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A Learning Concept for Behavior Prediction at Intersections

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***Abstract*— The idea presented in this paper is an online learning approach for behavior prediction of other road participants at an intersection. Learning traffic situations online has the advantage that it is possible to react to changes in driving behavior due to changes in the environment. If visual obstruction occurs because of changes in the environment, e.g. a growing corn field, the behavior of drivers changes. In contrast to pre-trained models an online learning concept is able to react to these changes in driving behavior.**
In this contribution Case-Based Reasoning, a concept which adapts human reasoning and thinking to a system, is used. The functionality of the concept is shown by predicting the maneuver of an approaching vehicle at an intersection. The presented concept is able to predict if a vehicle turns in front of the ego-vehicle or stops and give the ego-vehicle right of way.

I. INTRODUCTION

Predicting the behavior of other road participants is a necessary step to avoid critical situations and to enable comfortable driving. In the last years several concepts for predicting the behavior of other road participants have been developed. There are concepts for driving behavior prediction focusing on pre-trained models [1] [2] [3] [4] [5] and concepts involving online learning [6] [7].
In [1] situations are ordered into a hierarchy tree and a combination of general and specific trained classifiers, depending on the situation, is used to predict the behavior of other road participants. Dynamic Bayesian Networks (DBN) are used in [3] [8] [5] for behavior prediction. In [3] driver intention and expectation at an intersection are estimated from the joint motion of the vehicles. The DBN models the dependencies between the vehicles and takes the environment, like traffic rules and intersection layout, into account. Context dependent process models are learned from unlabeled observations in [5]. Random forests are used for learning the context models. They are embedded into a DBN, while online learning has not be integrated yet. In [8] also a DBN is used for modeling action recognition. The aim of this approach is to predict cut-in situations on highways. In [4] a Support Vector Machine in combination with Bayesian filtering is used to predict lane changes on highways. An explicit model for predicting following and turn maneuvers at an intersection is used in [2]. Another concept [9] focuses on computing the collision probability for all road participants on highways under the assumption that drivers try to avoid collisions. The risk estimation of drivers is learned from data in this context.
When using pre-trained models for behavior prediction it is hardly possible to react to changes in driving behavior. If visual obstruction at an intersection occurs this has an influence on drivers and thus a different driving behavior could be recognized at this intersection. An online learning concept is able to react to these changes and is able to learn changed behavior due to changes in the environment so that action prediction of other road participants is still possible.
In [6] an online learning approach for behavior recognition of the ego-vehicle is presented. With the help of an inertial measurement unit motion segments are extracted and change-point detection is applied to relate these segments to visual features from the camera. These motion segments are grouped automatically and are compared to new maneuvers online. In a preceding work of the presented concept a learning approach for predicting cut-in maneuvers of other road participants on highways is presented in [7]. The used Case-Based Reasoning (CBR) approach learns cases online and adapts the solution of the most similar case to the current situation. A concept for behavior prediction using CBR with a different case definition in comparison to [7] is presented in [10]. Another approach for predicting trajectories of other vehicles using CBR is used in [11].
The focus of this paper lies on investigating the feasibility of a learning concept to be able to react to changed driving behavior at site-specific intersections and to predict these situations properly. The learning concept based on Case-Based Reasoning for predicting the driving behavior of other road participants at site-specific intersections is proposed. The CBR concept developed in [7] is extended in this paper to consider context information, as the topology of an intersection. Also, an appropriate feature set for this application is presented. The influence of changes in the environment on driving behavior is shown. Additionally, the

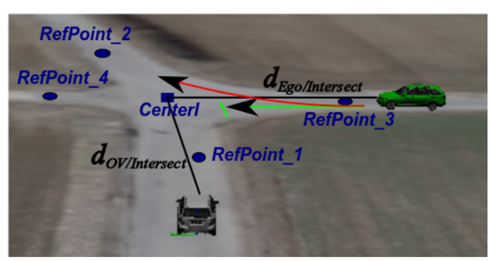

Fig. 1. The concept presented in this paper aims at classifying whether the observed vehicle (green) turns in front of the ego-vehicle (grey) or stops. The points which are marked in a map to include context information about the intersection are also illustrated.

