2012 Intelligent Vehicles Symposium
Alcalá de Henares, Spain, June 3-7, 2012

Driver Intent Inference at Urban Intersections using the Intelligent Driver Model

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***Abstract*— Predicting turn and stop maneuvers of potentially errant drivers is a basic requirement for advanced driver assistance systems for urban intersections. Previous work has shown that an early estimate of the driver's intent can be inferred by evaluating the vehicle's speed during the intersection approach. In the presence of a preceding vehicle, however, the velocity profile might be dictated by car-following behaviour rather than by the need to slow down before doing a left or right turn. To infer the driver's intent under such circumstances, a simple, real-time capable approach using an explicit model to represent both car-following and turning behaviour is proposed. Models for typical turning behavior are extracted from real world data. Preliminary results based on a Bayes net classification are presented.**

***Index Terms*— Driver Intent Inference, Intelligent Driver Model, Trajectory Data, Velocity Profile, Intersection Approach**

I. Introduction

Urban intersections have long been known to be a hotspot for accidents resulting in major injuries [1]. While passive safety systems can help to prevent such injuries for passengers inside a car, pedestrians and cyclists – so called vulnerable road users (VRU) – are left with limited protection.

Active safety systems aim to prevent or mitigate the effects of accidents before they happen. A typical application would be to warn the driver if he seems to have overlooked a relevant VRU. This poses two major challenges to the system: First, the early detection of VRUs which cannot satisfactorily be achieved by state-of-the-art onboard sensors, and second, to determine whether there is a need to warn the driver of that particular VRU.

The research initiative Ko-FAS [2] addresses the issue of detecting VRUs both by research on cooperative sensor technology [3] and stationary high resolution camera systems [4]. The general idea of Ko-PER [5], one of the projects associated with Ko-FAS, is to share the local perception of each individual car or infrastructure unit using a novel data fusion architecture [6] based on a manufacturer independent Car2X communication solution. Also, several approaches to lane level self localisation are investigated [5], [7].

To resolve the second issue of whether or not the driver should be warned, the trajectory on which he intends to cross the intersection needs to be determined. The task of estimating the driver's intent is addressed by this paper.

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A. Related Work

Driver intent inference for urban intersections has been an important research topic for the past couple of years. Approaches reported in literature include Bayesian networks [8], Monte Carlo Simulation [9], Hidden Markov Models (HMM) [10], [11], Support Vector Machines [12] and prototype based methods [13].

An important feature for estimating the driver's intent has been identified to be the speed profile of a driver approaching the intersection [14]. In the presence of a preceding vehicle, however, the velocity profile might be dictated by car-following behaviour rather than by the need to slow down before doing a left or right turn. For prototype based methods like [13] this is very difficult to account for due to the large number of possible situations. While HMM and Monte Carlo based methods are capable of dealing with interaction between vehicles in principle, doing so is computationally rather expensive.

In [15], the Gipps model was used to represent car-following behaviour directly. The deceleration of a driver in preparation of a turn maneuver was modeled deterministically by a set of fuzzy-logic rules based on the geometry of the path lying ahead. The driver's intent was estimated using a computationally expensive particle filter that limited the approach to non-realtime use.

B. Problem addressed

Similar to the approach taken in [15], this paper introduces a method to infer the driver's intent based on an explicit model for the vehicle's velocity profile. Explicit models are more transparent than machine learning methods and more robust when generalized to situations for which there is no training data available.

In contrast to [15], the *Intelligent Driver Model* [16] is used to represent both car-following and turning behaviour. Alternative parameter sets are extracted from real world data to account for different driving styles. The general idea is to compare the trajectory of the past few seconds with the simulated driver behaviour obtained from different parameter sets and driver intents to estimate their posterior probabilities. The resulting probability distribution can be used to make predictions both about the driver's intent and the future trajectory of the vehicle. Based on a Bayes net instead of a particle filter, our approach is real time capable and can be easily extended to include additional features such as turn indicator or lateral lane center deviation.

