A Multi Lane Car Following Model for Cooperative ADAS

Florian Laquai¹, Claudio Gusmini², Marcus Tönnis², Gerhard Rigoll¹ and Gudrun Klinker²

Abstract— This contribution presents a procedure to obtain a multi - lane car following model in order to simulate larger traffic scenes with different percentages of vehicles equipped with a certain assistance system. We introduce a way how to extend the Intelligent Driver Model (IDM) to support multiple lanes and model driver imperfections. The required parameters are obtained from an experiment in a 3D stereoscopic driving simulator in a CAVE and then transferred to an implementation of the Car Following Model in the traffic simulator SUMO. Promising results regarding the overall effect of the presented Advanced Driver Assistance Systems (ADAS) are obtained executing several hundred simulation runs of various scenarios.

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) are strong innovation drivers in the automotive field. These complex systems that employ sophisticated hardware and software technologies are usually prototyped for first tests in a laboratory environment and then tested by drivers in a driving simulator. In our case we implemented a system to support anticipative driving called ISPA (Intelligent Support for Prospective Action) as shown in [10] and [6]. Such experiments give feedback about the general feasibility of a system but provide only limited insight to the impact of such a system on a larger traffic scenario. One possibility to overcome the limitation of a single test driver would be a large number of connected driving simulators in which a group of people interact with the same scenario at the same time as presented in [9]. This imposes several practical and economical problems (reproducibility, hardware cost etc.), so a solution could be to retrieve a model of the typical behavior of an assisted and an unassisted driver to use it in a traffic simulation. That enables the possibility of nearly arbitrarily large groups of simulated drivers and simulation runs. Such a procedure obviously depends heavily on the quality of the driver model but can provide valuable insights on the general impact of a system.

II. CONCEPT

In many cases a microscopic car model can be separated into a Car Following Model (CFM) and a Lane Change Model (LCM). Most of the currently employed microscopic CFMs only take into account vehicles in front on their own lane. This happens regardless of the distances and relative positions of other cars on adjacent lanes. An example for

150120Speed [km/h] 90**Optimal Driver** 60 Careful Driver 30 Inattentive Driver 0 0 200400600 800 1,000 1,200Track Position [m]

Fig. 1. Deceleration curve of real drivers in a driving simulator approaching a traffic jam behind a long drawn-out curve from 1000m distance without assistance

a model considering several preceding vehicles is proposed by Zhu and Jia in [16]. They extend the General Optimal Velocity Model (GOVM, see [12]) by calculating a weighted sum of the optimal velocities for all relevant vehicles. The weight factor is exponentially decreasing for increasingly distant vehicles.

In an extreme scenario a conventional CFM would keep on speeding towards a distant car on the same lane and pass by cars on adjacent lanes at very high speeds. This might not be the case for a human driver who would also adapt his speed to nearby vehicles on adjacent lanes even if he does not intend to change lanes. Lane Change Models need to take into account neighboring vehicles by definition. This only has an influence on the speed if a higher level logic uses this information to adapt the desired speed to the average speed of the target lane as it is done by Luo and Bölöni in [8].

The proposed CFM is based on the IDM model of Treiber, Kesting, Hennecke and Helbing. Several CFMs were evaluated prior to this decision by comparing the behavior of real drivers in a driving simulator (see Fig. 1) to the output of several models in the same scenario. As can be seen in Fig. 2 the IDM model produces the most realistic behavior especially compared to the large oscillations of the Kerner model.

As described in the work of Tschöpe [14] the Enhanced IDM was extended by a state machine which configures the EIDM to introduce configurable reaction times and different driver types producing similar curves as depicted in Fig. 1. The three driver types differ in their quality of distance judgement and reaction time to an output of the ISPA system. An important result of these extensions is the possibility to produce a crash with the originally collision free Enhanced IDM. This modification is essential for running simulations

¹Florian Laquai and Gerhard Rigoll are with the Faculty of Electrical Engineering and Information Technology, Technische Universität München, Germany {Last Name} at tum.de

 $^{^2}Claudio$ Gusmini, Marcus Tönnis and Gudrun Klinker are with the Faculty of Informatics, Technische Universität München, Germany c.gusmini at gmail.com and {toennis / klinker} at in.tum.de



Fig. 2. Deceleration curves of different Car Following Models approaching a standing vehicle in the traffic simulation SUMO

which provide results about the number of crashes correlating with a specific assistance system.

