Supplement: Overtaking scenario from real driving data

Eleonora Andreotti, Pinar Boyraz, and Selpi

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This material is a supplement to our paper entitled *Mathematical Definitions of Scene and Scenario for Analysis of Automated Driving Systems in Mixed-Traffic Simulations*.

In this case study we focus on a complex one-minute scenario taken from a real driving data set, specifically from driver D1 of UAH-DriveSet [1], i.e. 20151110175712-16km-D1-NORMAL1-SECONDARY. Here the ego-vehicle, initially in a car following condition, attempts to overtake a truck but is blocked by the oncoming traffic in the opposite lane, and finally executes the overtaking maneuver when there is enough window of time and appropriate set of conditions.

1 Scene from real driving data

Tables 1-4 showed scenes taken from the UAH-DriveSet and demonstrates how the mathematical descriptions, using set theory, can expand the available information in a scenario description. In particular, we collected the objects, the states and attributes, and the positions of each object at a certain time from the UAH-DriveSet. Many other information on scene objects can also be inferred from the videos, such as the states and attributes of light and weather (for simplicity we do not add such information in this case study). Generally, if the dataset consists of other types of states and attributes for each object (e.g., in the case of data collected by drones as in highD [2] and indD [3]), our definitions would be able to represent them.
From UAH-DriveSet, we obtain information on the driving behaviour of the ego vehicle, as well as on the scenery of our scenario. For example, each driver can demonstrate `normal, drowsy` or `aggressive` behaviour and the types of roads can be `motorway` or `secondary` road. The states and attributes value of the `traffic` object represents the number of vehicle that the ego object is able to detect. The states and attributes of the `lane` object refers to the number of lanes on the road.

The trajectory of the ego-vehicle was reconstructed from the UAH-DriveSet, as illustrated in Fig. 1 (bottom), with respect to the center of the lane. The

Object	States & attributes set	Position set
Ego-object	Normal	Lat. 40.533852°; Long. -3.443120°; Alt. 661.6°
Light		
Weather		
Landscape		
Road	Secondary	
Traffic	1	
Lanes	2	
Max speed	90 km/h	

Table 1: Scene at 180.81 second after the start of the selected trip

Object	States & attributes set	Position set
Ego-object	Normal	Lat. 40.533848°; Long. -3.446019°; Alt. 656.8°
Light		
Weather		
Landscape		
Road	Secondary	
Traffic	2	
Lanes	2	
Max speed	90 km/h	

Table 2: Scene at 190.84 second after the start of the selected trip

red dashed line represents the vehicle position on average during the whole trip. We can notice that, on average, the vehicle drives on the right side of the lane (0.3 m from the center). Unlike its average behavior, in the minute shown, the vehicle is clearly shifted to the left. The maneuver that the ego-vehicle is trying to do is in fact an overtaking that is blocked by the oncoming traffic in the opposite lane. Another information that we can get from the data, thanks to GPS, is that the road is downhill, Fig. 1 (top).
An element that concerns scenes, and not scenery, is the number of vehicles that the ego-vehicle sees, Fig. 3 (bottom).

Object	States & attributes set	Position set
Ego-object	Normal	Lat. 40.533825°; Long. -3.448958°; Alt. 654.0°
Light		
Weather		
Landscape		
Road	Secondary	
Traffic	1	
Lanes	2	
Max speed	90 km/h	

Table 3: Scene at 200.89 second after the start of the selected trip

Object	States & attributes set	Position set
Ego-object	Normal	Lat. 40.533817°; Long. -3.453002°; Alt. 652.4°
Light		
Weather		
Landscape		
Road	Secondary	
Traffic	0	
Lanes	2	
Max speed	90 km/h	

Table 4: Scene at 210.90 second after the start of the selected trip

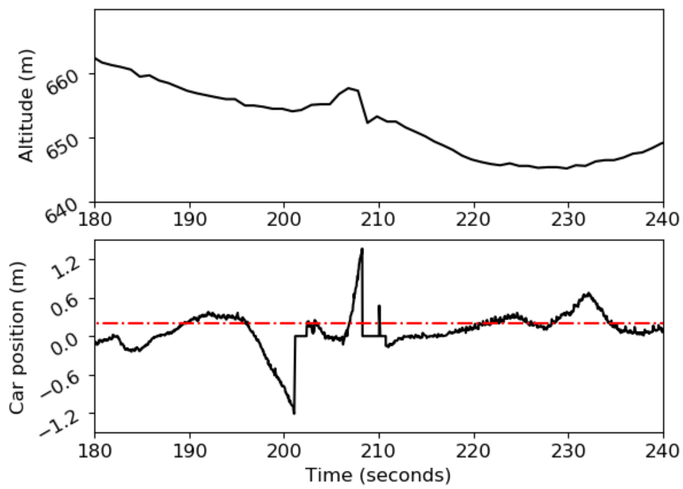

Figure 1: The trajectory of the ego-vehicle. Top: ego-vehicle altitude obtained from GPS. Bottom: ego-vehicle position with respect to the center of the lane. The red dashed line represents the ego-vehicle position on average during the whole trip.

