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Combining Behavior and Situation Information for Reliably Estimating Multiple Intentions

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Abstract— **Intersections are the most accident-prone spots in the road network. In order to assist the driver in complex urban intersection situations, an ADAS will be required not only to recognize current but also to anticipate future maneuvers of the involved road users. Current approaches for intention estimation focus mainly on discerning only two intentions based on a vehicle's behavior. We argue that for distinguishing between more than two intentions not just a vehicle's kinematic behavior but also its driving situation needs to be taken into account. In our system we estimate four different intentions by modeling and recognizing driving situations in a Bayesian Network and using the behavior as additional evidence. For the behavior based estimation we present a newly engineered feature, the Anticipated Velocity at Stop line, that turned out to be a very strong indicator for the intention. Our system is evaluated on a real-world data set comprising approaches to seven different intersections on which we can show that our approach is able to estimate a driver's intention with a high accuracy.**

I. INTRODUCTION

Research in the field of driving intention estimation, especially associated with intersections, has become a popular topic in academia as well as for automotive manufacturers. The growing interest is due to the fact that intersections are highly accident-prone spots in the road network and a safe crossing requires to take other road users and their intentions into account. As the majority of the accidents occurring at intersections are related to driver errors, an Advanced Driver Assistance System (ADAS) that provides support and warns of critical situations would be of great benefit.

In intersection scenarios especially those intentions need to be discernable that result in different maneuvers, like crossing straight versus turning. Knowing the path that another vehicle will take, is an important information for detecting possibly hazardous situations early on. Even estimating the intention of the ego-vehicle itself can be useful in multiple ways: For example to avoid turning accidents with parallel driving bicyclists or to prevent the driver from red-light running.

One major obstacle in anticipating a vehicles's upcoming maneuver is the fact that its behavior, that is its kinematic properties, is not solely dictated by the driver's intention but naturally also by the current driving situation. An intention estimation system therefore needs to consider both kinematic behavior and driving situation in order to arrive at accurate predictions.

Recently, several works for intention estimation in the context of urban intersections have been proposed. In [1] an approach is introduced that is able to distinguish between multiple different intents and is evaluated by discerning between right turn and go straight intersection approaches. Each driver intent is assigned a parametric longitudinal behavior model and is inferred using a Bayesian Network. One way of determining these longitudinal behavioral models is to incorporate map data and manually optimize the longitudinal model parameters. Even though this approach seems promising it requires an expert for parameterizing the underlying driver model and presupposes detailed knowledge of the correct paths inside of each regarded intersection. In a subsequent work [2], the authors extend this approach towards an architecture for generic driver intent inference, capable of reliably separating right turn from straight intersection crossings. However, this approach relies on measuring a driver's gaze direction, which can be hard to obtain.

Other approaches, like presented in [3], make heavy use of intelligent intersection safety systems (Car2X). These systems fuse available data from the infrastructure with data, requested from the involved traffic participants. The infrastructure itself estimates the maneuver of each approaching vehicle. While such an approach has benefits due to the quantity and quality of the available information and its holistic view, this method strongly relies on a sufficiently equipped road infrastructure.

Between two driving intentions is distinguished in [4], based on nonlinear constrained dynamic optimization. It is assumed that a typical driver tries to minimize jerk, time and steering effort. The intention whose anticipated trajectory minimizes the above mentioned costs, is selected.

Several approaches are based on directly comparing collected velocity profiles of intersection approaches to determine the driver's intentions. [5] states that generalized velocity profiles for different driving maneuvers can be captured using Gaussian Processes. Further, the authors of [6] describe in their approach the capability of Gaussian Processes to estimate driving intentions. For each maneuver a Gaussian Process is trained in order to distinguish between the underlying intention models, making use of the current position and velocity. Unfortunately, the Gaussian Processes trained for one intersection can hardly be generalized to another intersection.

