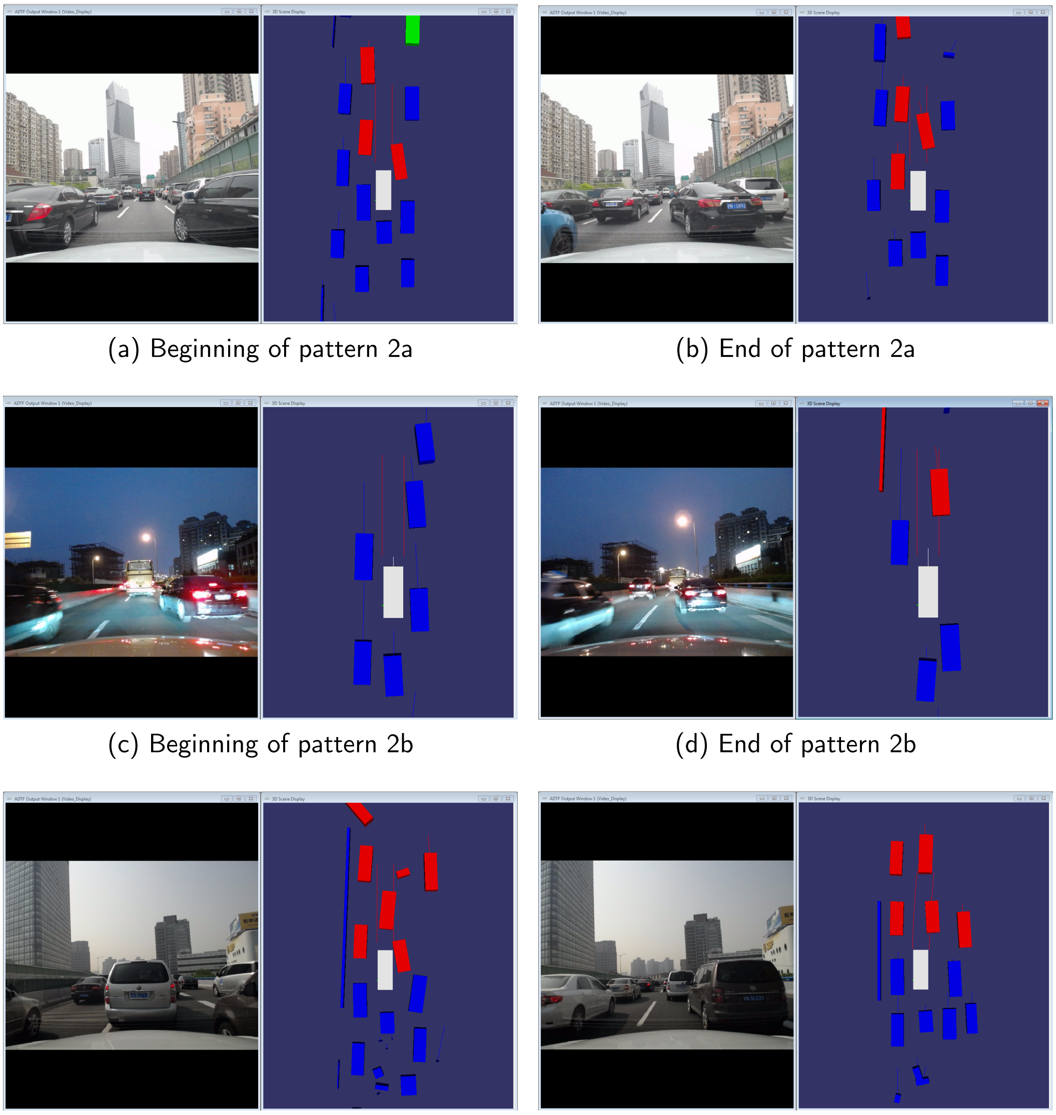
The first condition and the resulting patterns have already been described in [15]. Consequently the focus is on the second and the third condition. In case of the condition 2 the driver can react in three possible ways. All of them are shown in figure 1.4. In the first row one can identify a braking reaction 2a. Here the ego vehicle is pushed from the right (shown in figure 1.4a) and is braking to avoid a collision. The resulting cut in (shown in figure 1.4b) is particular narrow, but the describing parameters and emotions leading to this behavior are considered in section 1.4.2 and won't be analyzed in this section. Nonetheless the pushing behavior before the cut in can be observed. In contrast pattern 2b does not result in a cut in, since the pushing vehicle is ignored. In row two in figure 1.4c a fast vehicle is approaching on the right side. In figure 1.4d the same situation is displayed a little later. Obviously the approaching car was forced to brake, since the lane ended and the pushing was not successful. One important factor for this pattern and the success of a pushing maneuver is the longitudinal position of the pushing vehicle. This correlation will be