The capability of our approach is demonstrated for the

Fig. 1. Pedestrian crossing and intersection approach. The rightmost lane has been used for measurements and demonstration.

rightmost lane of the intersection approach shown in Figure 1. We define four possible driver intents to be recognized:

1) Go straight.
2) Stop at stop line.
3) Turn right.
4) Turn right, but stop at pedestrian crossing.

The remainder of this paper is organized as follows: In Section II, the general data collection and trajectory mapping framework is described. Section III introduces the IDM car-following model and demonstrates how it can be used to model turning behaviour. In Section IV, two alternative approaches to the classification task are discussed. Section V serves to discuss the performance of our approach at predicting right turns. Finally, Section VI concludes this paper.

II. Data Acquisition

Measurement data was collected from 4 different drivers at an inner-city intersection. The data set contains 118 right turns and 80 straight intersection crossings, including situations with and without a preceding vehicle. The corresponding GPS-Traces are shown in Figure 2.

Special care was taken to capture both defensive and sporty driving styles. Previous works have shown that a single driver exhibits a much larger variance in his intersection approaches than can be found between the average behaviour of different drivers [14]. Therefore, the number of different drivers used for data aquisition is not that important.

A common way to map two-dimensional trajectories onto one-dimensional lanes is to use lanemarkings obtained from digital maps or satellite pictures. Beside the disadvantage of having to deal with an additional map error, this approach does not work well at the inside of intersections that often lack lanemarking. Instead, we chose to use the GPS traces

TABLE I

Distance along Circular Arc Spline

Spline segment	0	1	2	3	4	5
Total distance [m]	0	33.52	42.00	45.92	51.98	57.36

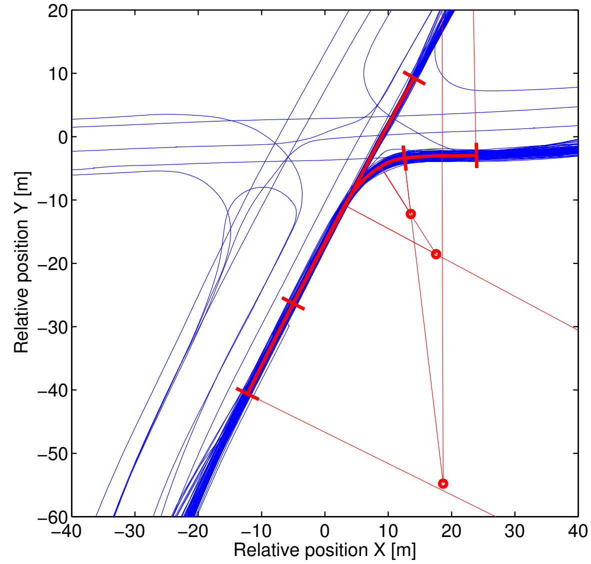


Fig. 2. GPS-Traces of intersection crossings and map consisting of two smooth circular arc splines. For the sake of clarity, auxiliary lines and arc centers are shown for the right turn branch only. Markers indicate the start and stop of the splines as well as the positions of the stop line and the pedestrian crossing.

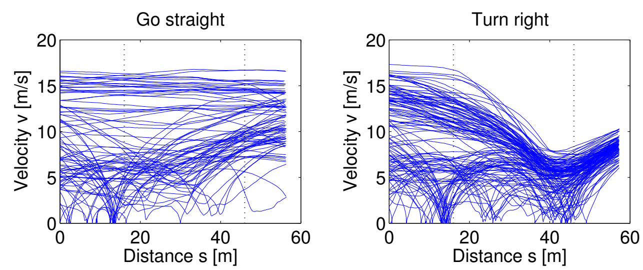


Fig. 3. Velocity profiles for going straight and turning right. The position of the stop line and that of the pedestrian crossing are indicated by dotted lines.

obtained by a high-precision differential GPS/INS platform to generate a map that represents the mean path of vehicles crossing the intersection rather than the lane markings.

Internally, the map uses smooth circular arc splines to represent the paths from one intersection entry to all possible exits. For the right turn path, the travelled distance at the end of each individual circular arc is summarized in Table I. An efficient algorithm to generate smooth circular arc splines is given in [17].

