Lane change behavior on motorways based on naturalistic trajectory data

Felix Hofinger*[1] and Martin Fellendorf[1]

[1]Institute of Highway Engineering and Transport Planning, Graz University of Technology, Rechbauerstraße 12/II, 8010 Graz, Austria

Short summary

Lane change behavior is a major aspect in traffic flow modeling. Since only a few empirical analyzes are available, validation of lane change models is frequently limited to macroscopic characteristics (e.g. number of lane changes). In addition, many existing lane change models do not reflect lane change behavior in complex situations realistic enough. Therefore, we investigate naturalistic trajectory data from German motorways and analyze gap acceptance behavior focusing on varying discretionary lane change objectives, especially on cooperative lane changes. We propose a methodology to classify different lane change objectives and analyze the critical time gap using the Raff´s method. The results show differences in gap acceptance between varying discretionary lane changes classes. Moreover, we found that drivers who perform a cooperative lane change accept rather low time gaps. The analyzes should provide a basis for validating existing and developing new lane change models.

Keywords: cooperative lane changing, gap acceptance, lane change analyzes, naturalistic trajectory data, traffic flow theory

1 Introduction

The effects of lane changing on traffic flow characteristics and traffic safety on motorways have been widely studied in the past. According to Zheng et al. (2010) lane changes can lead to traffic oscillations, which have a negative impact on traffic safety and traffic efficiency. To analyze these phenomena microscopic traffic flow simulation (TFS) is often used. Although, in the past new data-driven lane change models have been proposed, human driving behavior - and lane changing in particular - is still not fully understood. Besides the uncertainties in driver perception and anticipation (Endsley,1995; Calvert et al., 2020) it is difficult to classify different driving behavior. Most lane change models integrated into TFS software allow the user to define multiple parameter sets that should reflect different driver behavior groups. In addition, due to differences in gap acceptance behavior, mandatory and discretionary lane changes are typically distinguished. Mandatory lane changes need to be performed in order to follow a path, which is why drivers tend to accept lower time gaps compared to discretionary lane changes, which are usually performed to improve the own driving conditions. However, different incentives why a discretionary lane change is performed exist. Especially, in on-ramp areas and weaving sections drivers often try to assist neighboring merging vehicles by performing a cooperative lane change. Regarding lane changing in general there are still limited empirical analyzes available (Knoop et al., 2012). Nowadays, vehicle trajectory data is frequently used to get insights in this field of research (van Beinum et al., 2018; Sharma et al., 2020; Chauhan et al., 2022) . However, to the best of our knowledge no extensive analyzes regarding lane changing, focusing on gap acceptance properties of cooperative lane changes has been carried out.
This paper fills this gap by analyzing two naturalistic trajectory data-sets (highD & exiD dataset) from German motorways (Krajewski et al.,2018; Moers et al., 2022). For this study, we developed and applied a methodology to designate the lane change start. In a next step we analyzed the relevance of surrounding vehicles during the lane change decision period. Within that period we extracted multiple time steps and applied a probabilistic approach to get an indicator, if a preceding and/or right-preceding was relevant for the lane change decision or not. This was done utilizing the basic principles of the action-based Wiedemann car-following model (Wiedemann, 1974). As a last step, we analyzed the critical gap utilizing the method described in Raff (1950) by

investigating accepted as well as rejected time gaps on the target lane. In addition, we analyzed lane change duration, lane change length as well as the number of lane changes under given traffic flow characteristics.

2 Methodology of lane change analyzes

In this section we first give an overview over the used datasets within this study and explain the methodology to identify the lane change start using trajectory data. Then we show the classification framework of different lane change categories. This sections ends with a description of the gap acceptance analyzes.