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concept is extended to adapt learned information for one site-specific intersection to similar intersections.
The paper is outlined as follows: section II gives an overview of the concept. In section III the CBR concept for behavior prediction is introduced. The concept is evaluated, considering different driving styles and changes in the environment, in section IV. The concept is extended to different intersections in section V. Finally, the paper closes with a conclusion in section VI.

II. Overview

In this paper, intersections, without traffic lights, at which the ego-vehicle is on the major road are used for evaluation. The aim is to predict if a relevant vehicle approaching an intersection turns in front of the ego-vehicle or if it stops and lets the ego-vehicle pass. Context information like the center of an intersection (CenterI) and reference points (RefPoint), which describe the topology of an intersection, can be marked in a map (Fig. 1).
At geo-positions which are not marked in a map, like exits of a parking block, the system can be used to learn these new geo-positions in estimating the CenterI and the RefPoints of these geo-positions automatically. Therefore, the vehicles are detected by a laser sensor and the positions of the vehicles are tracked. The first position at which the observed vehicle has been tracked is used as the RefPoint. The point at which the vehicle is first located on the lane of the ego-vehicle can be stored as the CenterI. The geo-information is stored in the geo table of a relational database. At the stored geo-positions at the geo table the behavior of vehicles is predicted.
If the ego-vehicle approaches an already stored geo-position, an intersection in this case, it has to be checked if a relevant vehicle (observed vehicle), which might have an impact on the ego-vehicle, is in the scene. Because of the visible obstruction at most intersections the observed vehicle would be detected too late by environment perception. Therefore, two vehicles equiped with high-precision DGPS are used. With the help of Car2X communication it will be possible to transfer and extract information between the vehicles in the future. For this paper, data has been processed offline to be able to change the order of the recorded situations and thus to investigate the learning process on the different orders of the situations. But the concept is constructed for online learning behavior.
Important features of the maneuvers at a site-specific intersection are extracted and stored into the situation table of the database. After a comparison of stored and current features the solution of the most similar case in the database is adapted to the current situation. The result of the presented concept is a binary classification for each time step if a vehicle turns in front (red line in Figure 1) of the ego-vehicle or stops (green line in Figure 1).
After the situation is over, the observed vehicle turned or stopped, the system has to learn the new situation and therefore has to know the right maneuver conducted by the observed vehicle. If the observed vehicle stops and the ego-vehicle is 10 meters in front of the stopped observed vehicle the solution is "stop". If the observed vehicle is in the lane of the ego-vehicle the solution is "turn". When road markings are visible, extracted road markings like in [7] are used to determine a turn maneuver. Otherwise, the road width is estimated. Thus, the presented concept learns behavior of other road participants with unlabeled data. The concept can be extended to any vehicle constellation at an intersection.

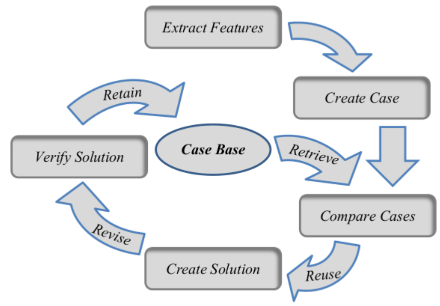


Fig. 2. The figure illustrates the cyclic process of CBR used for this application.

III. Case-Based Reasoning concept for behavior prediction

In this section Case-Based Reasoning (CBR) is introduced and the application to behavior prediction in traffic situations is presented.