A. The Behavior Map

Starting from a single lane Car Following Model (CFM) a concept is derived to expand it to multiple lanes and theoretically arbitrary numbers of vehicles or surveyed area sizes. In the work of Zhu et al. (see [16]) the GOVM is extended to take l preceding vehicles into account which are on the same lane. This is done with a weighted sum to "synthesize" a new optimal velocity of the n^{th} vehicle $V_{s,n}$ in the form $V_{s,n}(\Delta x, t) = \sum_{m=1}^{l} \alpha_m V(\Delta x_{n-1+m}(t))$. The weighting function α_m is defined as $\alpha_m = p^{(m-1)} - p^m$ with m = 1...l - 1 and 0 and <math>n = 1...N, N being the total number of preceding vehicles on the lane.

In contrast to that the Behavior Map stores weighting factors (here called Importance) based on actual driver behavior as well as several metrics that are needed for the IDM. This is not only done for the lane of the ego vehicle, but also for the two neighboring lanes on each side.

The following sections describe the overall process of generating a multi lane CFM based on the single lane Enhanced Intelligent Driver Model (EIDM, see [13] and [4]) which was enhanced by Tschöpe [14]. To extend the model not only to a multi lane model but to survey a specified area around the driver, the surrounding of the ego vehicle is segmented in a grid-like shape which is aligned to the lanes. Driving experiments provide representative metrics such as Time To Collision (TTC), relative speed (Δv) or Time Headway (THW) from real drivers which are stored in the grid as described in [3].

The idea behind the Behavior Map (BM) is to divide the area around the ego vehicle into several subdivisions which implies that the BM is moving with the ego vehicle. At first several shapes of these areas are proposed as depicted in Fig. 3. For the evaluation the grid shaped style to subdivide the surrounding area was chosen due to its simplicity and the fact that the grid can easily be aligned to the shape of the lanes. Each subdivision of a lane has a length of 7.5 meters to fit at most one standard sized vehicle. With a length of 53 columns a distance of 400 meters can be covered and 5 rows

are sufficient to cover the two adjacent lanes on each side when driving on a three lane road. The distance of 400 meters is derived from the preferred Time Headway of 3 seconds as proposed in [1] at a speed of $130 \frac{km}{h}$ on a German Autobahn.

Several metrics are stored for each division of the Behavior Map including:

- Relative speed (Δv)
- Time To Collision (TTC)
- Time Headway (THW)
- Importance Weight Index (IWI).

These metrics are later obtained by driving simulator experiments with real drivers.



Fig. 3. Possible patterns for subdividing the area surrounding the driver. Cars within the same color field are merged into one object.

III. SUPPLEMENTARY WORK

In order to run the required experiments several prerequisites need to be prepared. These include the driving simulator, the ISPA system and the traffic simulator SUMO which will be described in the following sections.

A. Driving Simulator

The driving simulator is situated in a 4-sided CAVE (Cave Automated Virtual Environment) which displays the environment and also parts of the cockpit. It also consists of a cockpit from an Audi TT equipped with a Force Feedback steering wheel and a digital instrument cluster. The software is based on 3DVIA Virtools and its car physics Buildings Blocks (BBs) as well as custom BBs for e.g. real time communication with the traffic simulator SUMO. The 3D model of the environment was generated with ESRI CityEngine which allows rapid generation of 3D models of cities and landscapes based on scripted rules that procedurally generate a model as described in [15]. With the Python interface of the CityEngine the street network can be exported and then imported into the SUMO framework.

B. ISPA Assistance System

For the ADAS functionality the ISPA system was chosen. It aims to provide information about upcoming traffic situations which the driver potentially cannot anticipate. Particularly it provides support in situations in which the driver needs to decelerate within the next 10 - 20 seconds, e.g. a traffic jam on a highway behind a curve. The information about this situation is received through Car2X communication which is expected to provide much more precise and up-to-date information than current technologies such as TMC.

ISPA calculates three distances to an obstacle that are required to reach the target speed for the following deceleration strategies:

• Stepping off the gas pedal (Coasting)



Fig. 4. ISPA User Interface: LED bar indicating obstacle distance together with suggested deceleration strength and instrument cluster with standard traffic symbol and distance indicator

- Comfort deceleration by applying the brake (-0.2 g)
- Strong deceleration (-0.4 g)

If the actual distance is smaller than one of these three distances, an output on the GUI is triggered. The GUI consists of two main components (see 4), a portion of the digital instrument cluster and an array of three RGB - LED modules (see also [6]). As soon as the ISPA system is triggered a standardized traffic symbol is shown in the instrument cluster along with a bar indicator representing the obstacle distance. The number of illuminated LEDs increases during the obstacle approach, their color encodes the proposed deceleration strategy with yellow corresponding to "Coasting", orange to "Comfort Deceleration" and red to "Strong deceleration". The maximum activation distance is 1000 meters where the lowest number of LEDs are illuminated.