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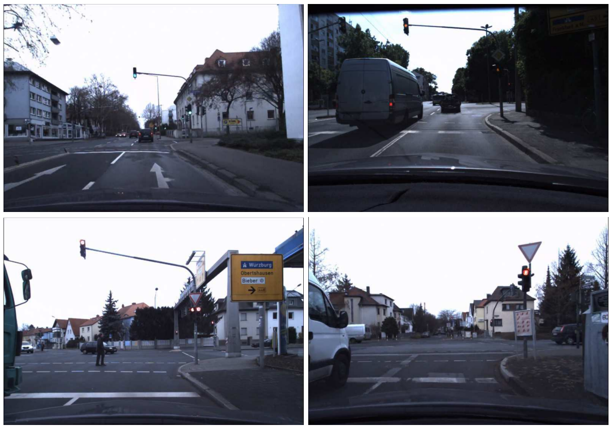


Fig. 1. Four of seven different approached intersections showing their variety

An approach for identifying critical situations using intention estimation is presented in [7], [8]. This method for intention estimation is based on Dynamic Bayesian Networks and attempts to detect mismatches between a vehicle's intended and expected maneuvers when approaching an intersection. As soon as the algorithm finds a significant difference between intention and expectation it defines the situation as critical. One downside of the method is that it is limited to situations at unsignalized intersections with only two vehicles.

In this paper we propose a method for intention estimation that takes a vehicle's driving situation explicitly into account. We argue that this allows to discern between intentions that cannot be told apart from a vehicle's behavior alone and thus enables us to consider a higher number of intentions. Our system combines kinematic behavior and situation information in order to discern between four different intentions. The method presented herein is robust to different intersection layouts and real-time capable. We also present our insight that one feature, the *Anticipated Velocity at Stop Line* (*AVS*) is a strong indicator for the intended maneuver. Our approach is evaluated on real-world recordings obtained on different intersections with different drivers.

The remainder of the paper is structured as follows. In Section II the acquisition of real world data is presented. Section III describes the detailed structure of our proposed system as well as methods and features used. The evaluation and the results obtained therein are the topic of Section IV. In Section V we conclude the paper with a summary of the gained insights and give a brief outlook on future work.

II. Data Acquisition

In order to evaluate our proposed system and the developed *AVS* feature on real world data, recordings from multiple test drives have been taken into account. The data was acquired using two different drivers approaching seven different intersections, resulting in a total number of 37 approaches. Four of these different intersections can be seen in Fig. 1. The recordings took place in an urban environment with regular traffic. Approaches where the ego-vehicle does not arrive at a red traffic light as first but instead as last vehicle in a row, have also been considered.

A. Test Set-up

The test car was equipped with a forward-facing laser scanner operating at 100Hz. It is able to detect vehicles directly in front and to determine the relative distance as well as the relative velocity respectively to the ego-vehicle. Furthermore, a consumer-grade GPS is used to determine the ego-vehicle's position. Information about the vehicle's velocity is obtained by tapping the CAN-Bus and sampling it at 100Hz. To have the ability of a subsequent qualitative analysis of the encountered scenarios and the possibility to annotate missing information, the test drives were recorded with a stereo-camera.

B. Data-Processing

In order to obtain missing, implicitly available features from the recording data further data processing has been conducted. The vehicle's acceleration is computed by deriving the recorded velocity. Since the noisy character of the velocity curves is increased by the derivation, we applied a smoothing moving average on the result, considering the $n = 20$ last data points.

As there was no traffic light recognition system at our disposal, the traffic light state of each approach was labeled by hand using the recorded video data. The position of an intersection's stop line was obtained by taking the average GPS position when the vehicle waits as first during a red traffic light. The distance to the stop line d is calculated by determining the difference between the stop line's GPS position and the vehicle's current position. For the purpose of training and benchmarking our proposed system the 'Car following' intentions are labeled by experts.