Compared to the standard polyline representation, smooth circular arc splines have a couple of advantages:

- finding the correct mapping of an arbitrary point is computationally very efficient,
- very compact representation, only few parameters needed to model the individual arcs,
- the mapping of a smooth two-dimensional trajectory is continuous in the distance coordinate s, the orthogonal deviation y and its derivative.

The velocity profiles are given in Figure 3. Apparently, a significant difference between the profiles for turning right and going straight can be observed starting from 20 to 30 meters onwards. In contrast, the drivers intent to stop at the pedestrian crossing before turning right seems to be predictable only for $s > 35\,\mathrm{m}$. A lot of trajectories include a stop at $s \approx 13\,\mathrm{m}$, which corresponds to the position of the stop line at the traffic light.

III. Driver Behaviour Model

Microscopic car-following models have long been used to simulate individual driver behaviour in the presence of preceding vehicles. A continuous, accurate but simple model is the Intelligent Driver Model (IDM):

$$\dot{v} = a\left[1 - \left(\frac{v}{u}\right)^{\delta} - \left(\frac{d^*(v, \Delta v)}{d}\right)^2\right], \tag{1}$$

$$d^*(v, \Delta v) = d_0 + T\,v + \frac{v\,\Delta v}{2\sqrt{a\,b}}. \tag{2}$$

The corresponding parameter values are given in Table II. With no preceding vehicle present, the calculated acceleration $\dot{v}$ is determined only by the maximum acceleration parameter a, the current actual velocity v, the desired velocity u and a fixed acceleration exponent δ. The influence of a preceding vehicle is represented by the ratio of the effective desired gap d^* and the actual gap d. The model is collision free, i. e. the deceleration is not bounded by any value but approaches the so-called comfortable deceleration parameter b asymptotically. In a typical instantiation of the model, the desired velocity u will be a fixed value depending on the legal speed limit and the individual driver. For right turn modeling, however, it needs to be set dynamically as drivers will slow down when they approach the intersection. For any observed velocity profile $v(s)$, the IDM equation (1) is rewritten to obtain the desired velocities $u(s)$ by

$$u(s) = \frac{v(s)}{\sqrt[\delta]{1 - \dot{v}(s)\,/\,a}} \tag{3}$$

for $\dot{v}(s) < a$ and set to $u(s) = 60\,\mathrm{km/h}$ otherwise. An example velocity profile and the corresponding desired velocity profile are shown in Figure 4. The advantage of representing observations by $u(s)$ rather than $v(s)$ is that the former can be generalized to arbitrary situations. This is demonstrated for a couple of velocity profiles that include a stop at $s \approx 13\,\mathrm{m}$, which are reproduced by an IDM simulation using the same desired velocity profile. The stop is modeled by placing a virtual zero-velocity obstacle at the stop line at $s = 16\,\mathrm{m}$ which is removed when v reaches zero.

To calculate the desired velocity profile, the maximum acceleration parameter a of the individual model needs to be known. Assuming a desired velocity of $60\,\mathrm{km/h}$ for $s \geq 48\,\mathrm{m}$, the model parameter a is first estimated based on the acceleration after turning and is then used to calculate the desired velocity profile for $s < 48\,\mathrm{m}$.

TABLE II

Parameters of the Intelligent Driver Model

Parameter	Value
max. acceleration a	$0..5\,\mathrm{m/s^2}$
acceleration exponent δ	4
desired velocity u	$0..60\,\mathrm{km/h}$
comf. deceleration b	$3\,\mathrm{m/s^2}$
min. gap to leading vehicle d_0	$2.0\,\mathrm{m}$
time gap to leading vehicle T	$0.8\,\mathrm{s}$