analyzed in detail later in this section. The last row in figure 1.4 gives an example for the pattern 2c. The ego vehicle is pushed from the right side and tries to avoid a collision by pushing into the left lane (shown in figure 1.4e). After the pushing situation is over the ego vehicle is driving back into its original lane. This can be seen based on the driving path prediction (visualized by the red lines in figure 1.4e), which indicates a right turn. This kind of interaction will also be analyzed in the following, since it gives insights into the minimum lateral distance required by the drivers.
Under condition 3 the possibilities are limited, since it is not possible to push a solid object without a collision. One can easily identify the possible patterns 3a in row one of figure 1.5 and pattern 3b in row two of picture 1.5. Again the braking reaction results in a regular cut in, as shown in 1.5b. The standard lane change parameters have already been considered in the merging behavior in section 1.4.2. Nevertheless the characteristics distances of this pattern can help modeling the virtual lane formation. The second pattern 3b is at least as important for the analysis of pushing behavior. As already described for the second condition 2 we can learn the characteristic lateral safety distance, as well as the influence of the longitudinal position of the pushing vehicle from those situations. In the shown situation (cf. figure 1.5c) the taxi on the right tries to push into the lane of the ego vehicle. The next figure 1.5d displays the reaction, the pushing vehicle is ignored. Those kind of situations will be analyzed to find parameters characterizing those desicions.
We did not investigated all possibilities, Table 1.1 displays the distribution of patterns. Obviously 1 was not monitored at all. This leads us to the conclusion, that pushing and the resulting virtual lane formation is only occurring in heavy traffic. This seems logical, since there is no need for virtual lanes if the physical ones are still empty.

Table 1.1: distribution of reaction patterns

1a	1b	1c	2a	2b	2c	3a	3b
0%	0%	0%	57%	11%	16%	13%	3%

Moreover, we can see that 70% of all analyzed pushing maneuvers result in a regular cut in (patterns 1a, 2a and 3a, meaning no virtual lanes are formed. However we were able to gain knowledge out of those maneuvers, too.
Table 1.2 shows the longitudinal heading of the pushing vehicle for a resulting cut in in comparison to the situations not resulting in a cut in. What we can conclude out of this is the importance of the longitudinal position of the pushing vehicle. In average the heading while pushing for cut in situations (braking) is more than three times the heading for pushing situations resulting in a virtual lane formation (moving lateral). For the pattern ignoring the heading is even less. So the importance of this parameter is obvious for the resulting behavior. Of course the behavior differs between drivers and interviews with Chinese drivers implicate, that the reactions 2b and 3b, i.e. to ignore the pushing car, are more likely to happen, in case the driver experienced a similar reaction himself before. The same is true for reaction 2c. Nevertheless we where not able to find a significant correlation in the evaluated situations. This does not prove the assumption wrong, we are just not able to prove it with the used database.
Reactions 2b and 3b make up 14% and could result in a critical situation, since the distances are small. For those patterns is the average minimal lateral distance between vehicles is $\Delta y_{\text{min}} = 7.6cm$ (cf. table 1.2). Even though the standard deviation is high this is a strong hint for the criticality of those situations. The distances give detailed insights into the interaction between drivers and support modeling drivers in that way.
Pattern 2c makes up 16% and here we can get insights into the interaction principle for successful virtual lane formations. If the pushing maneuver is successful it causes vehicles to drive parallel instead of causing strong braking reactions to avoid a collision. However, the result depends on the behavior of the vehicle the driver tries to push. The possible conditions and patterns remain the