III. System Overview

The goal of our system is to anticipate the intended maneuver of the ego-vehicle when it approaches a signaled intersection. Four different intentions are considered:

I. Go straight
II. Turn right
III. Stop at red traffic light
IV. Car following.

Most of the published work focuses on intentions *I* and *II* as they can be generally well discerned based on the longitudinal behavior of a vehicle. A correct estimation allows to anticipate conflicting trajectories early. Nevertheless, intention *III* is also highly relevant as its corresponding decelerating behavior can be mistaken for a right turn intention and it is useful to anticipate red-light running. It is one of the intentions that can hardly be distinguished by behavioral features alone and profits from situational cues. Intention *IV*, *'Car following'*, considers all cases where a vehicle's behavior is dominated by the behavior of its leading vehicle. Thus it is forced to slow down or stop because of a vehicle

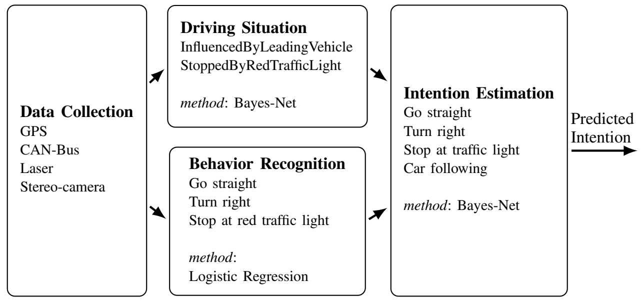


Fig. 2. System Overview

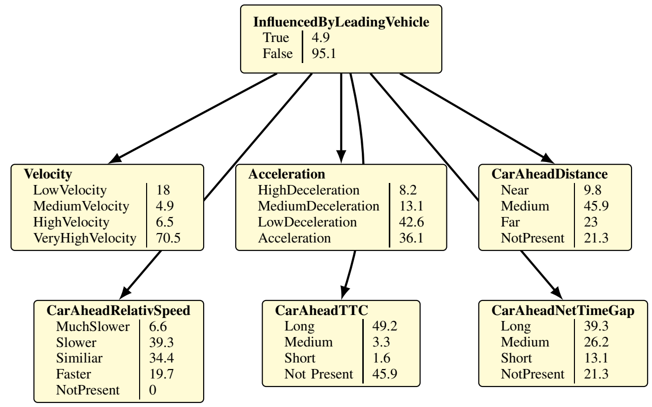


Fig. 3. A single configuration *InfluencedByLeadingVehicle* that has been mapped to a Bayesian Network using several discretized features and their probabilities in percent.

ahead. As this intention comprises various situations where a vehicle drives below the usual velocity, it requires situational cues for an accurate estimation. Besides using this intention for subsequent active safety systems its explicit consideration provides further benefit. As it has been shown in [1], a close preceding vehicle usually impairs a behavior-based intention estimation considerably. The explicit information about this case can be valuable for subsequent evaluating systems.

So in order to build a system that is able to distinguishing between all four intentions both a vehicle's driving situation and its behavior need to be taken into account. Models for driving situation and behavior are created separately and afterwards combined in a single Bayesian Network. Before presenting the combined system its individual components are introduced.

A. Driving Situation Modeling

The driving situation is modeled according to the framework proposed in [9]. In this framework, a concept termed *configuration* is used, which models how and by what a vehicle's behavior is determined. It is based on the intuition that a vehicle drives at a desired velocity unless it has to react to surrounding entities. For example, one configuration, tagged *StoppedByRedTrafficLight*, is active when the observed vehicle has to slow down or stop because of a red traffic light ahead. Each configuration comprises an affected and an affecting entity, in this case the braking vehicle and the traffic light, respectively. The focus on bilateral interactions accounts for the scalability of the approach.

A configuration is specified by defining the considered entities as well as relevant features in a graph, which are mapped to a Bayesian Network. An example of a Bayesian Network for the *InfluencedByLeadingVehicle*-configuration is given in Fig. 3.

The network models the situation in which an observed vehicle has to lower its velocity due to a nearby vehicle in front. The top node returns the probability of the corresponding configuration being active, while the lower nodes encode individual, discretized features and their probabilities in percent. Configurations focus on bilateral interactions between two entities for reasons of scalability. Hence in order to discern between multiple configurations, their individual networks have to be combined into a single Bayesian Network with an additional classification node. A more detailed account on this framework can be found in [9].

As only intentions *III* and *IV* require situational cues, the configurations modeled are the aforementioned *StoppedByRedTrafficLight* and *InfluencedByLeadingVehicle*. The way they are incorporated into the total system will be detailed in Subsection III-D.