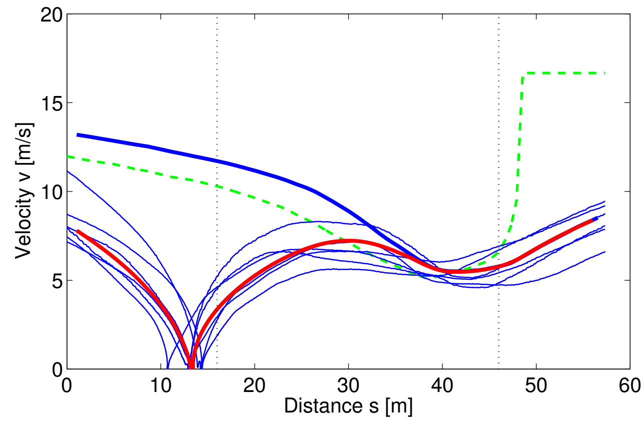


Fig. 4. Driver behaviour during right turn maneuver. Original trajectory (thick blue), synthesized desired velocity curve (dashed green), trajectories for stop at red traffic light and consecutive right turn (thin blue), simulated trajectory (thick red).

In order to obtain a small set of hypotheses covering a wide range of possible driver behaviours, the *k-means* clustering algorithm is used to group $N = 50$ non-stop right turns that have not been influenced by a preceding vehicle into three different models as shown in Figure 5. The cost function for the cluster assignment step has been chosen as

$$J_{ij} = \int_{0\,\mathrm{m}}^{48\,\mathrm{m}} \left(u_i(s) - c_j(s)\right)^2\,\mathrm{d}s \tag{4}$$

where $c_j(s)$ represents the j-th cluster center and $u_i(s)$ the desired velocity profile of the $i-th$ intersection crossing. The probability for an arbitrary crossing belonging to one of the three models as well as the probability distributions for the acceleration parameter a given a specific model M are obtained by counting the trajectories that have been assigned to each cluster center. The results are given in Figure 6. Model 0 refers to a constant desired velocity profile $s \mapsto u(s) = 60\,\mathrm{km/h}$ that is used to model straight intersection crossings, for which the distribution of a is assumed to be the same as the prior distribution $P(a)$ derived from right turn trajectories.

It is assumed that the presence of preceding vehicles will not influence the desired velocity profile $u(s)$. Instead, they are taken into account by the brake term

$$\dot{v}_{\mathrm{Brake}} = -a\left(\frac{d^*(v, \Delta v)}{d}\right)^2$$

of the IDM equation (1). Our approach uses $\dot{v}_{\mathrm{Brake}}$ also to model stops either at a red traffic light (being the first in the queue), or at the pedestrian crossing before turning right. The car-following parameters b, T and d_0 have been set to fixed values as stated in Table II.

IV. Driver Intent Inference

The parameter sets found in the last section can be used as hyphotheses H for the actual driver behaviour in an unknown

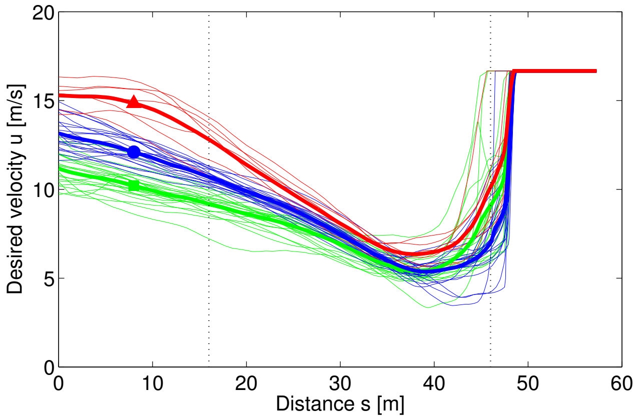


Fig. 5. Result of the k-means clustering algorithm. Cluster centroids (thick lines) for Model 1 (green square), Model 2 (blue circle) and Model 3 (red triangle) and their associated desired velocity curves.