Trajectory Dataset

For the presented analyzes we used the highD and exiD dataset, which are naturalistic trajectory datasets recorded by drones on German motorway segments (Krajewski et al.,2018; Moers et al., 2022). The highD dataset consists of 16.5 hours of trajectory data (around 110.500 vehicles, fidelity=$25Hz$) on six different locations on the open road. Within the exiD dataset there is trajectory data from six different locations (on-ramps, off-ramps, weaving segments) included, recorded within a time period of 16 hours. Although the number of driven kilometers is only about 60% in the exiD dataset compared to the highD dataset, the number of lane changes is much higher. We decided to analyze both datasets in order to be able to compare possible differences between on-/off-ramp areas and open road segments. To visualize the trajectory datasets we used the TraViA tool, which is advantageous for validating results and to analyze specific scenarios (Siebinga, 2021).

Lane change detection

According to Sharma et al. (2020) a vehicles lane-changing process starts when it begins to drift laterally and ends when it stabilizes its lateral position on the target lane. Human drivers drift laterally even in lane-keeping situations, which is why is not a trivial task to mark the starting time instances of a lane change process. We investigated the distance between a vehicles center-point and its left/right lane marking (depending on the lane change direction) since this attribute is not dependent on the road geometry, which is highly relevant in on-ramp areas. Within this study we calculated the exponential growth rate and applied an exponentially weighted moving average (EWMA) filter to smooth the noise in the data. This method is shown in Tang et al. (2020), the formula can be seen below:

$$\bar{x}_\alpha(t_i) = \frac{\sum_{k=i-D}^{I+D} x_\alpha(t_k) e^{-\frac{|i-k|}{\Delta}}}{\sum_{k=i-D}^{I+D} e^{-\frac{|i-k|}{\Delta}}} \tag{1}$$

where $x_\alpha(t_i)$ is the state value after filtering at t_i, D denotes the size of the sliding window and Δ represents the average of the sliding time window. The EWMA filter method leads to an exponentially decreasing weighting coefficient over time.

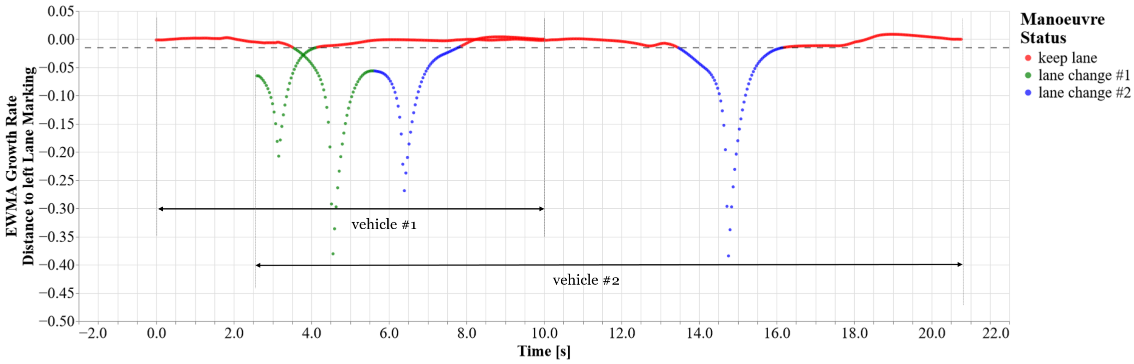
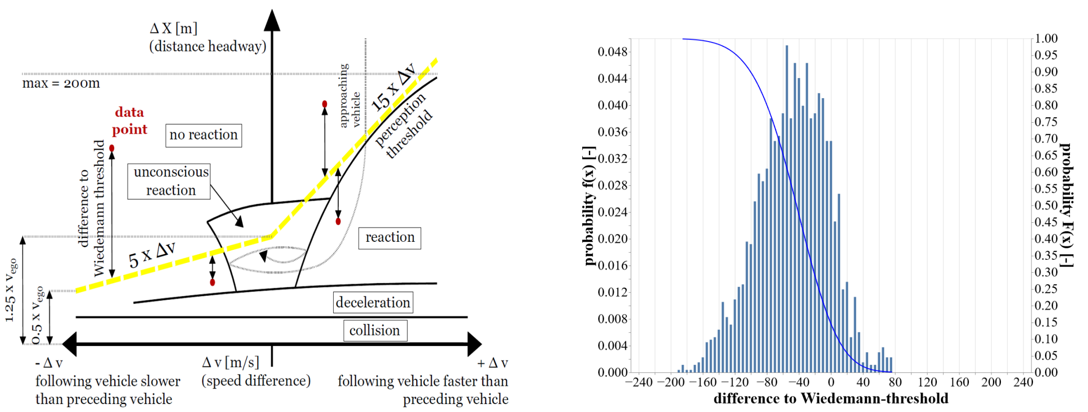