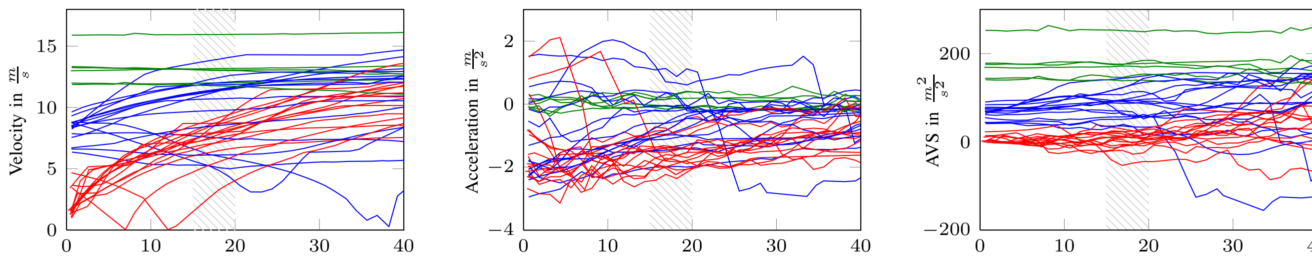
B. Feature Selection for Behavior Representation

Since intention *IV* can hardly be characterized by a single, specific behavior, only three behavior models, one for each of the intentions *I-III*, were developed. The overall approach was to inspect the available features and then select a suitable behavior classifier based on type and properties of the features that turned out to be strong indicators.

One feature that has proven to be a strong indicator for intention estimation is the velocity profile [6], [1] during the intersection approach. It is intuitively clear that a driver will slow down before performing a turning maneuver while he will keep his velocity when crossing the intersection straight. This property can also be found in the data we recorded, as it can be seen in Fig. 4 (a). When a driver intents to stop at a red traffic light his decelerating behavior is even more pronounced. Nevertheless, at a point 15 to 20 meters away from the stop line it is not possible to discern between *'Turn right'* and any of the other intentions reliably, as their velocity profiles overlap significantly.

Another feature that makes intuitively sense, is the acceleration. It is obvious that a vehicle, which has to be brought to a stop at a certain point, experiences a stronger deceleration than when it is only slowed down for a normal turn. Unfortunately, acceleration is a rather instable feature requiring significant filtering in order to account for its noisy nature. While this filtering stabilizes its values, acceleration is weaker than velocity, as illustrated in Fig. 4 (b)

Because combining both features lead to an unsatisfactory separation of the individual intentions an investigation on engineering new features was conducted. One important insight was that although the data is highly variable, the three intentions can be linearly separated based on their velocity when the distance to the stop line approaches zero. Another observation we made was that in most cases the velocity



(a) Distance to stop line in m (b) Distance to stop line in m (c) Distance to stop line in m

Fig. 4. Velocity profiles (a), acceleration (b) profiles and *AVS* feature (c) for 37 intersection approaches. The red lines show the velocity profiles for a red traffic light, green corresponds to straight intersection crossings and blue to right turn intersection crossings. The shaded gray area indicates the interesting range of 15 to 20 meters, where an estimation leaves sufficient time for a reaction if necessary.

profile in the last 20 meters to the stop line can be roughly approximated by a straight line. If we were able to predict the velocity at the stop line based on the current kinematic behavior to a sufficient accuracy, we would obtain a very strong feature. We tag this feature *Anticipated Velocity at Stop Line* (*AVS*).