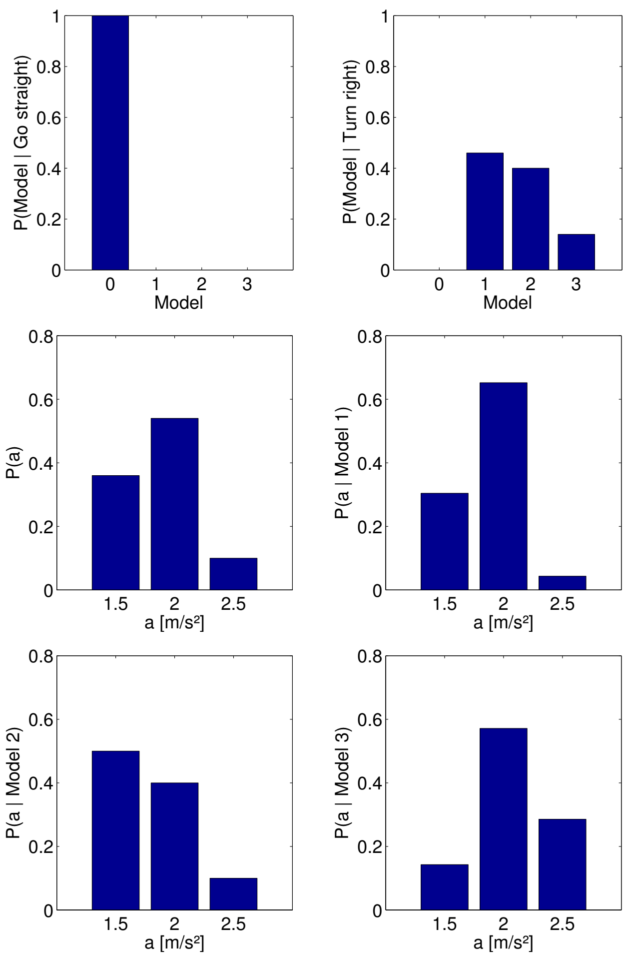


Fig. 6. Probability distributions for the applicable Model M and the acceleration parameter a.

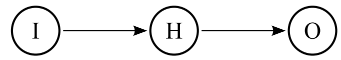
TABLE III

HYPOTHESES FOR DRIVER INTENT INFERENCE

Intention I	H: Model $\times\, a\,[\mathrm{m/s^2}]$	Obstacle
I_1: Go Straight	$\{0\} \times \{1.5, 2.0, 2.5\}$	–
I_2: Stop at stop line	$\{0\} \times \{1.5, 2.0, 2.5\}$	16 m
I_3: Turn right	$\{1, 2, 3\} \times \{1.5, 2.0, 2.5\}$	–
I_4: Turn right but stop	$\{1, 2, 3\} \times \{1.5, 2.0, 2.5\}$	46 m

situation. Including the option of stopping, there is a total of 24 hypotheses to be considered as shown in Table III.

The probability distribution of the actual driver intention I, the applicable hypothesis H and a not yet defined observation O can be modeled by a simple Bayes net:



The probability for a particular intention I_j given the observation O can be written as

$$P(I_j|O) = \sum_i P(I_j|H_i)\, P(H_i|O) \tag{5}$$

where $P(I_j|H_i)$ is either 0 or 1 depending on H_i. The probabilities for the individual hypotheses are given by

$$P(H_i|O) = \frac{P(O|H_i)\, P(H_i)}{\sum_j P(O|H_j)\, P(H_j)}. \tag{6}$$

The prior probabilities $P(H_i)$ can be obtained from

$$P(H_i) = \underbrace{P(a_i|M_i)\, P(M_i|I_j)}_{P(H_i|I_j)}\, P(I_j) \tag{7}$$

where I_j is the intention, M_i the model and a_i the acceleration parameter belonging to hypothesis H_i. The prior distribution of the intention I can be set heuristically or from statistical data. For demonstration purposes, we assumed a uniform distribution $P(I_j) = 0.25\,\forall\, j$ so the effect of different classification approaches can be seen more clearly.

The remaining term $P(O|H_i)$ represents the probability of a particular observation given the current driver behaviour can be modeled by the parameter set associated with hypothesis H_i.