C. SUMO Traffic Simulator

SUMO is an open source traffic simulator from the German Aerospace Center (DLR). It is a microscopic simulator which means that it models each traffic participant individually, but does not necessarily distinguish e.g. between a driver model and a car physics model. The usual way to use SUMO is to prepare a set of configuration files and then run the simulation which usually runs faster than real time, depending on the scenario. The driving simulator utilizes the TraCI (Traffic Control Interface) to access the simulation and extract all needed data.

IV. EXPERIMENTAL GENERATION OF THE BEHAVIOR MAP

To obtain the content of the Behavior Map it was chosen to run driving simulator experiments instead of using available real traffic flow data. The reason for this decision is that real traffic flow data can provide a baseline configuration but would not be directly comparable to the experiments with assisted drivers. Consequently all experiments had to be carried out in the same environment.

It is important to chose the appropriate tasks and number of drivers to get meaningful data from these test drives. The course was a 10 km long segment of a three lane highway with additional landscape elements such as trees, parking lots and other details. All other cars were controlled by SUMO with the CFMs of Tschöpe (see [14]) with and without ISPA assistance behavior. The tasks had to be carried out in varying order, with the assisted drives always at the end so drivers could get used to the simulator without having to deal with an additional assistance system.

The test corpus consisted of 20 people (16 male, 4 female) with an average age of 26,95 years. All held a valid driver license. In total 100 test drives were recorded with an overall driven distance of ca. 1000 kilometers at a sampling rate of 10 Hz.

A. Design

An important goal of the driving tasks is to "fill up" the Behavior Map as completely as possible. Therefore in some cases the drivers must be instructed to follow a car on an adjacent lane as if it was forbidden to overtake these cars. This way it is possible to create a controlled scenario to obtain the desired data also for parts of the Behavior Map which are usually less occupied by other vehicles. Generally the most natural way to gather the BM would be to let the drivers move freely through traffic. The main disadvantages in our case would be that this takes longer to cover significant parts of the BM and would require substantially larger well defined scenarios to produce various situations. Both reasons led to the experiment design explained in the following paragraphs which describe the different driving tasks which were all executed with and without ISPA assistance for the test persons except for the lateral following task.

1) Frontal Following Task: The goal of this task is to obtain the car following behavior regarding cars on the same lane. In contrast to most microscopic CFMs data is also collected and analyzed from cars in front of the direct predecessor. Drivers were instructed to follow the leading vehicles, to avoid dangerous situations and not to overtake to circumvent such situations. The course for this task consisted of three parts:

- 0 3km: Follow a single vehicle on the same lane
- 3km 4.5km: Follow a group of three cars driving side by side
- 4.5km 6km: Follow the same group, this time the leading cars have ISPA assistance

All leading vehicles were programmed to accelerate and decelerate randomly so the test persons had to react frequently to speed changes of their neighboring cars. If the other drivers constantly kept the same speed, too few interactions would result with the test vehicle.

2) Lateral Following Task: In this task cars need to be followed which are on different lanes even if drivers do not have a leading car directly in front of them. Again they were instructed not to overtake even if they would do it in a real world scenario. ISPA assistance was disabled as it only takes obstacles on the same lane into account. The drivers started on the far right lane and had to follow a car on the far left lane for 2km, then one on the middle lane for 2km. Then they moved to the far left lane and had to follow a car on the far right lane for 2km and after that on the middle lane again for 2km. As in the Frontal Following Task the other vehicles accelerated and decelerated in a similar way.

3) Free Driving Tasks: Here drivers were situated in a general highway scenario with several other cars. They could act at their own will as they would do in the real world. The intention was to gain a deeper insight on the natural driving behavior and to further fill the Behavior Maps with measurement data including overtaking maneuvers. This task had to be fulfilled with and without ISPA assistance and it was allowed to change lanes.