A. Case-Based Reasoning

Experienced drivers have the ability to judge driving situations in predicting the behavior of other road participants. The presented idea is to adapt this ability of human reasoning and thinking to a system. A concept which models the human natural reasoning process is Case-Based Reasoning. This concept adapts the solution of known and similar cases to the current case. A case in this context is an 'explanation for the solution' [12]. Consequently the features which best describe the solution of the problem form a case. In other words, driving experience in this context is modeled as cases. If a current situation is similar to a certain driving experience the solution of the known experience or case is adapted to the current one.
CBR is a cyclic process which is described in detail in [12] [13]. Four steps are elementary in this concept:

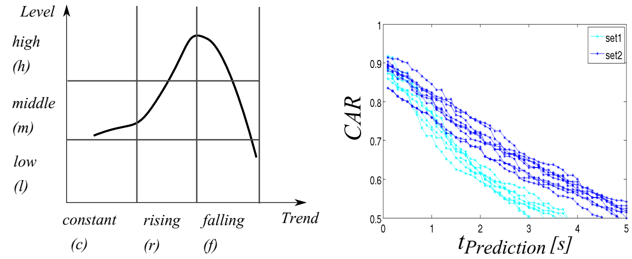
- Retrieve: Most similar cases are retrieved from the case base.
- Reuse: Several cases are compared to the current case and the solution of the most similar case is adapted.
- Revise: The solution of the reuse step is verified.
- Retain: Knowledge of the current case is retained for future reuse and the case base is updated by the current case with the determined right solution.

The cyclic process of CBR which is used for this application is illustrated in Fig. 2. In the following the cyclic process for this application is described in detail.
In the first step, features describing a situation best have to be extracted. For this application features for the behavior prediction of vehicles at intersections are selected and extracted. A situation in this case begins when an observed vehicle is approaching a stored geo-position, so a site-specific intersection. It terminates when the observed vehicle turns or stops at this intersection. The extracted features of a whole situation describe a certain case. This extraction step of features has to be done for each time step and in each time step the current case is compared to retrieved cases from the case base. As case base a database is used in which all cases are stored with their geo-position. The retrieve step for this application is done at the beginning of a situation. In this retrieve step all cases for this site-specific intersection and for all similar intersections are retrieved (see section V). After comparing all cases to the current one, the solution of the most similar case is adapted to the current situation at each time step. At the end of the situation, the observed vehicle turns into the lane of the ego-vehicle or the observed vehicle stops, the estimated solution can be verified by the right solution. The right solution can be determined online (see section II). In the retain step the case base has to be extended by new knowledge. The extracted features with the determined right solution, which are the current case, are saved into the case base and extend the experience or learned knowledge.

B. Feature extraction

In the present setup there is the opportunity to use all data provided by a high-precision DGPS, but the focus lies on basic features, also available in a tracking system. For behavior prediction at intersections different combinations of features are tested. In this context v_{Ego} is the velocity of the ego-vehicle, v_{OV} is the velocity of the observed vehicle, $d_{EgoIntersect}$ is the distance of the ego-vehicle to the CenterI of the intersection and $d_{OVIntersect}$ is the distance of the observed vehicle to the CenterI of the intersection. A possible feature set to use is the relative velocity v_{rel} (equation: 2), the distance of the vehicles and the ratio of the distances of the vehicles to the CenterI $d_{pos/intersect}$ (equation: 4) (set1). Instead of using the distance of the vehicles and the ratio of the distances of the vehicles positions to the intersection it is possible to use the ratio of the time to arrival of the two vehicles $r_{arrival}$ (equation: 3) (set2). A third option is set3 in which the relative velocity of the vehicles, the ratio of the distances of the vehicles positions to the intersection and the ratio of the time to arrival is used. If the observed vehicle stops at the intersection and then turns, the ratio of the distances of the vehicles positions to the intersection is an important factor.

$$CAR = \frac{\text{number of correctly classified situations}}{\text{number of all situations}} \tag{1}$$



(a) (b)

Fig. 3. Fig. 3(a) illustrates the extraction of an example time series into trend and level intervals. The comparison of the feature sets 1 and 2 is shown in Fig. 3(b). Fig. 3(b) illustrates that set2 has better CARs in long term prediction.