A. Simulation based approach

One possibility to estimate $P(O|H_i)$ at time t is to simulate the driver behaviour corresponding to hypothesis H_i for the time interval $[t - T_\mathrm{S}, t]$ with

$$\hat{s}_i(t - T_\mathrm{S}) = s(t - T_\mathrm{S}) \quad \text{and}$$
$$\hat{v}_i(t - T_\mathrm{S}) = v(t - T_\mathrm{S})$$

where $\hat{s}$ and $\hat{v}$ denote the simulated values for distance and velocity. For a typical right turn maneuver, the simulation results at two different times t are shown in Figure 7. There are no hypothesis curves for I_2, as the stop line of the traffic light has already been passed. The curves of the remaining hypotheses end up at different velocities $\hat{v}_i(t)$ and distances $\hat{s}_i(t)$. These are the expected values given that the current driver could be modeled by the parameter set of the corresponding hypothesis. One possible way to define the observation O is to use only the final values of the simulation and compare them to the actual values $v(t)$ and $s(t)$. Assuming normal distributed noise for both s and v, the probability $P(O|H_i)$ for hypothesis H_i is given by

$$P(O|H_i) = \frac{1}{2\pi\sigma_s\sigma_v}\, exp\left(-\frac{1}{2}\, e^2\right) \quad \text{with} \tag{8}$$

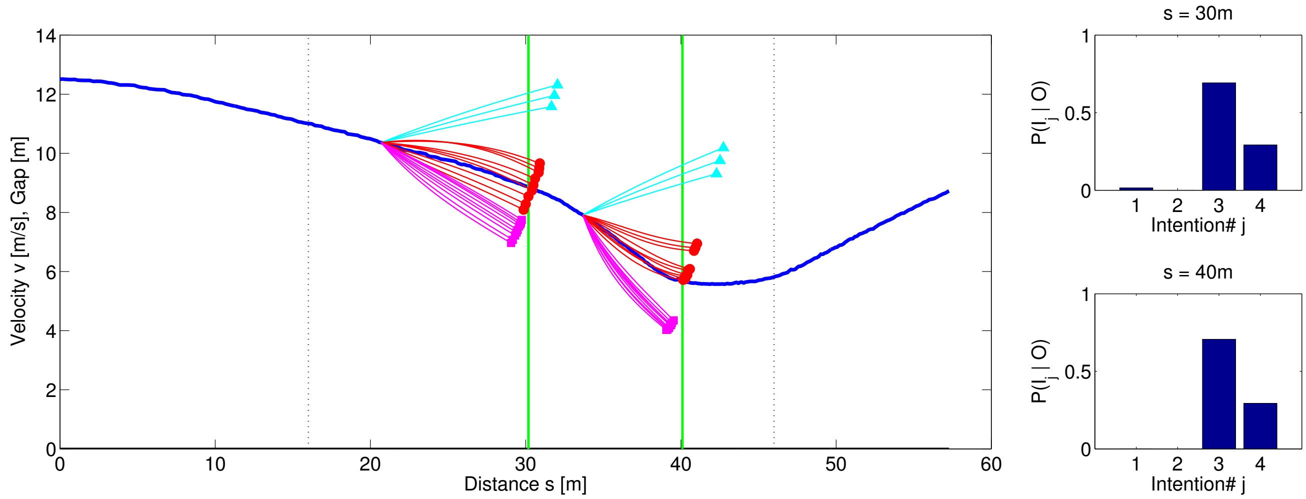


Fig. 7. Typical right turn maneuver in absence of a preceding vehicle. Simulation is carried out at $s = 30\,\mathrm{m}$ and $s = 40\,\mathrm{m}$, starting $1\,\mathrm{s}$ in the past. The predicted trajectories are colored and marked by their corresponding driver intention: Cyan triangle for "Go straight", red circle for "Turn right" and magenta square for "Turn but stop first". The resulting probabilities for the driver different intents are shown on the right.