B. Data Analysis

As mentioned before the space surrounding the ego vehicle is partitioned in a grid that is aligned to the lanes. In our case with three lanes a Behavior Map with five rows (the ordinate axis of Figures 5 and 6) and 53 columns (the abscissa axis of Figures 5 and 6) was created with a longitudinal delta of 7.5m per column resulting in a look ahead distance of 400m. The registration point of the ego vehicle is in the third row in the first column.

For all drivers the metrics "Relative Speed", "TTC", "Time Headway" and "Importance Weight Index" were calculated for each grid entry. From the first three metrics the Median is calculated over all entries per driver resulting in a single entry per metric in each grid cell for each driver.

The Importance Weight Index (IWI) is motivated by the idea that cars that have a high influence on a driver's speed choice have a low relative speed. It is limited to a range of [0...1] for later use and calculated as follows:

$$IWI = 1 - \frac{\Delta v - \Delta v_{min}}{\Delta v_{max} - \Delta v_{min}}$$
(1)

where

- Δv_{min} : global min. of all relative speeds in the BM
- Δv_{max} : global max. of all relative speeds in the BM
- Δv : relative speed of the respective entry in the BM

Not all tasks are suitable to obtain all possible metrics. For example the IWI should not be derived from the Following Tasks but rather the Free Driving Task as the others would not resemble the natural relative speed choice. The following table shows which tasks were used to derive which metrics:

Task	THW	Δv	IWI	THW _{ISPA}	Δv_{ISPA}	IWI _{ISPA}
Frontal Follow	X					
F. F. (ISPA)				х		
Lateral Follow	x			х		
Free Driving	x	х	х			
Free D. (ISPA)				х	х	х
TABLE I						

Obtainable behavior metrics (Time Headway (THW), relative speed (Δv), importance weight index (IWI)) from varying tasks

From this data analysis finally two BMs result: one with and one without ISPA assistance. The described driving tasks do not produce enough varying situations to guarantee full coverage of the behavior maps with measurement samples as seen in Fig. 5.



Fig. 5. Coverage of measurement data (number of vehicle occurrences per grid tile) for the Behavior Map from the 20 test persons (Ego vehicle positioned in the middle of the leftmost column, abscissa axis corresponding to road ahead, ordinate axis corresponding to neighboring lanes)

Fig. 5 shows that in our scenarios the first 10 columns of the first row and the first 5 columns of the second row have not been covered by another vehicle at all. Fields in these rows are only covered in cases in which the driver is on the far right lane and approaches cars on both lanes to his left at high relative velocities. This behavior is rarely observable because it is forbidden by German law. The uncovered area in front of the ego vehicle results from the minimum safty gap the test persons kept during the experiment, we call this the "Safety Zone". Uncovered areas in the BM were filled by linear inter- and extrapolating of neighboring values.



Fig. 6. Top: Time Headway, Bottom: Importance Weight Index in the Behavior Map from the 20 test persons (Ego vehicle positioned in the middle of the leftmost column, abscissa axis corresponding to road ahead, ordinate axis corresponding to neighboring lanes)

The other metrics, except relative speed, are plotted in Fig. 6 as the pattern for relative speed is the inverted version of the IWI Behavior Map. It is also possible to analyze

the impact of the ISPA assistance from the BM metrics. Generally this can be done with the following equation Eq. 2:

$$\Delta B(r,m) = B_{ISPA}(r,m) - B(r,m)$$
(2)

where

- r: row relative to the ego vehicle (from 1 to 53).
- *m*: metric which is contained in the BM (*Time Headway, relative speed and Time To Collision*).
- *B*(*r*, *m*): value contained in the averaged BM which contains all driver behaviors without driver assistance.
- $B_{ISPA}(r,m)$: value contained in the averaged BM containing all driver behaviors with ISPA assistance.
- $\Delta B(r,m)$: difference between the values contained in the ISPA and standard BMs for the defined row and metric.

For the metric TTC this impact is plotted in Fig. 7 whereas square markers denote a statistically significant difference at the 5% level. The test was done with a Mann-Whitney-U-Test.