2 Scenario

In the video overtake_normal.mp4 [4] we simulated, using SUMO, a scenario inspired from 20151110175712-16km-D1-NORMAL1-SECONDARY data sample. In our simulation we have reconstructed, through the exact coordinates and Open Street Map (OSM) the route of the vehicle (red vehicle), we have inserted the lead vehicle (blue truck) and the traffic in the opposite lane that blocks overtaking (yellow vehicles).
All information regarding the scenery is included through the net file in SUMO. *States and attributes* of dynamic objects and the dynamic objects themselves can be defined in the add file as vType. Here the parameters of the actors are

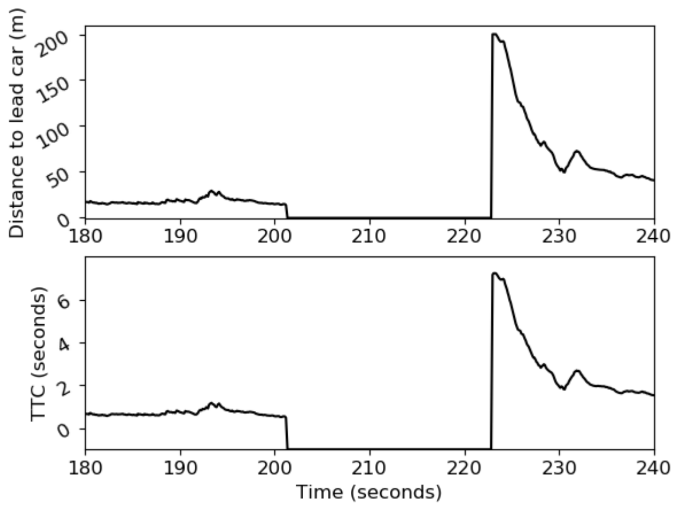

Figure 2: Top: Distance between the ego-vehicle and the lead vehcile (truck). Bottom: TTC (time to collision) between the ego-vehicle and the lead vehcile (truck). Values below zero mean that the algorithm does not recognize any lead vehicle (i.e. in the specific case, the ego vehicle is performing an overtaking).

set. *Actions and events* and *goals and values* are contained in rou and add files: here, the routes of the vehicles, the time and lane of departure, the speed of departure and the speed at which they intend to arrive and where they intend to arrive, are described. SUMO allows us to describe the dynamics of objects as an omniscient observer, therefore it is possible to simulate the *actions & events functions*, which indirectly depend on *x-actions & events* and *x-goals & values functions*, but not directly the functions *x-actions & events* and *x-goals & values functions*, where x can be the ego-vehicle (red one), the lead truck (blue one) or the oncoming traffic (yellow vehicle). But let's see why and how these functions depend on other functions.

For example, it is not possible to describe the visual perception of the ego-vehicle, in particular, to simulate the obstruction of the visual field due to the truck. On the other hand, it is possible to take it into account indirectly in the function $f_{ae}(x)$, where x is the ego-vehicle, through the lcLookaheadLeft parameter.

With default parameters of SUMO the ego-vehicle changes lane after 45 seconds and returns to the left one after 15 seconds. Let us consider two parameters closely related to perceptions, skills and eagerness: the lcLookaheadLeft, i.e. the driver's ability to recognize the vehicles in a certain distance before changing the lane to the left, and the lcOpposite, i.e. the eagerness for overtaking through the opposite-direction lane. By changing these two parameters we get different results.

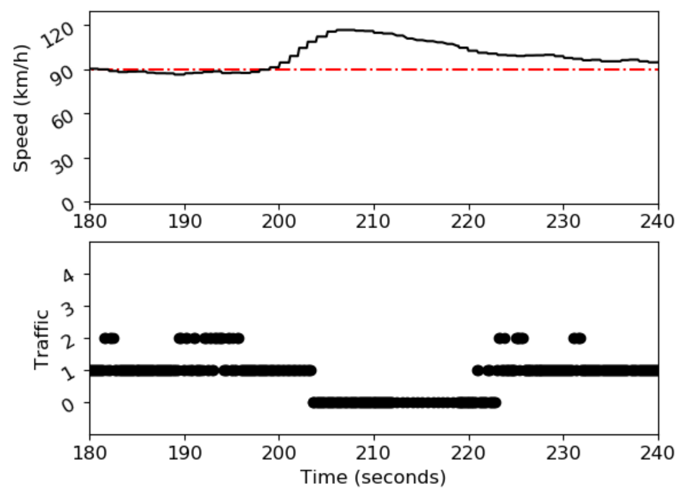

Figure 3: Top: ego-vehicle speed in solid line, the maximum speed allowed on the road is represented in dashed line. Bottom: Traffic (number of vehicle) seen from the ego-vehicle.