The *AVS* feature predicts the estimated velocity at the stop line based on the current acceleration, velocity and distance. It combines all available longitudinal kinematic information. The *AVS* is determined using the simple kinematic extrapolation

$$v_s = v + at_s, \tag{1}$$

where v denotes the current velocity, a the current acceleration and t_s the expected time to the stop line. While determining

$$x_s = \frac{1}{2}at_s^2 + vt_s + x, \tag{2}$$

for $x_s = 0$ and $x = -d$, where d indicates the distance to the stop line, we obtain two possible solutions for t_s

$$t_{s,1} = \frac{-v + \sqrt{v^2 + 2da}}{a} \tag{3}$$

$$t_{s,2} = \frac{-v - \sqrt{v^2 + 2da}}{a}. \tag{4}$$

Between these two possible solutions we have to decide which to choose in order to determine the correctly anticipated velocity at the stop line t_s. We assume $v, d > 0$ for intersection approaches, while discarding negative values for t_s in context of real-life traffic scenarios. For $a < 0$ two possible solutions $t_{s,1}, t_{s,2} > 0$ come into question. The stop line is passed twice. Hence, we have to take a closer look at this specific scenario. Looking at (3), for real-numbered solutions and $v > 0$, $d > 0$, $a < 0$ the inequality

$$\sqrt{v^2 + 2da} < v$$

holds true. Thus it follows from (3) that $t_{s,1}$ takes on strictly positive values. Additionally, it can easily be inferred form (3), (4) and that $t_{s,1} < t_{s,2}$ and we can therefore conclude $t_{s,2} > 0$. The vehicle then passes the stop line at $t = t_{s,1}$ for the first time. Based on the assumed constant negative a after passing the stop line, the vehicle's velocity becomes negative. Hence, the vehicle starts driving backwards and passes the crossing for $t = t_{s,2}$, again. We are interested in $t_{s,1}$ since the first crossing of the stop line is crucial. Moreover, passing the stop line a second time, backing up, does not correspond to a realistic driving scenario; this is why we discard $t_{s,2}$. Note that $t_{s,1} < 0, t_{s,2} > 0$ cannot be encountered while assuming $v, d > 0$. Therefore, the logical conclusion for all realistic scenarios is $t_s = t_{s,1}$. Thus, we obtain with (3) and (1),

$$v_s = \sqrt{v^2 + 2da}. \tag{5}$$

As already mentioned it is possible that neither (3) nor (4) have a real-numbered result and $t_{s,1}, t_{s,2} \in \mathbb{C}$. This is the case, for $-a < \frac{v^2}{2d}$, when the vehicle's negative acceleration is high enough that it does not reach the stop line at all.

In order to obtain a purely real-numbered result and to have a fully continuous function for all possible input values $d, v \in \mathbb{R}_+$ and $a \in \mathbb{R}$ the square of (5) is considered. Our introduced feature *AVS* is finally given by

$$AVS = v^2 + 2da.$$

The *AVS* feature values for the previously regarded intersection approaches are shown in Fig. 4 (c). Obviously, the different behaviors can now be separated much more easily.

C. Behavior-based Intention Estimation

The previous step identified velocity, acceleration, and *AVS* as suitable features besides the distance to the intersection itself. As we strive for a system that estimates upcoming maneuvers several seconds before the actual maneuver, we did not consider the vehicle's yaw rate. Although it is a strong indicator for turning maneuvers, significant changes of the yaw rate can only be observed a short time before and during the actual turning maneuver.

As method for the behavior-based intention estimation, Logistic Regression was selected. With this choice, the intention is directly classified using the selected features, since Logistic Regression is a linear classification algorithm. Besides providing class probabilities it has other advantages like its high accuracy and its training and prediction speed.

For a set of N features $x_1, ..., x_N$ and $N + 1$ regression coefficients $\beta_0, ...\beta_N$, it arrives at a prediction hypothesis h for a binary classification task by

$$h(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + ... + \beta_N x_N)}} \tag{6}$$

Due to the sigmoid function used here, its output is guaranteed to be in the range $(0, 1)$, which is suitable for its interpretation as probability. For multinomial classification tasks, one common approach is to combine the result of multiple binary classifiers.

In first tests, using only distance and *AVS* gave already good results and adding the velocity provided further improvement. As adding acceleration to this constellation lead only to a small decrease in accuracy, it is not used here.

Given the features, the classifier returns three values P_I, P_{II}, P_{III} denoting the probability of the vehicle behaving according to intentions *I*, *II* or *III*, respectively.