Fig. 7. Impact of the ISPA assistance on Time To Collision metric. The plot is derived from the Behavior Maps of the assisted and baseline groups $(\Delta TTC = TTC_{\text{ISPA}} - TTC_{\text{Baseline}})$

For a more intuitive and flexible use of the aggregated data the experiment participants were divided into three groups (inspired by [11]):

- 1) Prohibited overtaking on the right side
- 2) Low Time Headway
- 3) High relative overtaking speed

The categories are defined by the following characteristics:

- 1) Coverage with a least one car in the first or second row of the first column of the BM
- 2) As mentioned in [11] a minimum Time Headway of 2s shall be kept. The average THW is computed for the third lane from the second to the 10^{th} grid tile. If it is lower than the overall average of all drivers of 4.23s, he is assigned to this category
- Similar to the THW the average relative speeds of all drivers from column 1 to 5 are averaged for the 4th lane. If the relative speed exceeds the overall average of 18.54^m/_s, he is assigned to this category

During the preparation of a SUMO simulation this classification enables the selection of distinct driver characteristics.

V. MODEL GENERATION

With the gathered data and the Behavior Maps a multi lane CFM can be constructed. When a driver model is instantiated in SUMO several parameters such as various reaction times, desired speed and activated ISPA system are set as well as the content of the Behavior Map. The latter can be done in three ways: either a distinct driver or a mix of parameter sets from within a driver group or from all drivers of the recorded experiments can be chosen. That way also synthesized Behavior Maps can be generated in order to achieve a higher number of variations when running batch simulations. For this goal a random weighting factor for each driver within a group is generated which is then used to obtain a linear combination of the parameter sets.

During a simulation run the following steps are taken to derive a speed value for the next simulation step:

- · Calculate the modified IDM for all occupied grid tiles
- Apply behavioral constraints
- Calculate the preliminary speed value
- Apply external constraints

A. Applying the Behavior Map to the IDM

During runtime the modified single lane IDM is being calculated with the values for each grid tile that contains vehicles. This results in an acceleration value related to every grid tile. Partitioning the area around a vehicle with a grid would lead to jumps in the final acceleration when a vehicle moves from one grid tile to a neighboring one. Consequently the relative position of the vehicle within a tile is used to linearly interpolate the chosen values based on the adjacent tiles. The acceleration is converted to a speed value using the chosen time step size of the simulation.

B. Behavioral constraints

Some constraints are needed to cover a wide range of possible situations. Without further rules it would not be possible that the ego vehicle overtakes another vehicle even if there is no coverage for the Time Headway in the BM. The ego vehicle would stay behind the other vehicle with the minimum gap of the IDM. This can be circumvented by comparing the resulting relative speed derived from the calculated speed with the relative speed value from the BM. If the calculated relative speed for the next time step is smaller than in the BM, the free road term of the IDM is used which results in an acceleration up to the relative speed stored in the BM. As a result overtaking is then possible.

Also when the ego vehicle is being overtaken undesired behavior could occur. Covering a grid tile with high Time Headway values in the BM would result in a sudden strong deceleration of the ego vehicle. This can be overcome by analyzing the relative speed. If the relative speed is negative (the other vehicle is faster), the old speed value is kept.

C. Deriving a final speed value

A list of all other cars covered by the BM is then populated and sorted by the corresponding IWI. If two cars should have the same IWI, the one that is closer to the ego vehicle is put on the higher ranked list entry. After that the weighted average of the speed values is calculated with the IWI being the weighting factor. This is done starting with the highest ranked vehicle and continues until the sum of all IWIs reaches 1 or the end of the list ist reached. In the latter case the free road term is added with the remaining weighting factor.

D. External constraints

These constraints include speed limits, maximum acceleration and deceleration and maximum speed of the vehicle. If one of the constraints is triggered, the final speed value is set to the value corresponding to the constraint.

VI. TRAFFIC SIMULATION

As a last step the proposed model is evaluated in the SUMO traffic simulator. As some of the parameters for each instance of the model can be modeled in a stochastic way with their expected value and variance, simulation runs similar to the Monte Carlo method can be run. The only stopping criterion is a fixed number of simulation runs. For the scenarios different states of a traffic jam were chosen: approaching the jam, moving with the jam in a stop-and-go manner and dissolving of the jam. In each state a comparison is made between the single lane CFM and the proposed multi lane version. The Behavior Map for each driver is composed by a superposition of the maps of all 20 previously recorded real drivers.

A total of 120 simulation runs have been conducted per scenario, 60 with and 60 without ISPA with three different base configurations per group. This means that configuration EGO1(ISPA ON) in Tab. II has been used 20 times for the whole simulation series.

ID	ISPA	Max. Speed $\left[\frac{m}{s}\right]$	Accel. $\left[\frac{m}{s^2}\right]$	Decel. $\left[\frac{m}{s^2}\right]$
EGO1	OFF/ON	33	0.6	5.5
EGO2	OFF/ON	36	0.8	6.5
EGO3	OFF/ON	39	1.0	7.5

VEHICLE CONFIGURATIONS USED IN THE DRIVING EXPERIMENTS, EACH CONFIGURATION WAS USED 20 TIMES.