By increasing the lcLookaheadLeft parameter from 2 (default) to 6, for example, the ego-vehicle does not overtake on the route considered. Instead, by decreasing the lcLookaheadLeft parameter from 2 to 1, and increasing the lcOpposite parameter from 1 to 2, for example, the ego-vehicle changes lanes after 33 seconds but returns with an urgent lane change after only 3 seconds due to the oncoming traffic in the opposite direction in the adjacent lane. In this case, the complete overtaking maneuver always starts after 45 seconds and is completed after 16 seconds.
In our scenario, the overtaking attempts (AOT) are recorded in lanechange-output's SUMO file as "reason=urgent" lane changes performed by the ego vehicle.

We have still a different scenario by further increasing the lcOpposite parameter to 4 but leaving the lcLookaheadLeft parameter unchanged (dafault, i.e. 2), in this case, even if the ego-vehicle is able to recognize the vehicles in the opposite lane, its eagerness for overtaking leads the ego-vehicle to make an incorrect assessment and therefore a crash, see Fig.4.

In Table 5 we have summarized these results, also taking into account other parameter values.

We have therefore shown how different perceptions and eagerness of the ego-vehicle, with the same external conditions, can lead to different scenarios.

On the other hand, if we eliminate the traffic and run the simulation with only the ego-vehicle and the lead truck, we notice that the overtaking maneuver

		lcLookaheadLeft			
		1.0	**2.0**	6.0	10.0
	1.0	OT	OT		
lcOpposite	2.0	1AOT + OT	1AOT + OT	2AOT	
	4.0	C	C	C	

Table 5: Maneuvers for different parameters. OT = overtaking, nAOT = n number of attempts to do overtaking, C = crash.

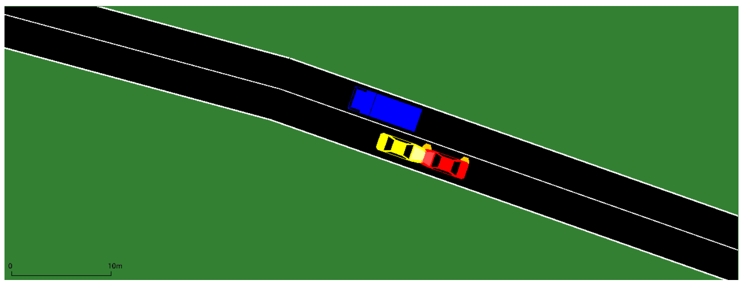

Figure 4: Crash

occurs earlier, precisely at the 33rd second. This confirms the many attempts of overtaking seen in the real driving data set, which is blocked by the oncoming traffic. In conclusion, with SUMO, it is possible to simulate the actions events functions, which indirectly depends on *x-actions & events* and *x-goals & values* functions, but not directly the functions *x-actions & events* and *x-goals & values* functions.

3 Conclusion

In this supplementary material we have shown that
- it is possible to represent real driving data using our mathematical definitions
- once the real driving data has been represented using our definitions, these data can be entered and simulated through software, in our case SUMO.

Through this procedure it is easy to ascertain what information is missing from the scenario to be fully described. We have highlighted what information exists in the dataset but cannot be implemented by the software (for example drifting trajectory, perceptions, object's points of view) and at the same time what information is not present in the dataset but that could be implemented with the software. Using our tool (i.e. mathematical descriptions using set theory), which does not have any preference to any dataset and software (i.e. it is data and software independent), we have an easy and simple language that allows the transition from the dataset to the software to create more realistic and complex driving scenarios and vice versa and which aims to take into consideration all aspects not yet considered in the datasets or in the software. Therefore, our description methodology could be seen as a mathematically sound facilitator for transferring and representing the information existing in real-driving data sets or naturalistic driving data-sets, while also designing the next set of data collections to match it better with the existing software for repeatable and reliable analysis.

References

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[2] R. Krajewski, J. Bock, L. Kloeker, and L. Eckstein, "The highd dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 2118–2125.

[3] J. Bock, R. Krajewski, T. Moers, S. Runde, L. Vater, and L. Eckstein, "The ind dataset: A drone dataset of naturalistic road user trajectories at german intersections," 2019.

[4] E. Andreotti, P. Boyraz, and Selpi. Supplement: Overtaking scenario from realdriving data. Youtube. [Online]. Available: https://https://www.youtube.com/watch?v=YVcsGNfIafY