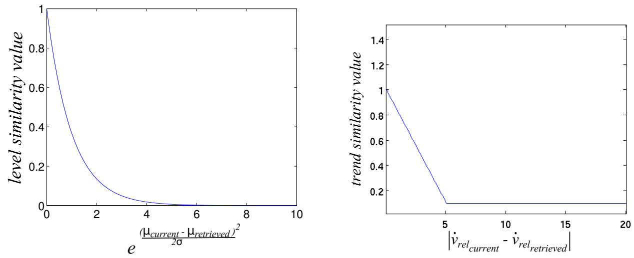
The three feature sets are compared and evaluated by the classification accuracy rate (CAR). On the whole 290 situations are evaluated using the different feature sets. At the beginning 9 situations are in the case base. All remaining situations are classified by the present concept and the CAR is calculated relative to the prediction time. Several runs with these situations are evaluated. Feature set2 showed better CARs than set1 in long term prediction, so more situations are classified properly earlier in time (Fig. 3(b)). By comparing set2 and set3, set3 has little better CARs also in long term prediction. Thus, for evaluation set3 is chosen. The three used features

$$v_{rel} = v_{\text{Ego}} - v_{\text{OV}} \tag{2}$$

$$r_{arrival} = \frac{\frac{d_{\text{EgoIntersect}}}{v_{\text{Ego}}}}{\frac{d_{\text{OVIntersect}}}{v_{\text{OV}}}} \tag{3}$$

$$d_{pos/intersect} = \frac{d_{\text{EgoIntersect}}}{d_{\text{OVIntersect}}} \tag{4}$$

are calculated in each time step. For extracting the arising time series different methods can be found in literature [14] [15]. Temporal Abstraction is already used in combination with Cased-Based Reasoning [16] and an extended version of Temporal Abstraction [17] is used for this presented approach. Using a combination of state and trend Temporal Abstraction the time series are extracted into trend and level intervals. The trend intervals are determined using fixed borders to extract the time series in rising (r), constant (c) and falling (f) trend intervals. The level of the features is divided into high (h), middle (m) and low (l). Fig. 3(a) illustrates the extraction method of an example time series. The partition of the possible three different trend and level intervals is too coarse for this application. Therefore, the trend intervals are determined in proportion to their slope. So, two rising intervals in a sequence with different slope values are possible. The slope values of the features for each trend interval and the mean and variance of the features for each level interval are stored additionally.



(a) (b)

Fig. 4. Similarity functions to calculate the trend and level similarity values between the current and retrieved cases. The trend similarity function is illustrated in Fig. 4(b) (as an example of v_{rel}), the level similarity function is shown in Fig. 4(a).

C. Comparing Cases

After retrieving cases from the case base a similarity factor for each retrieved case to the current case has to be calculated. The solution of the most similar case is reused for the current situation, so that the similarity measure plays an important role in the CBR process. On the basis of $d_{EgoIntersect}$, the distance of the ego-vehicle to the CenterI of the intersection, the trend and level intervals of the current case are compared to the trend and level intervals of each retrieved case.

The trend similarity values are calculated by a linear decreasing function dependent on the difference of the current and retrieved stored slope value of each comparable trend interval (Fig.4(b)). The greater the slope difference of the compared intervals the smaller is the trend similarity value for the compared cases. For each level interval in the feature extraction step the mean value and the variance have been stored. The level similarity value is calculated by an exponential function depending on the difference of the mean values and the variances of the comparable intervals (Fig.4(a)). The calculated trend and level similarity values for all features are multiplied. The result for each case is the case similarity value, which indicates the probability that the solution of the retrieved case can be adapted to the current case.

IV. Evaluation on a site-specific intersection

In this section the learning aspect is motivated and the effect of changes in the environment is investigated.

A. Learning behavior at a site-specific intersection

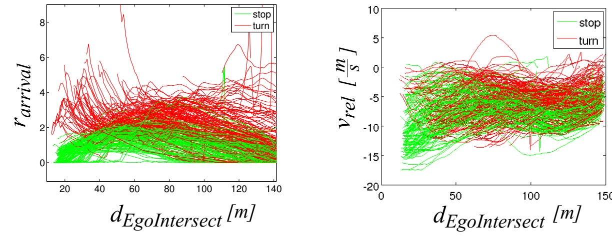
Every driver has an individual driving style. Driving styles cover a wide range from sporty driving to very carefully driving. The challenge is to make a right behavior prediction for each different driving style. For this subsection 230 situations with visual obstruction driven by 11 drivers are evaluated. The situations have a wide range from very careful to sporty driving.

