Sequence analysis of glance patterns to predict lane changes on urban arterial roads

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Abstract— **Acceptance of currently available advanced driver assistance systems (ADAS) plays a major role for building users' trust in car automation in general. One important precondition for acceptance is the ability of ADAS to provide assistance specifically in appropriate situations and avoid false alarms when no assistance is required. Present study investigates the potential of glances as early predictor variable for lane change maneuvers in urban areas. A subsample from an on-road field test was analyzed, including 50 standardized trips on urban arterial roads from 14 drivers. In total, 898 lane changes were classified according to direction and motivation for the maneuver. Turn signal usage and glances patterns were analyzed in a 10 s time window before crossing the lane. Results show a relatively high turn signal usage, specific glance patterns for left and right lane changes and low glance activity for lane changes due to added lanes on the left and right side. To identify and cluster glance patterns, sequence analysis using optimal matching was performed for lane changes due to a slower vehicle ahead. Sequence analysis originates from biology research to identify common DNA-strands and allows comparison of sequences considering simultaneously order, number and duration of events. Results suggest a four cluster structure for the glance patterns. One cluster is composed of few and short left glances, whereas a second group shows a high density of left glances about three seconds before the maneuver. Cluster three is characterized by a high frequency of glances over the whole time period, while the fourth cluster consists of truncated sequences because of prior lane changes. Implications for predicting lane change maneuvers on urban arterial roads are discussed in the final part.**

I. INTRODUCTION

Lane change is a maneuver that poses high demands on the driver [1] and is connected with a substantial accident risk. In Germany 2011, 13% of accidents with personal injury on motorway were associated with lane change maneuvers, 5% on roads within built-up areas [2]. Lane Change Decision Aid Systems [3] aim at providing assistance for this type of maneuvers. Estimations of the safety potential for lane change assistance/blind spot warning ranges up to 24% of addressable lane change-crashes [4] and 25% of crash severity reduction [5]. However, to fully exploit this potential it is essential that drivers accept these systems and use them in daily live. One important precondition for acceptance is the ability of ADAS to provide reliable assistance specifically when required. False alarms in situations where the driver has no intention to change the lane could annoy, distract and irritate drivers. As a consequence, ADAS are disregarded or disabled and the potential safety benefit gets lost. Driver intent information is supposed to reduce the mismatch between driver expectations and system reactions. If an intended lane change can be predicted before it is initiated, 1) lane change assistance can be activated specifically at this moment, 2) parameters of other ADAS such as lane departure warning, adaptive cruise control or collision warning can be adapted to avoid nuisance alerts and 3) workload-manager can use the information to suppress unnecessary non-driving activity, e.g. messages from the navigation system or incoming calls.

Several studies focus already on the assessment of lane change intentions, for an overview see Henning [6]. Best prediction rates can be achieved by data fusion from three sources [7]: 1) driver behavior observation e.g. eye-tracking or head-tracking, 2) Sensor information about the environment, e.g. front/side radar and lane detection and 3) vehicle parameters, e.g. turn signal, speed, acceleration, steering wheel angle... etc. Different algorithms are used to integrate these data sources and predict the intention for a lane change, e.g. Hidden Markov Models, fuzzy logic, cognitive models, neural networks and regression models [6]. The turn signal appears as rather unreliable indicator for lane changes: In a blind observational study, Ponziani [8] observed 2,000 lane changing vehicles at different places and recorded 52% of lawful turn signal usage. Similar values are reported by Lee et al. [9] with 44%, ranging from 11% to 94% for different lane change types. Due to this uncertainty, gaze behavior is considered as a promising predictor at an early stage of maneuver planning. The time period of three to four seconds prior a lane change is considered as critical phase of visual search to determine the feasibility of the maneuver [7, 10, 11]. As gaze behavior is linked to the early cognitive phase of information gathering, warnings e.g. from collision avoidance systems are supposed to show a higher impact compared to action execution at a later stage [12]. Even prior to information gathering, motives for lane changes can be determined. Lee et al. [9] identified a set of 11 reasons for lane changes on interstates and U.S. highways: exit-respectively entry to a highway, slow lead vehicle, return to the original lane, tailgating vehicle, obstacle, merging vehicle, lane drop, added lane, unintended and other. This classification provides a useful basis to distinguish lane change maneuvers, identify potential predictor variables and perform distinct analysis for each maneuver type.