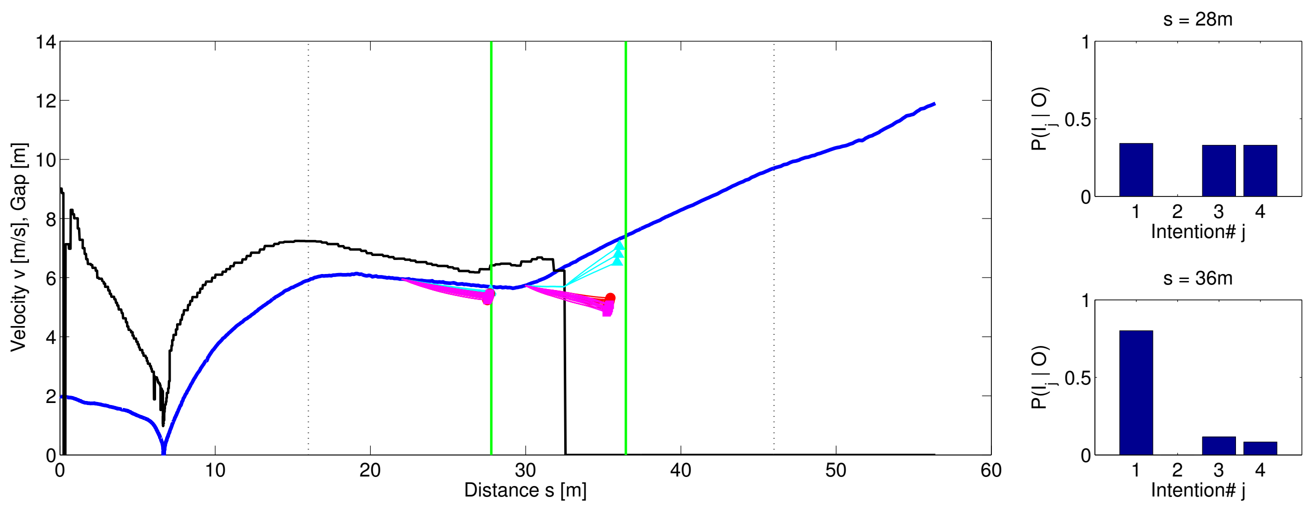


Fig. 8. Classification results for going straight in the presence of a leading vehicle. The gap d between the two vehicles is represented by the black line.

$$e = \sqrt{\left(\frac{s(t) - \hat{s}(t)}{\sigma_s}\right)^2 + \left(\frac{v(t) - \hat{v}(t)}{\sigma_v}\right)^2}. \tag{9}$$

For $\sigma_s = 1.2\,\mathrm{m}$ and $\sigma_v = 1.2\,\mathrm{m/s}$, the posterior distribution of the driver intent is shown on the right in Figure 7. Finding appropriate values for σ_s and σ_v is important as they have a major influence on how easy a hypothesis will be favoured above others. Further investigations are necessary to determine realistic values based on precision and recall of a subsequent classification step.

One advantage of using explicit models to infer the driver's intent is that arbitrary environmental conditions such as the presence of a leading vehicle can be easily taken into account. Figure 8 shows the simulation results for a straight intersection crossing which is influenced by a preceding vehicle that is slowing down to do a right turn. For $s = 28\,\mathrm{m}$, all hypotheses H lead to similar results due to the car-following situation. Only after the leading vehicle has turned, the curves corresponding to intention I_1 for going straight show a significantly different behaviour which is reflected in the calculated probabilities $P(I_j|O)$ as shown on the right in Figure 8. This means that the approach is well suited to express ignorance in situations for which the driver's intent cannot be determined by the velocity profile alone.

B. Comparison based approach

As an alternative to the simulation based approach, the current driver intention can also be estimated by comparing the actual acceleration $\dot{v}(\tau)$ with

$$\hat{\dot{v}}(\tau) = \hat{\dot{v}}(\, v(\tau), \Delta v(\tau), d(\tau), u(s(\tau))\,)$$

for $\tau \in [t - T_S, t]$ using an error metric similar to (8). First tests have shown results similar to those of the simulation based approach. A potential advantage is that the number of discrete timesteps used for comparison can be chosen to meet computational demands. Also, the comparison based approach is likely to be more robust in the presence of false positive detections of a leading vehicle.