Figure 5 shows the original data of $r_{arrival}$ and v_{rel} relative to $d_{EgoIntersect}$ and indicates the wide range of driving styles of the different situations. Additionally, what is striking is the fact that the decision for the maneuver by the driver of the observed vehicle is made shortly before the ego-vehicle approaches the intersection. Fig. 5 shows that similar courses of the features at higher $d_{EgoIntersect}$ can have different solutions in the end. The trend and level similarity values are calculated by comparing the whole history of the situation weighted equally over time. The consequence is that features have to be compared relative to $d_{EgoIntersect}$. Therefore, a weight function which weights the interval comparison higher with smaller $d_{EgoIntersect}$ is integrated into the concept.

The situations are manually sorted into three categories: average driving, very careful driving and sporty driving. The arrangement into the three categories is done by assessing all situations by watching the videos of the ego-vehicle's front camera. For the average driving style, situations are chosen in which drivers behaved in a normal way at the intersection. These situations would be expected by the driver of the ego-vehicle. For situations which show very careful driving, drivers stopped although normally they would have turned in front of the ego-vehicle. Sporty driving situations are situations in which drivers of the observed vehicle turn scarcely in front of the ego-vehicle.

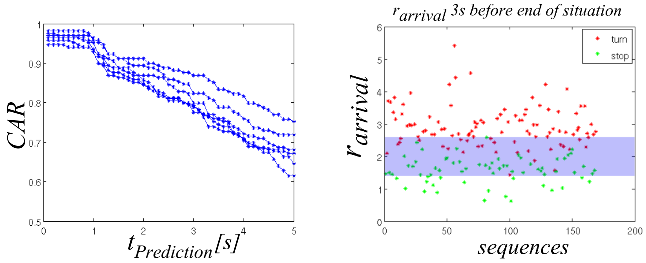
Fig. 6(a) shows several runs with the average driving style situation set. The order of the situations is chosen randomly and it is illustrated that the order of the situations plays an important role. At the beginning the first randomly chosen 9 situations are not evaluated. They form the first case base for the following evaluated and stored situations. The average CAR for the behavior prediction 1s before the situation terminates is 0.94. The average CAR for 3s is 0.81. The evaluation of all average driving style situations shows that the presented concept is able to make in a high percentage a correct behavior prediction at intersections.

To show that the situations of average driving are not that similar a comparison to the $r_{arrival}$ at a certain time is made. For this purpose, two bounds for $r_{arrival}$ which separate the turn and the stop maneuvers for a certain predicted time are calculated. Above the upper bound only $r_{arrival}$ of turn maneuvers exists and under the lower bound only $r_{arrival}$ of stop maneuvers are found (Fig.6(b)). For a prediction horizon of 3s 60% of the situations can be classified properly by the actual $r_{arrival}$. In comparison to that result a correct classification of 81% can be made by the presented learning



(a) (b)

Fig. 5. The ratio of the time to arrival of the two vehicles 5(a) and the relative velocity 5(b), are illustrated relative to $d_{EgoIntersect}$. The features from all turn maneuvers are plotted in red, in green the features of all stop maneuvers are shown.



(a) (b)

Fig. 6. The evaluation of all average driving situations is illustrated on the left hand side. On the right hand side $r_{arrival}$ of these situations is plotted for the prediction horizon of 3s before the situation terminates. With $r_{arrival}$ at 3s 40% of the situations lie in the blue area, in which both turn and stop situations can be found.

TABLE I

EVALUATION OF SPORTY AND VERY CAREFUL SITUATIONS ON THE BASE OF THE AVERAGE DRIVING SITUATIONS.