A. Scenario "Approaching a traffic jam"

Different variations of this scenario have been tested. The simplest variant is to have a single vehicle approach another vehicle which is standing still at the 500m mark. A velocity plot of 20 of the 60 simulation runs with and without ISPA is shown in Fig. 8. All vehicles start with a speed of $33\frac{m}{s}$ and accelerate to their maximum speed as determined by Tab. II. After 100m the standing vehicle comes into the coverage of the BM resulting in a deceleration. The shape of the velocity curves with and without assistance are different especially in the range 200m - 500m where the unassisted drivers slow down to a speed of ca. $20\frac{m}{s}$ and keep it until 100m in front of the obstacle. In contrast to that the assisted drivers slow down to a range of $5\frac{m}{s} - 15\frac{m}{s}$ before finally stopping during

the last 100m. The relevant safety metrics for this situation are collected in Tab. III.



Fig. 8. Head on approach to a single standing vehicle with (top) and without (bottom) ISPA (only 20 of 60 simulation runs are displayed)

	ISPA	$\operatorname{Dec} \frac{m}{s^2}$	$\Delta v \left[\frac{m}{s}\right]$	Gap $[m]$	TTC $[s]$
Ι	OFF	-1.58	15.36	68.56	12.26
II	ON	-1.33	9.43	106.35	22.79

TABLE III AVERAGE METRICS OF THE EXPERIMENT INCLUDING A SINGLE STATIONARY VEHICLE ON THE SAME LANE.

The same situation was tested with the only difference that the static obstacle was not a single car but a group of 30 cars starting at the 500m mark. A single lane driver model regarding only one leading vehicle would behave exactly the same way in this situation. But the plots in Fig. 9 and the metrics in Tab. IV show a different behavior as expected for a multi lane CFM.

When we compare the unassisted cases (the bottom plots) in Fig. 8 and Fig. 9 it can be seen that the speeds shifted to a range from $10\frac{m}{s} - 20\frac{m}{s}$ in the 200m - 400m range. A comparable shift is present also for the assisted case suggesting that drivers did not only rely on the ISPA system for deceleration but also used their own judgment if other cars were in sight. The curve shapes in Fig. 9 can now be compared to the ones in the concept description in Fig. 1. All driver types can be identified, especially the stepwise speed decrease is also reproduced by the combination of the state machine introduced by Tschöpe (see [14]) and the Behavior Map.

In Fig. 10 the velocity plots show the approach of a single vehicle standing on the middle lane. The upper plot shows an approach on the fast lane where the vehicle slows down



Fig. 9. Head on approach to a group of 30 standing vehicles with ISPA assistance (top) and without assistance (bottom). Only 20 of 60 simulation runs are displayed.

Exp.	ISPA	$\operatorname{Dec} \frac{m}{s^2}$	$\Delta v \left[\frac{m}{s}\right]$	Gap $[m]$	TTC $[s]$	
Ι	OFF	-2.05	15.17	100.98	15.55	
Π	ON	-1.18	6.87	147.79	38.42	
TABLE IV						

AVERAGE METRICS FOR ASSISTED DRIVERS (EXP. I) AND BASELINE DRIVERS (EXP. II) FOR MULTIPLE STATIONARY VEHICLES.

to a range of $20\frac{m}{s} - 30\frac{m}{s}$ and then accelerates again to the desired speed. This would not have happened with a single lane model which would have shown no reaction to this obstacle.

The lower plot in Fig. 10 shows an approach on the slow lane. As the model was configured to make no lane changes in this scenario the only possible reaction would be to stop behind the standing vehicle. As some of the test persons also overtook on the slow lane several times in the driving simulator, the model showed this behavior, too. Here it is important to know that these are no programmed behaviors but result solely from the recorded Behavior Maps.

B. Scenario "Stop-and-go traffic"

Two sub scenarios can be distinguished for this scenario: approaching Stop-and-go traffic and moving within Stopand-go traffic. For both variants not a single car was sent into the scenario, but a group of 12 cars with varying percentages of ISPA equipped cars (0%, 25%, 50%, 75% and 100%). Each configuration was simulated in 300 runs, e.g. in the second run the possibility that a car was equipped with ISPA was set to 25%. Then the safety metrics already introduced before were calculated for the 300 runs of each configuration. The jam was simulated by three cars standing side by side at the 1000m mark.