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However, most of the previous studies focus on lane change maneuvers on highways. The German research initiative UR:BAN (http://urban-online.org/) aims at bringing driver assistance into the urban environment. Present study is carried out in the framework of this project and aims at identifying early predictors of lane change maneuvers on two-lane arterial roads in city areas. In contrast to highways, urban arterial roads are characterized by higher complexity due to crossings, mixed traffic (e.g. bicycles), traffic lights, vehicles entering from left and right and obstacles such as parked cars. The focus is on the motive and information gathering stage before the actual execution of the maneuver. Therefore we 1) explore naturalistic lane change maneuvers in the urban area using the motives-classification approach of Lee et al. [9], 2) analyze turn signal use and glance behavior for each of these lane change types and 3) identify typical cluster of glance patterns for one lane change type using a sequence analysis approach.

II. Research Design and Procedure

Present study was conducted as secondary analysis of an on-road field test in a repeated measurement design. The original purpose of the study was to assess the usage and acceptance of adaptive cruise control, therefore participants were allowed to use this assistance system. Fourteen participants drove an instrumented BMW 525d unaccompanied several times on a predefined and standardized route in Chemnitz, Germany. The sample consisted of 6 women and 8 men with a mean age of 28 years (SD = 1.65) and an average total driving experience of 137,286 km (SD = 107,889). Due to contractual obligations regarding insurance provided by the vehicles' rental agency, drivers had to be Chemnitz University of Technology employees. The experimental car was equipped with a video data acquisition system, capable of recording the interior of the car (face video, dashboard, pedals) and the road ahead (Fig. 1). This system was composed of four cameras connected to a central computer, which recorded images at a frequency of 50 Hz. Additionally, GPS and G-sensor signals were collected at 1 Hz.

Figure 1. Left lane change to an added lane (turn lane)

The route had a total length of 37 km, including an urban two-lane stretch of 5 km with a speed limit of 50 km/h (Annaberger street), another urban two-lane part of 10 km with a speed limit of 70 km/h (Südring and Neefe street) and a motorway stretch of 22 km. The motorway part was excluded for this study, as the focus is on lane change maneuvers in urban areas. To assure that all participants completed the exact same route, the course was saved in the in-built navigation system of the car. To exclude novelty effects due to familiarization, the first three trips were not included in the analysis. In total, a subset of 50 trips was analyzed in regards to lane change maneuvers.

A. *Video annotation and data processing*

All video annotations were made using the Annotation software ELAN (http://tla.mpi.nl/tools/tla-tools/elan/). To ensure a consistently high standard of reliability and quality, all annotations were double-checked by a second annotator. Lane change maneuvers were coded using the front video. The moment of lane change was defined when the centre of the vehicle crossed the line between two lanes (Fig. 1). Every lane change was categorized according to the motives-classification of Lee et al. [9], with an additional indication of the lane change direction (left/right). The dashboard video was used to annotate the activation of the turn signal. Glances were annotated in a time interval 10 s prior to the lane change using the face video. Discrete glance positions included ahead, rear mirror, left, right and other (Fig. 2). The positions ahead and other were merged to "ahead" for all subsequent analysis.

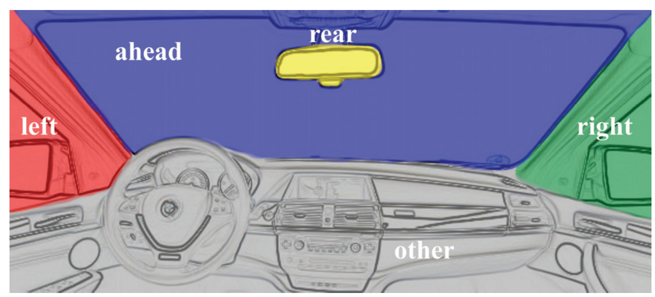

Figure 2. Glance areas

The complete dataset including video annotations, GPS and G-sensor signals was stored and synchronized in a PostgreSQL-database. As a pre-analysis revealed that only 0.48% of single glances lasted shorter than 100ms, all data was aggregated from 50 Hz to 10 Hz.