	Learning		No learning		average driving
	sporty	careful	sporty	careful	
CAR (0.1s)	0.70 ± 0.045	0.93 ± 0.00	0.50 ± 0.074	0.87 ± 0.00	0.96 ± 0.014
CAR (1s)	0.65 ± 0.066	0.84 ± 0.038	0.50 ± 0.074	0.75 ± 0.038	0.94 ± 0.015
CAR (2s)	0.63 ± 0.070	0.55 ± 0.038	0.49 ± 0.067	0.29 ± 0.038	0.87 ± 0.027
CAR (3s)	0.60 ± 0.051	0.20 ± 0.066	0.46 ± 0.047	0.09 ± 0.038	0.81 ± 0.036

concept. This evaluation shows that the situations of average driving are not that simple to predict and that a learning concept for those average driving situations has to be used to achieve a high CAR.

The advantage of a learning system is that new situations or new behavior can be learned online. Therefore, the sporty and very careful situations are evaluated separately on the base of the average driving style situations. For the first evaluation the new situations are learned and stored in the case base. This evaluation is compared to a second evaluation in which these new situations are not learned. This implies that they are only evaluated on the database of the average driving style situations. The evaluation is made with different databases of all average driving situations. In Table I it can be seen that a correct prediction of the sporty and very careful driving situations is possible if the new behavior has been learned. The challenge to solve is that sporty driving maneuvers are similar to the stopping situations of the average driving style situations and the very careful maneuvers are similar to the turn maneuvers of the average situation set. A long term prediction of the careful driving situations is difficult, even when these situations are learned. One reason is that for a prediction horizon of 3s the careful driving situations are very similar to the turn maneuvers of the average driving style situations. An additional reason is that only 15 careful driving situations are evaluated and stored in the case base. The most important fact to notice is that situations which differ from already learned ones can be learned by the presented concept. If more situations with careful driving can be learned probably better results can be achieved. If no learning of situations is possible new behavior

(a) (b)

Fig. 7. The test intersection is shown. Fig. 7(b) shows the intersection in winter. 60 sequences are recorded under this condition. The driver of the observed vehicle and the driver of the ego-vehicle can see each other when approaching the intersection. In autumn the view of the drivers is blocked by a cornfield (Fig. 7(a)). Under this condition 230 sequences are recorded. The red circle in Fig. 7(a) shows the position of the observed vehicle in the offline evaluation step. Under recording conditions the driver of the ego-vehicle can not see the red circle and thereby the position of the observed vehicle.

and changes can not be detected and the evaluated CAR is worse in comparison to the evaluated CAR with learning.

B. Effect of changes in environment

An interesting question is if changes in the environment have an influence on driving behavior and hence, on predicting driving behavior. Therefore, an environmental change at an intersection is investigated. In winter, it is possible for the observed vehicle driver to see the ego-vehicle. In autumn, a cornfield blocks the view and the two drivers can not see each other (Fig. 7). Sixty situations without visual obstruction and 230 with visual obstruction are recorded driven by 11 different drivers. First, the different situations are evaluated using the learning concept. Second, it is investigated if the situations without visual obstruction can be predicted without learning on the case base of situations with visual obstruction.

Because of the wide range of different driving styles the order of the different situations is important (see subsection IV-A). As in the last section, the order of the situations is changed randomly and the CAR for the right behavior prediction of 0.1s to 5s is evaluated and shown in Table II. For this evaluation all situations are learned into the case

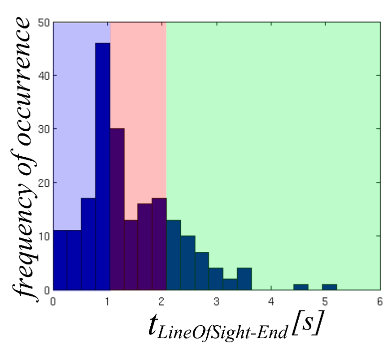
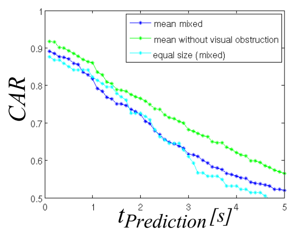


Fig. 8. A line of sight is calculated and the time from the point the drivers see each other to the end of the situation is illustrated in the histogram. It can be seen that in the blue and red area the frequency of occurrence is almost the same. On the whole, after seeing the ego-vehicle in 80% of the situations the drivers decide in 2s or less for a maneuver.