Fig. 10. Approach to a single vehicle standing on the middle lane from the fast lane (top) and the slow lane (bottom) without ISPA (only 20 of 60 simulation runs are displayed)

ISPA	v	Δv	Dec.	Gap	THW	TTC
	$\left[\frac{m}{s}\right]$	$\left[\frac{m}{s}\right]$	$\left[\frac{m}{s^2}\right]$	[m]	[s]	[s]
0%	14.66	4.33	-1.35	80.72	13.29	25.82
25%	13.25	3.90	-1.19	85.43	14.47	28.62
50%	11.99	3.53	-1.12	89.69	15.68	30.81
75%	10.88	3.21	-1.03	93.83	16.91	33.05
100%	9.84	2.90	-0.93	97.17	17.96	35.07

TABLE V

AVERAGE METRICS FOR A GROUP OF 12 CARS APPROACHING A TRAFFIC JAM. TESTS WERE CARRIED OUT WITH VARYING PERCENTAGES OF ASSISTED DRIVERS.

Table V shows the safety metrics for each configuration of ISPA equipped cars. A bold number means that a Mann-Whitney-U-Test showed a significant difference to the value in the subsequent row at the 5% confidence level. For this setting this means that an increase of 25% of equipped cars shows an significant improvement of all safety metrics.

The results when the inspected group of 12 cars moves with a Stop-and-go jam can be analyzed in Tab. VI. This shows that the effects of the increasing assistance level are not as clear as in the previous situation. But still there is a positive trend visible for each step. An explanation for this could be the less controlled development of the situation.

C. Scenario "Dissolving traffic jam"

This situation is modeled by starting with all 12 cars standing still with no obstacles in front of the group. All cars in the front row can then accelerate freely to their desired speed while the others interact with the first cars. That means that their behavior maps come into effect. Table VII shows an significantly increasing negative relative speed, higher gaps

ISPA	v	Δv	Dec.	Gap	THW	TTC
	$\left[\frac{m}{s}\right]$	$\left[\frac{m}{s}\right]$	$\left[\frac{m}{s^2}\right]$	[m]	[s]	[s]
0%	15.77	0.56	-1.80	78.78	18.41	28.67
25%	15.12	0.47	-1.56	78.37	18.12	31.64
50%	14.41	0.43	-1.44	77.04	17.44	32.70
75%	13.87	0.40	-1.36	76.17	17.07	33.60
100%	13.25	0.36	-1.21	74.38	16.31	34.81

TABLE VI

AVERAGE METRICS FOR A GROUP OF 12 CARS APPROACHING STOP-AND-GO TRAFFIC. TESTS WERE CARRIED OUT WITH VARYING PERCENTAGES OF ASSISTED DRIVERS.

and increasing TTC for every increase of equipped cars.

ISPA	$\Delta v \left[\frac{m}{s}\right]$	Gap $[m]$	TTC $[s]$				
0%	-2.87	287.97	41.50				
25%	-3.03	300.48	53.37				
50%	-3.19	316.88	68.87				
75%	-3.30	324.18	71.11				
100%	-3.45	336.45	77.02				

TABLE VII

AVERAGE METRICS FOR A GROUP OF 12 CARS ACCELERATING AFTER A TRAFFIC JAM. TESTS WERE CARRIED OUT WITH VARYING PERCENTAGES OF ASSISTED DRIVERS.

VII. CONCLUSIONS AND FUTURE WORK

We presented a possibility to extend a commonly known single lane Car Following Model to a multi lane model based on real driver behavior. The results are promising as it was possible to reproduce behaviors such as overtaking on the slow lane, passing a slower vehicle with reduced speed or consideration of cars behind directly adjacent cars. This was possible by applying Behavior Maps that contain characteristic metrics of real drivers for a certain area of the driver environment.

This approach could by applied to other CFMs as well because it does not rely on specific properties of the EIDM. In some cases it will probably be necessary to recalibrate the base models on real traffic data to achieve representative results. It also must be mentioned that the BM approach consumes significantly higher computation ressources because a CFM is not evaluated only once per vehicle but as many times as the BM contains cells.

Because only the Car Following Model of SUMO was changed, the Lane Change Model stayed untouched. This led to the problem that lane changes practically never occured because the distance to the leading car never dropped below the threshold to invoke a lane change. For a proper integration the Lane Change Model should also be adapted.