B. *Sequence analysis*

Sequences can be defined as "... an ordered list of elements, where an element can be a certain status (e.g., employment or marital status), a physical object (e.g., base pair of DNA, protein, or enzyme), or an event (e.g., a dance step or bird call). The positions of the elements are fixed and ordered by elapsed time..." [13]. Sequence analysis methods were originally applied in biology research to identify common DNA strands. In sociological research, sequence analysis is used to investigate employment biographies, school-to-work transitions and life cycle events [14]. Glances can as well be seen as a time-ordered sequence of distinct states. In our case, sequences are composed of 4 distinct states with a maximum sequence length of 100 elements (10 s x 10 Hz). The major advantage of sequence analysis, compared to other statistical techniques, is that sequences are analyzed as a whole, considering simultaneously number, order and length of events. The aim is to identify similarities and dissimilarities between sequences. One of the most used techniques for comparing sequences is the optimal matching algorithm [14]. The distance between two sequences is thereby defined as the number of operations needed to transform one sequence into another. Allowed operations are 1) substitution, 2) insertion or 3) deletion of elements at a specific position. The resulting distance matrix between all pairs of sequences is used as input for a subsequent cluster analysis to group similar patterns. An important aspect in optimal matching is the definition of costs for the basic operations, as it influences the preference of operations for transforming one sequence into another (see [15] for a detailed discussion). Costs can either be defined by theoretical assumptions or by computing transition frequencies in the dataset. However, as sequence analysis has an explorative character, there is no "true" cost structure [14] and simulation as well as practical experience proved optimal matching as relatively robust to changes in the cost structure [16].

III. Results

A. Lane change types

Table 1 shows type and number of all lane changes, as well as turn signal use and glance statistics. In total, 898 lane change events were identified, classified into 8 distinct types. Slow lead vehicle includes lane changes only to the left side to overtake a vehicle driving at slower speed, e.g. a truck. Specific scenarios in the urban context, such as parking and/or standstill vehicles at traffic lights are included as well into this category. Added lane means lane changes to the right or left on additional lanes, e.g. the road goes from two to three lanes. In our sample, all added lanes were turn lanes (see example in Fig 1). All lane changes in order to enter a road (e.g. from a feeder road) were coded as type enter. On present route only left lane changes for entering were observed. Construction zones on the right lane forced lane changes to the left due to obstacles. Lane changes because of other vehicles entering the roadway were classified as merging vehicles. Unknown refers to all lane changes without identifiable reason. Return includes right lane changes to return to the preferred driving lane, e.g. after an overtaking maneuver. Lane drop refers to lane changes due to the reduction of lanes, e.g. from two to one lane.

In contrast to the 11 categories used by Lee et al. [9], unintended lane changes were not classified, tailgating vehicles could not be identified because there was no rear-view-camera available and highway exits were not coded as only the urban part of the route was considered. Exit maneuvers were classified as added lane, as in all cases an additional turn lane was present.

B. Turn signal use and glances prior to lane changes

The turn signal was used in 89% of the lane changes, ranging from 71% for the unknown type up to 100% for merging vehicles (Table 1). These values are considerably higher than results from other studies [8, 9]. Glance sequences were analyzed in the time window 10 s prior to a lane change. If another lane change happened within this time frame, the sequence length was reduced accordingly resulting in sequences shorter than 10 s. The mean sequence duration over all lane change types was 9.58 s, ranging from 7.73 s for the merging vehicle type up to 10 s for entering and lane drop maneuvers (Table 1). Columns 6 to 9 of Table 1 show the mean number of glances to the left, right and rear mirror, whereas columns 10 to 12 list the respective mean total glance duration for each lane change type. Glances ahead are not listed separately; they cover the remaining sequence duration.

The first six rows of Table 1 show lane changes to the left. Consequently, the number as well as the duration of glances to the left side was considerably higher than for lane changes to the right. Especially for entering, obstacles and slow vehicles ahead more than two left glances per sequence were observed (2.23 to 2.67) with a mean total duration ranging from 1.79 s to 2.36 s. A lower mean number and duration of glances resulted for the lane changes due to unknown reasons (1.41 times, 1.18 s) and added lanes on the left side (1.20 times, 1.05 s). There were almost no glances to the right side during left lane changes. Glances to the rear mirror ranged from 0.17 to 0.56 times with a total duration from 0.11 s to 0.36 s.