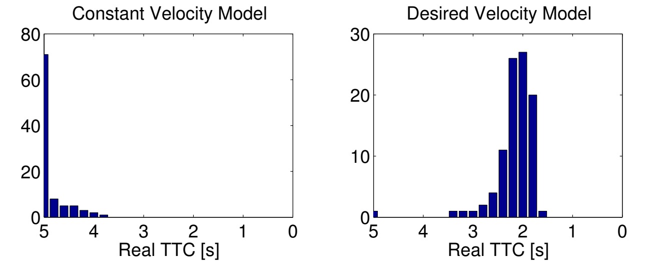


Fig. 9. Comparison between the constant velocity and the desired velocity based TTC estimation. $Real\ TTC$ refers to the timespan between the first $TTC \leq 2\,\mathrm{s}$ estimate and the actual time at which the pedestrian crossing is reached. Values larger than $5\,\mathrm{s}$ are represented by $TTC = 5\,\mathrm{s}$.

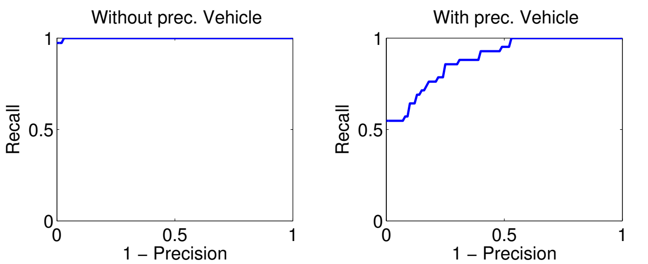


Fig. 10. Classification results for velocity profile based right turn prediction at $TTC = 2\,\mathrm{s}$. Left: ROC based on 76 right turns and 33 straight crossings without the presence of preceding vehicles, but with occasional stops at the traffic light. Right: ROC based on 42 right turns and 47 straight crossings in the presence of a preceding vehicle.

V. Discussion

A possible application of driver intent inference at intersections is to warn the driver of cyclists moving parallel to the road if and only if he intents to do a right turn. Assuming a reaction time of up to $1.5\,\mathrm{s}$ and a turning velocity of around $6\,\mathrm{m/s}$, $TTC = 2\,\mathrm{s}$ would be an appropriate value for the time-to-collision treshold at which the corresponding driver assistance system issues the warning. However, estimating the remaining TTC is non-trivial since its conventional constant velocity definition does not hold due to the turn-related deceleration. Much better results have been obtained by simulating the driver behaviour according to the desired velocity profiles of the hypotheses H. A comparison between the two approaches is shown in Figure 9. The desired velocity based TTC estimation overestimates the remaining TTC by a maximum of $0.5\,\mathrm{s}$, which still allows for a reaction time of $1\,\mathrm{s}$. The underestimates are mainly due to slow preceding vehicles. The receiver operating characteristic (ROC) curves for the classification results of the simulation based approach are given in Figure 10.

VI. Conclusions and Future Work

In this paper, a simple, transparent and real-time capable approach to driver intent estimation for urban intersections has been presented. A method has been proposed to extract characteristic desired velocity profiles from real world data that allow the IDM to account for turn related deceleration. For the example of a right turn assistant, it has been shown that good classification performance can be achieved with the simulation based approach even in the presence of a preceding vehicle. If the driver intent can not be inferred in a particular situation, the approach is able to express ignorance which is an advantage if combined with additional features like the lateral displacement or the turn indicator.

Future work will be concerned with the evaluation of the computationally even more efficient comparison based approach. Also, a method needs to be found to generalize the desired velocity profiles $u(s)$ to arbitrary intersections, or alternatively, to obtain such profiles from regular traffic by evaluating either traces of standard low-precision GPS receivers or sensory data of infrastructure mounted sensor units.

VII. Acknowledgements

The authors are committed to many colleagues of the Ko-PER project community for valuable clues and fruitful discussions. The Ko-PER project is funded in part by the Bundesministerium für Wirtschaft und Technologie of the Federal Republic of Germany under grant no. 19 S 9022.

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