(a) Beginning of pattern 2a (b) End of pattern 2a

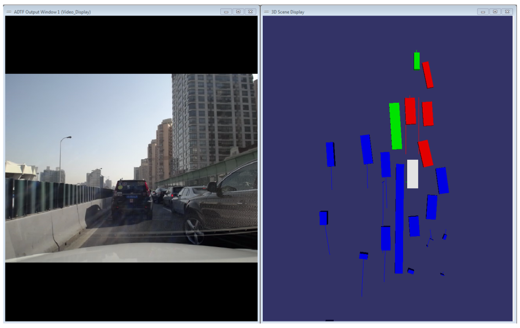
(c) Beginning of pattern 2b (d) End of pattern 2b

(e) Beginning of pattern 2c (f) End of pattern 2c

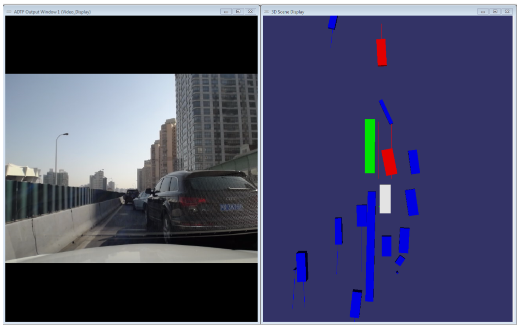
Figure 1.4: Possible reaction patterns in case of heavy traffic (condition 2). The ego vehicle is shown in white. The red boxes are obstacles detected by the Velodyne and integrated vehicle sensors while the red lines represent the prediction of the vehicle path. The blue boxes are Velodyne objects and the green ones are objects only detected by integrated vehicle sensors. The small lines starting in the center of the boxes are speed indicators.

Table 1.2: characteristic values for the analyzed patterns

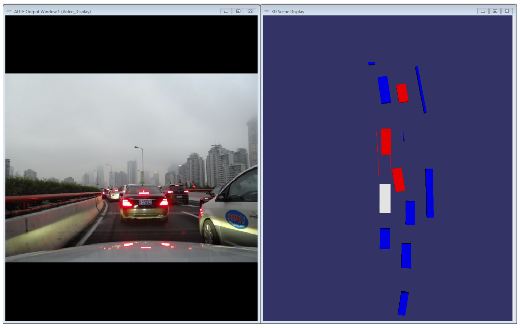
		pattern		
		braking (a)	ignoring (b)	moving lateral (c)
$\Delta x_{\text{min}}[m]$	mean	3,082	0,101	0,813
	standard deviation	1,892	1,814	2,004
$\Delta y_{\text{min}}[m]$	mean	0,274	0,076	0,235
	standard deviation	0,189	0,192	0,262