D. Overall System

The overall system consists of a Bayesian Network that combines both the *InfluencedByLeadingVehicle*- and the *StoppedByRedTrafficLight*-configuration for the driving situation recognition and the behavior-based intention estimation. The latter is incorporated by a dedicated node for which the evidence, as given by the probabilities returned by the Logistic Regression, is entered. The Bayesian Network is depicted in Fig. 5.

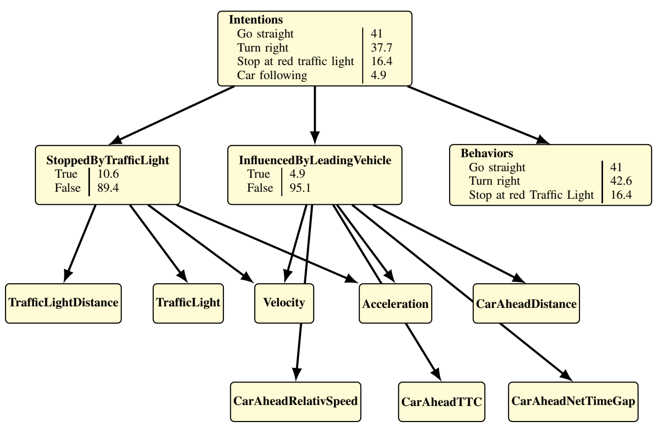


Fig. 5. The complete Bayesian Network for estimating the driver's intention. Combining the two configurations *InfluencedByLeadingVehicle* and *StoppedByRedTrafficLight*, as well as the probabilities from the behavior estimation

Evidence from this node, labeled 'Behavior' in Fig. 5, and of both configurations is then combined into a single classification node, which returns probability estimates for all four intentions. Since we modeled the configurations and the behavior separately, their most certainly existing dependence is expressed by this classification node, labeled 'Intentions' in Fig. 5.

The system is designed to run continuously during an intersection approach. Based on the current velocity and the current distance to the stop line it computes a Time-To-Intersection (TTI) by simply dividing the distance by the velocity. As soon as the TTI falls below a certain threshold, which is 1.5 seconds in our case, the system enters all current features as evidence into the Bayesian Network as well as the probabilities obtained by the Logistic Regression, and then returns the most probable intention of the classification node as estimation.

IV. Results

The newly introduced feature as well as the overall system are evaluated using the real world data acquired as described in Section II. In total 37 approaches at seven intersections are available for evaluation. In order to provide sufficient training data, both Logistic Regression and Bayesian Network use all measurements from each event in the training set where the vehicle is less than 25 meters away. This yields about 600 cases per fold for training. Given the features, our unoptimized Python implementation takes less than 5 ms for a single estimation.

A. Time To Intersection Estimation

The performance of the proposed methods are measured by their accuracy for different estimated TTIs. An accuracy reported at a TTI of 1.5 seconds means that the intention estimation was triggered in the moment the estimated TTI fell below 1.5 seconds.

In order to verify that our model achieves an accurate estimation for the actual remaining time to an intersection, the actual remaining TTI was compared to the estimated TTI for all events. Fig. 6 (a) contains a histogram of the actual remaining TTI at the time our model firstly predicted a TTI of 1.5s.

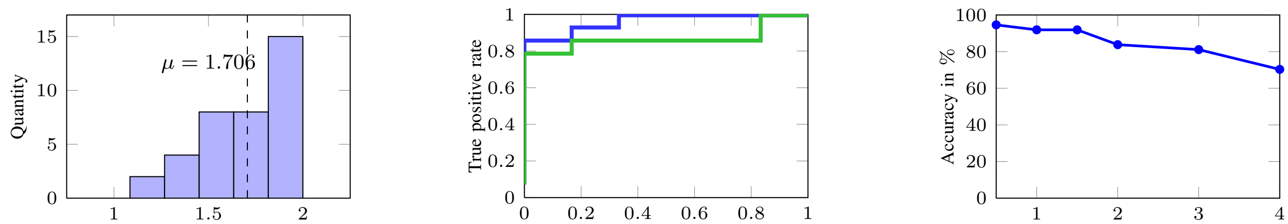
It shows that assuming a constant velocity leads to conservative estimations, where only six approaches are over-estimated, while the mean of the actual TTI exceeds our prediction.