Figure 1: Classification of maneuver status

After analyzing descriptive statistics and visualizing the time series data we set a threshold of the exponential growth rate to -0.015m, which marks the time instances, when a lane change begins/ends. The threshold is represented by the dashed horizontal line in figure 1, in which the exponential growth rate of the distance to a vehicle's left/right lane marking of two vehicles are shown. The first vehicle (0.0-10.0s) is performing two lane changes immediately after each other, whereas the second vehicle (2.6-20.7s) does have a lane-keeping phase between the two lane changes. Moreover, vehicle 2 was already performing a lane change when it entered the field of view of the drone. These lane changes were not further investigated as a classification of the lane change objective was not possible.

Classification of lane change objective

In order to classify the drivers lane change objective, we applied a probabilistic approach using the basic principles of the action-based Wiedemann car-following model (Wiedemann, 1974). Using the time instance of the lane change begin as starting point, we extracted multiple time steps (*e.g. 4, 3, 2, 1, 0s before lane change begin*) within the lane change decision period, which we set to maximum 4 seconds, according to the work in Guo et al. (2021). For each of these time instances we calculated a datapoint considering the relative velocity and the distance headway, given that there was a preceding vehicle present. As a next step we computed for all datapoints the difference to a simple linear threshold utilizing the basic principles of the Wiedemann car-following model. A datapoint below the yellow dashed threshold in figure 2a, indicates that a preceding/right-preceding might have been relevant during the lane change decision period. After calculating a difference-value for all datapoints considering all lane changes we computed a distribution (see figure 2b), which allows us to get an indicator regarding the likelihood, that a surrounding vehicle was relevant for the lane change decision.



(a) Usage of basic principles of Wiedemann-model

(b) Histogram and 1-CDF distribution for "difference to Wiedemann threshold"

Figure 2: Probabilistic approach to classify relevant surrounding vehicles during lane change decision

Besides the probability value, whether a preceding/right-preceding vehicle was relevant during a certain time instance during the lane change decision, we analyzed a tendency how the probability-value evolves over time. Using these two indicators we defined a framework in order to classify whether a preceding/right-preceding vehicle was relevant or not, which can be seen in table 1. We used this classification in order to categorize different discretionary lane change objectives, which are displayed in table 2. If a vehicle was performing a lane change from the first lane to the second lane and there was no relevant preceding vehicle (*value=-1*) detected but a relevant right-preceding vehicle (*value=1*), then the lane change was classified as a *cooperative* lane change. On the other hand, lane changes were marked as *overtaking*, if there was no relevant right-preceding vehicle present and the drivers intention was to change lane in order to overtake the preceding vehicle. If there was no relevant surrounding vehicle detected in the trajectory data we categorized the lane change objective as *unclassified*. In addition, we introduced a *mixture* class, which represents lane changes, in which both, a relevant preceding and right-preceding vehicle were present. For mandatory lane changes as well as for lane changes to the right-hand side we did not consider the impact of surrounding vehicles.