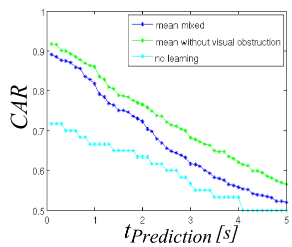
TABLE II

EVALUATION ON THE INFLUENCE OF ENVIRONMENTAL CHANGES.

	Visual Obstruction	Mixed
CAR (0.1s)	0.91 ± 0.011	0.89 ± 0.019
CAR (1s)	0.86 ± 0.017	0.82 ± 0.021
CAR (2s)	0.76 ± 0.012	0.72 ± 0.021
CAR (3s)	0.68 ± 0.014	0.62 ± 0.028
CAR (4s)	0.62 ± 0.013	0.56 ± 0.033
CAR (5s)	0.56 ± 0.022	0.52 ± 0.035



(a)



(b)

Fig. 9. In Fig.9(a) it is investigated if the same amount of situations with and without visual obstruction show different results to the used composition of situations. Fig.9(b) shows an evaluation with regard to 60 situations without visible obstruction on the basis of all situations with visible obstruction. The 60 situations are only evaluated and not learned into the database.

base. The first randomly chosen 9 situations are not evaluated because they are the base for further solution determination. The case base is chosen as small as possible to show that even with a small case base at the beginning driving behavior can be predicted because of learning situations over time. An uneven number of situations in the case base at the beginning is chosen to show that the concept can deal with a different number of cases, which have different solutions (for example 5 cases with solution turn and 4 cases with solution stop). The evaluation in Table II shows that slightly better results can be achieved by evaluating only the visual obstruction situations than mixing the situations of with and without visual obstruction. It is also noticeable in the standard deviation of the results that the order of the situations has an important influence on the CAR. One reason is the small case base at the beginning and in parts the high similarity of situations having different solutions (see subsection IV-A).

To assess the achieved prediction results it is important to investigate at what point in time the driver of the observed vehicle decides for a maneuver. For all situations with visual obstruction the driver is able to decide for a maneuver at the earliest if the drivers see each other. Therefore, a line of sight is calculated. The time period begins with the point in time in which the drivers see each other and ends with the end of the situation. It can be seen in Fig.8 that in around 80% of the situations the drivers see each other at most 2s before the situation terminates and make the decision in this period of time. With this knowledge, the results shown in Table II for predicting behavior at an intersection with visual obstruction are good.

Two further interesting aspects are illustrated in Fig.9. In this figure the mean CARs of all visual obstruction situations (green) and all mixed situations (blue) are illustrated. On the left hand side (9(a)), it is investigated if the results differ with a different composition of the two different situation sets. For investigation the same amount of situations with and without visual obstruction are used. Therefore, 60 situations with visual obstruction and 60 without are evaluated. The results for an equal amount of situations with and without visual obstruction do not show significantly different CARs. So, the results are not dependent on the composition of the different situation sets.

In Fig.9(b) it is investigated if situations without visual obstruction can be predicted properly only on the case base of situations with visual obstruction. Therefore, the situations without visual obstruction are not learned, that is the database size is fixed. If the situations without visual obstruction are not learned the CAR for every prediction horizon is much worse than with learning. This figure also illustrates that the driving style in situations with visual obstruction and without visual obstruction differs. This evaluation shows that if situations are learned, driving behavior can be predicted even if driving behavior changed due to environmental changes.

V. EVALUATION ON DIFFERENT SITE-SPECIFIC INTERSECTIONS

The aim of a prediction system is not to retrieve only cases from a known intersection. It should be possible to predict behavior at intersections at which the ego-vehicle has not been before. The idea is that driving behavior prediction can be made on the base of cases from similar intersections. In the following, a similarity measure for different intersections is presented and the concept is evaluated for two other intersections.