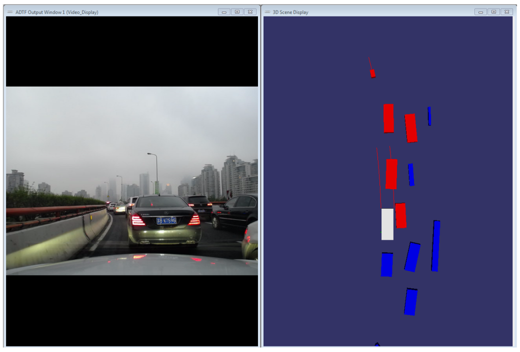
(a) Beginning of pattern 3a



(b) End of pattern 3a



(c) Beginning of pattern 3b



(d) End of pattern 3b

Figure 1.5: Possible reaction patterns in case of a solid obstacle (condition 3). The ego vehicle is shown in white. The red boxes are obstacles detected by the Velodyne and integrated vehicle sensors while the red lines represent the prediction of the vehicle path. The blue boxes are Velodyne objects and the green ones are objects only detected by integrated vehicle sensors. The small lines starting in the center of the boxes are speed indicators.

same. Not to repeat the already explained cases we only consider the situations, when the pushed car can move away. Table 1.2 displays typical minimal lateral distances, as well as the standard deviation. What tracks attention is the higher value of the average of the lateral distance here. One could conclude that this value is the true lateral safety distance and the very small values for cases 2b and 3b result from a higher level of aggressiveness or impatience.

As soon as possible vehicles start merging into their original lanes and the original value of the lateral orientation is used again. This can already be seen in figure 1.4f, when the ego vehicle is driving back into its original lane. This procedure is characterized by the car following and lane changing parameters. Depending on traffic conditions, driver type and emotions the situation is solved as soon as possible, meaning as soon as enough space is available. A similar strategy is used in VISSIM [3], where the traffic density is monitored and the lateral resolution is set back to normal lanes, as soon as driving on virtual lanes is not necessary anymore.

1.4.4 Implementation

To qualitatively recreate the observed behavior in the SUMO simulator, a model for lateral distance keeping was added. The desired lateral distance h between an ego vehicle and another vehicle that overlap along their length is defined as:

$$h = m \cdot r \cdot \min(1, \frac{\max(v, |u - v|)}{v_l}) \tag{1.2}$$

This value grows with the involved speeds of the vehicles: Either the speed of the ego vehicle v or its difference to the speed of the other vehicle u up to a limit of v_l where it is assumed to grow no further. The gap depends on a calibration factor m and a situational coefficient r described below. The coefficient r is defined as $1 - p$ when in the context of a strategically urgent lane change and 1 otherwise. In this case m denotes the desired gap at velocities of v_l. The value of m can be set using the driver parameter *minGapLat*. The value of v_l is currently set to $50km/h$. The value of p can be set using the driver parameter *lcPushy*. Its significance is described below. During each simulation step, vehicles perform lateral movements to ensure that a gap of h is maintained to all surrounding vehicles. In case there is insufficient lateral space to fulfill requirements on both sides of the vehicle, the desired lateral position is computed by dividing the available physical space in proportion to h_{left} and h_{right}, the minimum value of h on the left and right sides respectively. To distinguish the degree to which vehicles engage in *pushing* behavior the driver parameter p (*lcPushy*) is used. For $p = 0$, drivers only undertake lane change maneuvers where the destination may be reached without interfering with surrounding vehicles. Otherwise, the lane changing is undertaken to within the lateral gap h of that driver. If this gap undercuts the value of another vehicle, it will move laterally in the same direction in subsequent simulation steps to maintain its gap, thus being *pushed*. Due to the definition of the situational coefficient r, this leads to the creation of virtual lanes whenever the following conditions are met:

- a vehicle cannot continue on it's current lane
- the necessary lane change is blocked by neighboring traffic
- the neighboring traffic has sufficient space on the opposite side
- the p value of the vehicle is high enough to displace the neighbors and open enough space to allow changing to the target lane

1.5 Validation concept

The validation concept is based on single vehicle and traffic flow data.
We observed a highway intersection shown in figure 1.6. To do so we modeled the inflow and outflow as shown and measured the resulting traffic flow on the highway at the marked induction loops. To meet the characteristic driver distribution in Chinese traffic which comprises aggressive, moderate and conservative drivers, a representative distribution of parameters was used for calibration. Practically this was done with a script to generate a certain vehicle distribution with different attributes. This was done for the three different kinds of drivers. This guarantees a realistic number of vehicles in