B. Evaluation of the AVS Feature

The benefit of our newly introduced feature is evaluated by comparing the classification performance of the behavior-based intention estimation in two settings: In one setting the more established features velocity and acceleration are used and in the other setting they are replaced by the *AVS* feature. In both settings the distance is also available as feature. The goal is to discern intended right turn from intended straight crossing maneuvers. The intentions are predicted at a TTI of $2s$.

As the ROC curve of Fig. 6 (b) illustrates, the single *AVS* feature achieves a significantly better estimation accuracy than when relying on the unprocessed kinematic features. For our application the *AVS* feature offers several advantages in comparison to the established longitudinal kinematic features. Firstly, the correct classification rate is superior and secondly, the dimension of the input feature space is reduced which results in reducing the overall complexity of the underlying classification process.

It has to be noted that our evaluation was performed using a rather small data set consisting of only 20 approaches, with 14 right turns and 6 straight intersection crossings. While for these events the results seem promising further testing has to be done in order to derive valid generalizations. Still, it is striking that *AVS* performs well over all intersections used in the test set.



(a) Actual TTI in s (b) False positive rate (c) Estimated TTI in s

Fig. 6. (a) Histogram of the actual TTI at a predicted TTI of 1.5s; (b) Behavior recognition of 'Go straight' and 'Turn Right' using Logistic Regression. Blue curve: evaluation based on input features d and *AVS*. Green curve: evaluation based on input features d, v and a. The ROC curve is adapted by varying the threshold for the Turn right maneuver; (c) The accuracy of the overall system, dependent on the prediction horizon

C. Overall System Performance

Finally the complete system, as described in Section III-D for discerning four considered driving intentions is evaluated using the acquired real world data. The 37 approaches are distributed over the four intentions as follows: *I* 'Go straight' 6 approaches, *II* 'Turn right' 14 approaches, *III* 'Stop at red traffic light' 13 approaches and *IV* 'Car following' 4 approaches.

Due to only having 4 cases of 'Car following' we chose a four fold stratified cross-validation to ensure the presence of a 'Car following' approach in every fold.

The performance for a $TTI = 1.5s$ is given in the confusion matrix in Table I. We obtain an overall classification accuracy of 91.9% and are able to identify 50% of the approaches labeled as 'Car following', correctly. Considering the rather small number of training examples for 'Car following' approaches, the system shows satisfactory results. Furthermore, Fig. 6 (c) shows the development of the classification accuracy dependent on the prediction horizon. Our system is able to identify the correct intentions in more than 80% of the events when the predicted TTI is 3 seconds.

V. Conclusion and Future Work

In this paper a method for intention estimation was presented that is robust to different intersection layouts and is capable of discerning between four different intentions reliably. The method is based on the intuition that some intentions can only be recognized if, besides a vehicle's behavior, also its driving situation is taken into account. We show that on a data set with a high variability our system is able to accurately anticipate the intended maneuver 1.5 seconds in advance.

Additionally, we found that one feature, the Anticipated Velocity at Stop line, is a strong indicator for a driver's intention. With this feature we are able to separate different behaviors more reliably in contrast to solely relying on the more established kinematic features. One possible explanation is that a driver roughly plans its velocity at a certain point and tries to reach this velocity with a minimum jerk.

In order to strengthen the expressiveness of our findings we will have to increase the size of our data set. It will be interesting to evaluate our system on more cases of 'Car following'. Especially cases where the ego-vehicle had to stop shortly in front of a crossing needs further investigation. It is possible that there is a need for introducing acceleration models in order to discern different intentions after the ego-vehicle has slowed down and starts to continue its intersection approach. Nevertheless, note that our approach proves effective on many different intersections where for each only few data samples were available.

In future work annotating the state of a traffic light could be replaced by state-of-the-art detectors. An interesting research topic would be to investigate how the estimation accuracy can be further improved by adapting the system to an individual driver.

I	II	III	IV	← Prediction / Actual ↓
6	0	0	0	I
0	13	1	0	II
0	0	13	0	III
0	2	0	2	IV

TABLE I

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