A further improvement would be the application of separate Behavior Maps corresponding to different situations such as free driving on a highway, traffic jams, driving in urban environments etc. Currently all those situations are condensed in one common Behavior Map. In this research effort the map has a grid-like shape. As mentioned in the beginning different shapes can be worth investigating because they potentially better resemble the human understanding of space.

VIII. ACKNOWLEDGMENTS

The initial steps of the ISPA system were funded by BMW Forschung und Technik GmbH. Several students of the Technische Universität München contributed to this work, especially Claudio Gusmini, Werner Tschöpe, Tong Lin and Fabian Chowanetz.

REFERENCES

- T. J. Ayres, L. Li, D. Schleuning, and D. Young. Preferred timeheadway of highway drivers. In 2001 IEEE Intelligent Transportation Systems Conference Proceedings, 2001.
- [2] M. Behrisch, L. Bieker, J. Erdmann, and D. Krajzewicz. Sumo-Simulation of Urban MObility: An overview. In SIMUL 2011, The Third International Conference on Advances in System Simulation, pages 63–68, Barcelona, Spain, October 2011.
- [3] Claudio Gusmini. Modeling group dynamics in the context of anticipative driver assistance. Master's thesis, Faculty of Informatics, Technische Universität München, 2012.
- [4] Arne Kesting, Martin Treiber, and Dirk Helbing. Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 368(1928):4585–4605, 2010.
- [5] H. Kumamoto, F. Sawazaki, K. Tenmoku, and H. Shimoura. A cognitive animation simulator for a group of car drivers. In *Vehicle Navigation and Information Systems Conference*, 1994. Proceedings., 1994, pages 395–400, 1994.
- [6] F. Laquai, F. Chowanetz, and G. Rigoll. A large-scale LED array to support anticipatory driving. In *Proc. IEEE Systems Men and Cybernetics (SMC 2011)*, page 543–548, Anchorage, AK, USA, 2011. IEEE.
- [7] F. Laquai, M. Duschl, and G. Rigoll. Impact and modeling of driver behavior due to cooperative assistance systems. In V.G. Duffy, editor, *Proc. 3rd Intern. Conf. on Digital Human Modeling (HCI 2011)*, page 473–482, Orlando, FL, USA, 2011. IEEE.
- [8] Y. Luo and L. Bölöni. Modeling the conscious behavior of drivers for multi-lane highway driving. In 7th International Workshop on Agents in Traffic and Transportation (ATT-2012), pages 95–103, June 2012.
- [9] C. Maag, D. Muhlbacher, C. Mark, and H.-P. Kruger. Studying effects of advanced driver assistance systems (adas) on individual and group level using multi-driver simulation. *Intelligent Transportation Systems Magazine*, *IEEE*, 4(3):45–54, 2012.
- [10] D. Popiv, K. Bengler, M. Rakic, M. Duschl, and F. Laquai. Reduction of fuel consumption by early anticipation and assistance of deceleration phases. In *Proc. of World Automotive Congress Fisita 2010*, Budapest, Hungary, 2010. Fisita.
- [11] R. Risser and C. Brandstaetter. *Die Wiener Fahrprobe*. Lebensraum Verkehr. Literas Univ.-Verlag, 1985.
- [12] S. Sawada. Generalized Optimal Velocity Model for Traffic Flow. International Journal of Modern Physics C, 13:1–12, 2002.
- [13] Martin Treiber, Ansgar Hennecke, and Dirk Helbing. Congested traffic states in empirical observations and microscopic simulations. *Physical Review E* 62, 62:1805–1824, 2000.
- [14] Werner Tschöpe. Ein Fahrermodell zur Evaluierung vorausschauender Assistenz. Master's thesis, Faculty of Electrical Engineering and Information Technology, Technische Universität München, 2012.
- [15] Peter Wonka, Daniel Aliaga, Pascal Müller, and Carlos Vanegas. Modeling 3D urban spaces using procedural and simulation-based techniques. In ACM SIGGRAPH 2011 Courses, SIGGRAPH '11, pages 9:1–9:261, New York, NY, USA, 2011. ACM.
- [16] Wen-Xing Zhu and Lei Jia. Analysis of a new car-following model with a consideration of multi-interaction of preceding vehicles. In *Intelligent Transportation Systems Conference*, 2007. ITSC 2007. IEEE, pages 320–324, 2007.