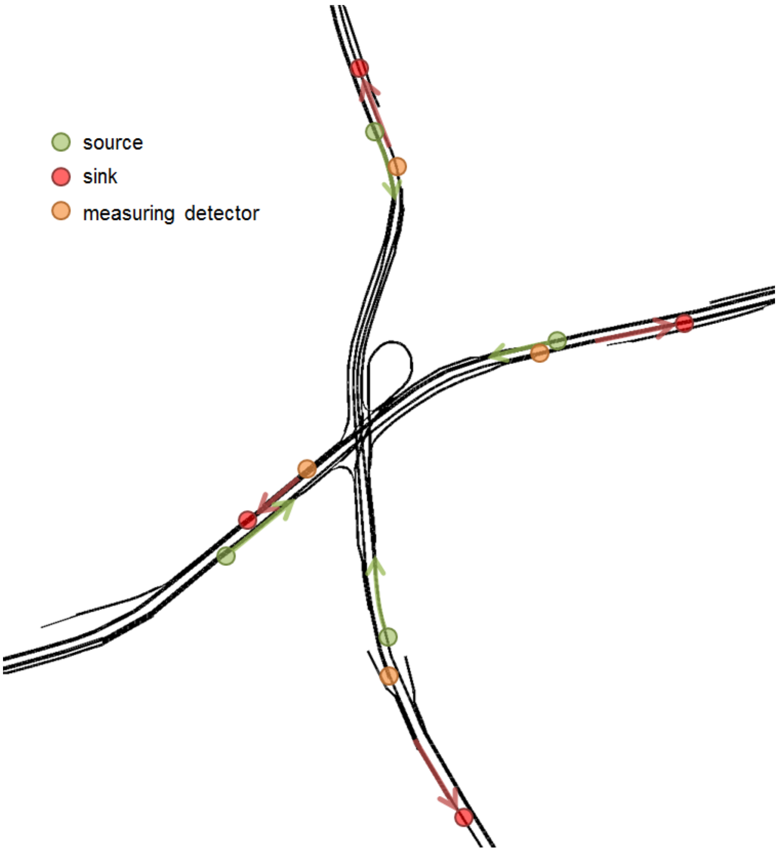


Figure 1.6: Observed area with detector positions. This figure shows the area on the Inner Ring in Shanghai, simulated and observed for validation purpose. It also displays the sources and sinks of cars, as well as the measurement positions.

the observed area. This is important, since one major factor for all types of lane changes is the traffic density [16]. We compared the parameters of the occurring pushing and merging situations with the values described in 1.4. Due to that we proved the validity of the car to car interactions in pushing and merging situations.
Moreover the validation concept enables us to compare measurement data of real traffic flow and measurement data of the simulated traffic flow. This macroscopic validation is still subject to ongoing research at the moment, which is why it won't be described here.

1.6 Conclusion and future work

The previous sections have shown that it is possible to prove the influence of emotions in naturalistic driving data. Moreover we introduced an implementation for the emotional memory and the concept of pushing behavior for virtual lane formation.

The analysis of lane changing and merging behavior has been discussed in section 1.4. In this context the implementation of the emotional memory and the virtual lane formation has been described. The emotional memory enables us to integrate one more important factor of human behavior in our simulation tool. The analysis of the process of virtual lane formation is one important step to the simulation of heterogeneous traffic, not only in Shanghai. The validation concept, presented in section 1.5, combines the validation on microscopic and macroscopic level.
Future work will focus on the improvement of the emotional memory, especially the improvement of models for the long term effect. Moreover the effects of the emotional memory, the pushing behavior and the virtual lane formation will be validated as a whole. For this purpose the validation study, especially traffic flow data, will be used to complete the validation on the microscopic and macroscopic level.

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