Table 1: Classification framework of relevant/not-relevant surrounding vehicles

probability (p) preceding vehicle	**probability (p)** right-preceding vehicle	**tendency**	**classification**
$p > 0.2$	$p > 0.5$	-	1/ relevant
$0.1 < p < 0.2$	$0.2 < p < 0.5$	1/ increasing	1/ relevant
$0.1 < p < 0.2$	$0.2 < p < 0.5$	-1/ decreasing	0/ unclear
$0.025 < p < 0.1$	$0.0 < p < 0.2$	1/ increasing	0/ unclear
$0.025 < p < 0.1$	$0.0 < p < 0.2$	-1/ decreasing	-1/ not relevant
$p < 0.025$	$p < 0.0$	-	-1/ not relevant

Table 2: Classification framework of a drivers lane change objective

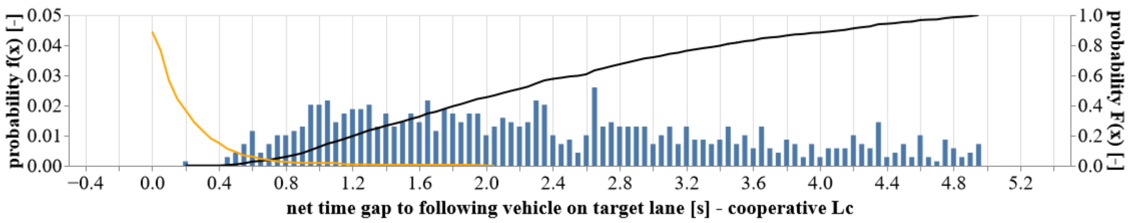
		relevance classification		
origin lane	**target lane**	**right-preceding vehicles**	**preceding vehicle**	**lane change objective classification**
0	1	-	-	merging
1	0	-	-	diverging
0	2	-	-	merging/overtaking
2|3	1|2	-	-	right
1|2	2|3	1	-1	cooperative
1|2	2|3	1	0	cooperative
1|2	2|3	1	1	mixture
1|2	2|3	0	-1	cooperative
1|2	2|3	0	0	unclassified
1|2	2|3	0	1	overtaking
1|2	2|3	-1	-1	unclassified
1|2	2|3	-1	0	overtaking
1|2	2|3	-1	1	overtaking

Gap acceptance analyzes

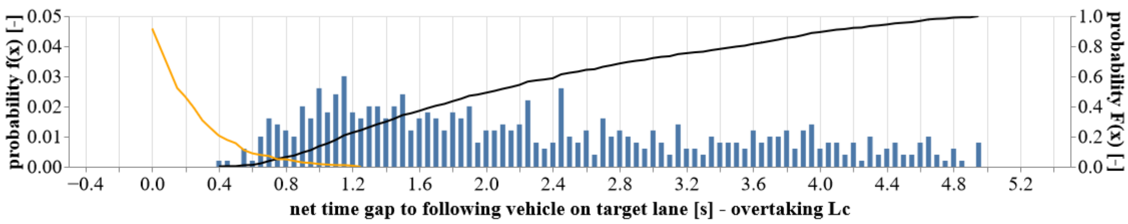
To investigate gap acceptance characteristics, it is necessary to identify the relevant vehicles on the target lane, especially in dense traffic situation in which multiple vehicles are changing lane at the same time. Therefore, we extracted the vehicle IDs on the target lane multiple times during the lane change decision and the lane change execution phase. By doing so we identified situations, in which the vehicle IDs of the preceding and following vehicle on the target lane changed over time, which enabled us to investigate rejected gaps too. If a temporary left following vehicle overtook during the lane change decision period and thus was the preceding vehicle after the lane change, we indicated the time gaps during the lane change decision period as rejected. This approach allows to extract the critical time gap, as it is shown in Raff (1950). Regarding gap acceptance we analyzed the net time gap, net distance headway, relative velocity and time-to-collision (TTC) to the following vehicle on the target lane and for varying lane change objectives. Moreover, we investigated the number of lane changes under given traffic characteristics like traffic volume. Due to space limitations, we will focus on the accepted time gaps within the result discussion in section 3.