Lane changes to right appeared as combination of glances to the right and the rear mirror (Table 1, rows 7 to 9). For the return to the preferred lane, 1.32 glances to the right and 1.35 glances to the rear mirror could be observed with a duration of 1.16 s (right) and 0.95 s (rear). Similar values resulted for lane drops with 1.20 right glances and 1.08 glances to the

TABLE I. Lane change types, turn signal use and glance statistics

Lane change type	Direction	Number of events	Turn signal use (%)	Glance sequences 10 s prior to lane changes						
				Sequence length (s) M(SD)	*Number of glances M(SD)*			*Total glance duration (s) M(SD)*		
					Left	*Right*	*Rear*	*Left*	*Right*	*Rear*
Slow lead vehicle	Left	148	88	8.97 (2.23)	2.23 (1.45)	0.02 (0.18)	0.32 (0.57)	1.79 (1.30)	0.01 (0.12)	0.22 (0.42)
Added lane	Left	134	82	9.67 (1.06)	1.20 (1.18)	0 (0)	0.35 (0.58)	1.05 (1.06)	0 (0)	0.25 (0.45)
Enter	Left	129	94	10.00 (0)	2.67 (1.21)	0.01 (0.09)	0.17 (0.49)	2.36 (1.04)	0.01 (0.05)	0.11 (0.42)
Unknown	Left	34	71	9.38 (1.85)	1.41 (0.89)	0 (0)	0.56 (0.70)	1.18 (0.84)	0 (0)	0.36 (0.44)
Obstacle	Left	13	77	9.26 (1.58)	2.38 (0.87)	0 (0)	0.31 (0.48)	2.03 (0.79)	0 (0)	0.18 (0.32)
Merging vehicle	Left	10	100	7.73 (2.47)	1.40 (0.52)	0 (0)	0.40 (0.97)	1.01 (0.57)	0 (0)	0.27 (0.62)
Added lane	Right	200	92	9.93 (0.3)	0.16 (0.38)	0.52 (0.76)	0.68 (0.73)	0.10 (0.29)	0.46 (0.68)	0.46 (0.55)
Return	Right	180	93	9.69 (1.23)	0.09 (0.30)	1.32 (1.19)	1.35 (1.02)	0.08 (0.32)	1.16 (1.07)	0.95 (0.84)
Lane drop	Right	50	80	10.00 (0)	0.30 (0.68)	1.20 (0.78)	1.08 (0.75)	0.25 (0.67)	1.13 (0.78)	0.78 (0.67)
		898	89	9.58 (1.37)						

rear mirror, lasting 1.13 s (right) and 0.78 s (rear). The lowest glance activity was observed for right lane changes on added lanes: The number of glances ranged from 0.16 (left), 0.52 (right) to 0.68 (rear) with durations of 0.10 s (left) and 0.46 s for glances to the right and rear mirror.

Overall, lowest glance activity could be observed for lane changes on added lanes, either to the right and the left side. Glance patterns for left lane changes show a high proportion of left glances with some few glances to the rear mirror, whereas right lane changes appear as a combination of right and rear glances.

In addition to these descriptive statistics, the evolution of glances and turn signal use provides hints on the timing of the parameters. Fig. 3 shows exemplarily the cumulative percentage of glances (right y-axis) and turn signal use (left y-axis) for the lane change type slow vehicle ahead. The black turn signal curve shows a sharp increase at about three to two second before changing the lane, ending up at 88% at the moment of crossing the lane. Left glances (red curve) show an increase in almost the same time interval, however, glance activity is noticeable already before activating the turn signal.