To calculate a similarity value for different intersections two factors are important:

A Topology of the intersection

B Velocity profile of the observed vehicle

Therefore, for each geo-position in the geo table in the database the average trajectory of the observed vehicle is stored additionally. The trajectories of the different intersections are compared using Dynamic Time Warping (DTW) [18]. The velocity profile is calculated by comparing supporting points of the trajectories. Both resulting factors are multiplied to get a value for the similarity of different intersections.

Two more intersections are evaluated and compared to the one evaluated in the last section *Intersection1*. Situations of both additional intersections were evaluated on only the recorded situations with visual obstruction (visual obstruction DB) and on all recorded situations (with and without visual obstruction) (mixed DB) at *Intersection1*. The topology of *Intersection2* is different from *Intersection1* and the velocity profile is different as well. At *Intersection1* a velocity of $50\frac{km}{h}$, at *Intersection2* a velocity of $30\frac{km}{h}$ is permitted. The third intersection investigated in this context *Intersection3*, is similar to *Intersection1* in both relevant factors. At *Intersection2* around 30 and at *Intersection3* around

TABLE III

EVALUATE DIFFERENT INTERSECTIONS.

		Intersection2		Intersection3	
	without DB	visual obstruction DB	mixed DB	visual obstruction DB	mixed DB
CAR (0.1s)	0.65 ± 0.055	0.53 ± 0.057	0.51 ± 0.047	0.78 ± 0.0	0.78 ± 0.0
CAR (1s)	0.59 ± 0.053	0.46 ± 0.057	0.41 ± 0.048	0.77 ± 0.0	0.78 ± 0.0
CAR (2s)	0.57 ± 0.066	0.46 ± 0.057	0.41 ± 0.048	0.71 ± 0.0	0.65 ± 0.0

20 situations were recorded with 2 different drivers for each intersection. The new situations of *Intersection2* and *Intersection3* are not learned for this evaluation. Table III shows that at intersections with high similarity values (*Intersection1* and *Intersection3*) the behavior of other road participants can be predicted properly using cases from similar intersections. Situations at *Intersection3* can be predicted by using cases from *Intersection1*. *Intersection2* is not similar to the two other intersections in the two chosen relevant factors. Driving behavior prediction at *Intersection2* using only the cases of *Intersection1* is poor. If no similar intersections can be found in the database, cases at this intersection can only be learned. The column 'without DB' shows the evaluation of all situations of *Intersection2* without using the database of stored situations from *Intersection1*. The first 9 situations of *Intersection2* are not evaluated for this evaluation. Following situations are evaluated and learned (stored in the DB).
Generalizing, if no similar intersection can be found in the database the first 9 situations at the unsimilar intersection (*Intersection2*) are not evaluated and they form the case base for further behavior prediction. At an unsimilar intersection, comparing to already known intersections in the database, behavior prediction can be done by comparing the current case with already learned cases at this specific intersection. The CAR for only using the learned cases from one intersection depends on how many situations at this intersection have already been evaluated. The evaluation of a new intersection with no similar cases found in the database is dependent on the order of the situations and the case base at the beginning. Investigations on this aspect show that with 100 detected situations it is possible to get a proper CAR for different prediction horizons. It has been shown that the similarity of intersections can be determined on the base of the presented two relevant factors for predicting behavior of other road participants properly at similar intersections.

VI. CONCLUSION AND FUTURE WORK

In this paper a concept for behavior prediction of other road participants at intersections is presented and evaluated on real data. Case-Based Reasoning is used for behavior prediction. The used feature determination and extraction and the comparison step were presented in detail. The functionality of the concept has been shown at one site-specific intersection and an approach for behavior prediction at several intersections was presented. It has been shown that the presented learning concept is capable in predicting turn or stop maneuvers of other road participants at intersections. The concept was evaluated in considering different driving styles and changes in the environment. In both aspects the advantages of the presented learning approach were shown and that the classification accuracy rate can be increased in an effective way when new situations can be learned.
In the future, the evaluation of this concept on a wider range of different intersections has to be done. In a further step, it will be interesting to compare the presented concept to a probabilistic approach, like Learning Dynamic Bayesian Networks.

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