3 Results and discussion

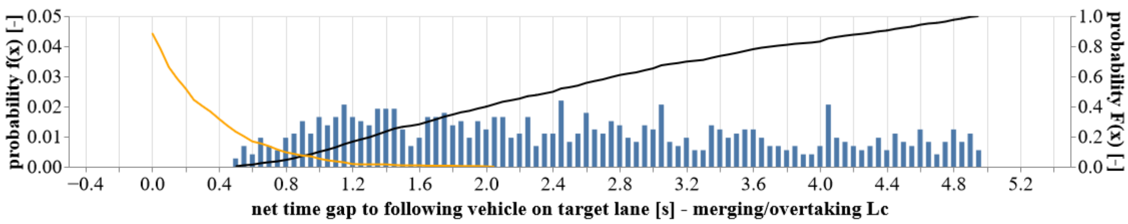
By applying the methodology described in section 2 we computed a distribution for varying lane change objectives considering the net time gap to the following vehicle on the target lane. Relatively high time gaps to the following vehicle have a rather low impact on gap acceptance behavior, which is why we excluded all time gaps bigger than 5s. In figure 3 the gap acceptance distributions for different discretionary lane change objective classes can be seen. The histogram and the corresponding black cumulative distribution function show the accepted time gaps in the instance of the lane change start. The yellow function reflects the cumulative distribution function of all rejected gaps. The intersection between the distributions is defined as the critical gap (Raff, 1950). Comparing the distribution functions shows, that there is a minor difference between cooperative lane changes (3a) and lane changes, which are performed in order to overtake a preceding vehicle (3b). The accepted gaps as well as the critical gap of 0.68s for cooperative lane changes is rather low. This could be due to the fact, that altruistic behavior is mainly observed among experienced drivers, since they are able to anticipate surrounding vehicles pretty good. Figure 3c shows a critical gap of 0.9s for lane changes, which are performed immediately after conducting a merging lane change from an on-ramp. Hence, these complex lane change manoeuvres are mainly performed if the time gap on the target lane is sufficient big. This can be seen in the black distribution function as well, which shows less time gaps below 1s. In figure 3d the distribution of accepted time gaps for lane changes to the right-hand side is displayed. The following vehicles on the target lane are usually slower, resulting in lower accepted time gaps compared to all other lane change classes. We did not display a distribution for rejected time gaps, as not sufficient situations could be observed.



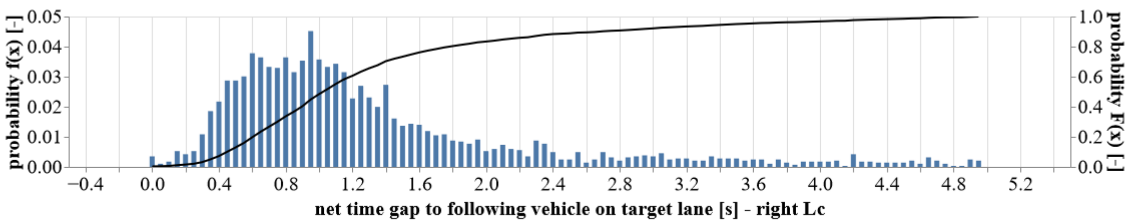
(a) analyzing critical gap - cooperative lane changes



(b) analyzing critical gap - overtaking lane changes



(c) analyzing critical gap - merging/overtaking lane changes



(d) Gap acceptance - right lane changes

Figure 3: Gap acceptance analyzes for different lane change objectives

4 Conclusions and outlook

This paper presents empirical analyzes regarding human lane change behavior by investigating naturalistic trajectory data recorded at German motorway segments. We showed a methodology to detect the time instance, when a vehicle starts to drift laterally and we proposed a probabilistic rule-based classification of different lane change objectives. Moreover, we analyzed gap acceptance characteristics for different discretionary lane change objectives. Surprisingly, drivers who perform a cooperative lane change accept rather low time gaps to their following vehicle on the target lane. This might be the case as these drivers are usually quite experienced and are able to anticipate the surrounding vehicles quite good. However, to underline these assumptions further investigations also with data from driver simulator studies should be focused on. In addition, we plan to train a Long-short-term-memory (LSTM) Neural Network for classifying different lane change objectives, which might lead to improved intermediate results. The presented analyzes gave new insights regarding human lane change behavior and they can serve as a good starting point for further validation of existing lane change models or even for the development of new models.

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