C. Sequence analysis for lane change type slow vehicle ahead

Descriptive statistics provide information about importance and timing of glances before lane changes. However, the structure of glance patterns as a whole, i.e. the combination of order, number and length of glances is not considered simultaneously. Sequence analysis using optimal matching is a method for exploring and clustering similar patterns, preserving this information. We applied sequence analysis on the 148 lane change events due to a slow vehicle ahead in order to cluster glance patterns within this lane change type. To perform the calculations, we used the sequence analysis package of STATA (for details on the algorithms see [13]). Transition rates are used to compute the cost matrix and distance measures are standardized to balance the influence of different sequence length [13]. To group similar glance patterns out of the resulting distance matrix, agglomerative hierarchical cluster analysis is applied, using Ward's criterion [16]. Ward's linkage computes the increase in error of squares after merging two clusters into one and seeks for the minimal increase at each clustering step. To decide about the most appropriate number of cluster, stopping indicators can be used next to the interpretability of the cluster solution. STATA offers two stopping rules, the Calinski/Harabasz pseudo-F index and the Duda-Hart Je(2)/Je(1) index [17]. Results suggested a four cluster solution, as both of the indexes show the highest values at this stage of cluster merging.

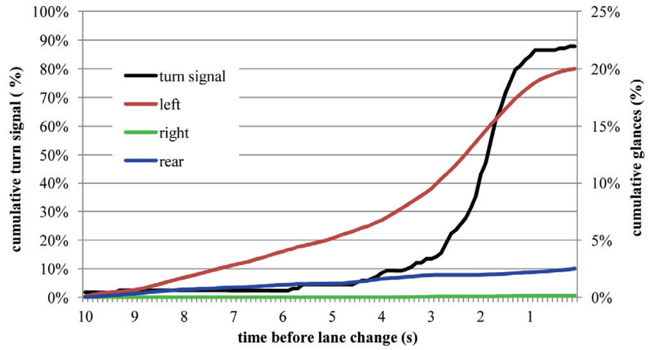

Figure 3. Evolvement of turn signal use and glances for lane change type slow vehicle ahead

Fig. 4 shows all 148 glances patterns as sequence index plots, clustered into the four groups. Every line represents one glance sequence in the 10 s time window and colors indicate the glances. Cluster one is composed of 51 sequences showing relatively small numbers and durations of left glances, combined with longer periods of glances ahead in between. The 32 sequences in the second cluster can mainly be characterized and distinguished from other clusters by a higher density of glances in the time window from 3 s until changing the lane. Cluster three shows 45 sequences with a considerably higher frequency of left glances during the whole period of time. Visual inspections of the video files revealed that these glance sequences were mostly associated to situations with higher traffic density on the left lane. The final cluster four is composed of 20 truncated sequences, i.e. lane changes, where another lane change happened in the 10 s time interval beforehand. This was mainly the case when multiple lane change maneuvers were executed, i.e. entering a road and subsequently overtaking a slower vehicle ahead. Rear glances show less distinctive power, as they appear sparsely in all clusters.

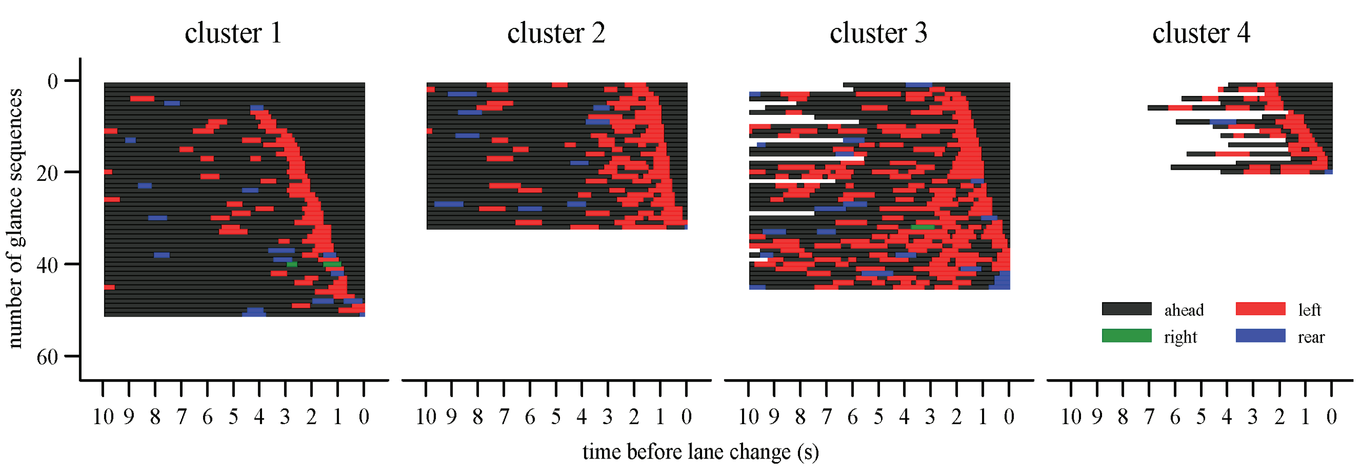

Figure 4. Sequence analysis for lane change type slow vehicle ahead

IV. DISCUSSION

Lane changes occur due to different reasons and this motivational factor plays a central role in predicting the maneuvers. Thus, a lane change classification approach was used to categorize lane change maneuvers on urban arterial roads, based on the approach of Lee at al. [9]. Despite the classification was established for lane changes on highways and freeways, most of the categories can be applied as well in the urban context. Differences arise especially with parking vehicles and standstill vehicles on traffic lights, which were both integrated as extreme cases of a slower lead vehicle.

The classification itself gives already hints on potential early intent indicators for the different lane change types. Inevitable lane changes due to infrastructure changes, such as entering a road when driving on a feeder road, lane drop or to some extent as well obstacles (e.g. construction zones) could best be predicted by GPS and map information. The same data source could provide at least probabilities for the lane change types merging vehicle and added lane. However, for the latter types drivers can still decide whether to change the lane or go straight ahead. Therefore additional information is required from driver observation and sensors scanning the environment. Lane changes due to tailgating vehicles and slower vehicles ahead are primarily related to the surrounding traffic. Sensors for monitoring the vehicle environment could therefore provide best information at an early stage. The history of lane changes provides information about the probability for returning to the preferred lane. Learning from past events could even be extended to record regular trips of a driver and adjust lane change probabilities according to this source of information.

It is undoubted, that best prediction can be achieved by combining all these various sources of information. However, to find the best ways of combining them requires information on the specific predictive potential of single indicators. Therefore this study focuses specifically on glance patterns and turn signal use as lane change intent indicators. Previous studies report the turn signal as rather unreliable indicator of lane changes with usage rates of 44% [9] and 52% [8]. Participants in this study used the turn signal in 89% of all lane change maneuvers, which would allow for a high prediction rate. However, the resulting high turn signal usage could be influenced by the experimental setting, as participant knew that they were recorded on video. To explore alternative early lane change intent indicators, glance patterns were analyzed in a 10 s window prior to lane crossing.

Results show a high proportion of left glances with few rear and almost no right glances for left lane changes, whereas lane changes to the right appear as a combination of right and rear glances. Less glance activity can be noted for lane changes due to added lanes, both on the right and left side. A plausible explanation for this fact could be the absence of traffic from behind, as all additional lanes were turn lanes. A more detailed analysis of glance timing for the "classical" lane change type slow vehicle ahead show results that are mainly in line with previous studies [7, 10, 11]. A considerably increase in glance activity can be observed three to four seconds prior to the lane change, however, glance activity is also noticeable beforehand. Sequence analysis allows for a more detailed insight into the structure of glance patterns by comparing and clustering similar sequences. The resulting four clusters of glance patterns provide information on aspects that should be considered for predicting the maneuver. One issue concerns the identification of preceding maneuvers (e.g. multiple lane changes), as glance sequences are truncated. A second aspect concerns traffic density on the target lane: Although glances are generally concentrated in the time interval of 3 s before crossing the lane, visual search starts already beforehand if there are vehicles on the target lane. This could be used for an earlier detection of lane change intent by combining glance patterns with sensor information on traffic density. Moreover, it can be argued that prediction of this lane change subtype is more important compared to lane changes with low or no traffic on the target lane because criticality and the need for assistance is potentially higher.

Further research within the project framework aims at validating the glance patterns in terms of sensitivity and specificity for the distinct lane change maneuvers. Therefore a second on-road test will be conducted using a vehicle instrumented with radar sensors and head/eye-tracking. Based on these findings, real-time algorithms will be developed and implemented in a demonstrator for predicting lane change maneuvers on urban arterial roads.

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