Proceedings of the
2007 IEEE Intelligent Vehicles Symposium
Istanbul, Turkey, June 13-15, 2007

Driver Braking Behavior during Intersection Approaches and Implications for Warning Strategies for Driver Assistant Systems

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***Abstract*—Data from vehicles approaching an intersection during a red-light phase has been recorded by measuring real traffic in urban areas. Using a laser scanner based tracking system, vehicle velocities during approaches to the red light have been estimated and various metadata (such as object class, distance to the intersection when the traffic light turned from green to orange and weather data) has been collected. The experimental setup is validated using a Real-Time Kinematic (RTK) GPS system. The resulting information can be used when designing warning strategies for Advanced Driver Assistant Systems (ADAS). Examples of a warning strategy estimation for a misinterpretation of the traffic situation for both the host vehicle's driver as well as other drivers endangering the host vehicle are presented.**

I. Introduction

Analyses of accident statistics have shown intersections to be a major source of conflicts. In urban areas in Germany, collisions at intersections is the predominant accident type [1]. Technical systems assisting the driver at specific intersection scenarios are being developed ([2], [3], [4]) and sensor-equipped cars have been built up to do research on driver behavior and test Advanced Driver Assistant Systems under real traffic conditions (e.g. [5]). Many of these systems aim to avoid automatic intervention into vehicle control and are restricted to present warnings to the driver when possible. Those systems face a "warning dilemma" [6]: A warning is to be issued as late as possible, so that the driver is not bothered with unnecessary warnings. On the other hand, a warning has to be early enough to enable the driver to react suitably in order to avoid the dangerous situation.

Risk assessment systems can benefit from accurate information about typical driver behavior. This is the case for both, systems that try to detect known dangerous object configurations as well as system approaches that simulate all possible future object paths. While the former can use this information to separate normal from atypical and potentially dangerous situations, the latter can possibly use such information for more accurate object path prediction. When studying the warning dilemma for stop sign assistance, experiments were done with test subjects that approach a stop sign [6]. In general however, not much investigation about typical driver behavior approaching intersections has been done.

This work studies the approach of vehicles to crossings with traffic lights, which involves an additional parameter that affects driver behavior: The distance of the vehicle to the stopping line when the lights turn from green to orange and the driver decides to stop. Also, in this work test persons did not drive a test vehicle, but real traffic has been examined using a tracking system based on a laser scanner manufactured by IBEO AS, Germany. This system is briefly described in Section II-A.

Driver behavior recording using a vehicle driven by test persons or examining real traffic both have their own inherent advantages and disadvantages. A big advantage of recording normal traffic scenarios is that it is easier to get a sample set that contains a representation of all sorts of drivers, even those that might be harder to win as test persons for an experiment. Secondly, when driving in their own cars, unaware that an experiment is going on, drivers will act more naturally. This is harder to accomplish when putting drivers in a test car, where they know that data will be recorded. Thirdly, all kinds of vehicle types can be examined, not only a limited number of test vehicles.

The biggest challenge of this approach is that it is difficult to measure the vehicle data accurately and reliably enough for data collection. It will be shown in Section II-C that the laser scanner based tracking system performs very well in the chosen experimental setup.

II. Data Collection

This section describes the steps needed to reliably collect detailed traffic data.

A. Laser Scanner based Object Tracking

Recent work described the use of a laser scanner for object tracking [7] using a Kalman Filter [8]. The tracking algorithm employed here uses the "rectangle tracking" technique, which means that for each tracked vehicle, a length, width, and orientation are estimated and the tracking reference point is chosen stationary on a fixed point inside the resulting rectangle. This way, the tracked reference point does not move inside the object when an object is passing by and is thus seen from different sides, so ostensible additional velocities of the object reference point inside the tracked objects are inhibited.

The Kalman Filter works with an object model of constant acceleration and yaw angle [9]. However, since a laser scanner only measures distances directly and a Kalman Filter naturally lags behind when estimating derived states, only the estimated position is used in this work. The object velocities can be

Fig. 1. Data recording vehicle with embedded laser scanner. The vehicle cannot be recognized as sensor equipped test vehicle at first glance.

more accurately estimated by postprocessing the position data offline. This is done with a smoothing spline interpolation. By optimizing the spline parameters according to a cost function that includes the smoothness of the resulting curve, the object position over time can be obtained as an analytic smooth spline from which the derivative can then be taken to get the object velocities.

B. Experimental Setup

The tracking algorithms use an IBEO AS laser scanner which is embedded into the front bumper of a test vehicle, allowing for unintrusive measuring of flowing traffic, Fig. 1. The hiding of the sensors is important in order to get information about typical driving behavior, because drivers tend to change their behavior when they realize that they are monitored, as it can be seen from visible speed traps.

The tracking algorithms perform best when the rear parts of vehicles are observed, because the sharper shape corresponds better to the idealized rectangular object form. At the same time, it is also important to get a good measurement of the object length to allow for a robust tracking of the reference point. It was found that the best layout for the experiment was a parked car about $100\,m$ in front of a traffic light, Fig. 2. The passing cars allow for both an accurate object length estimation and robust tracking. Objects are very close when they enter the field of view of the laser scanner, so due to the radial measurement principle, there are many scan points

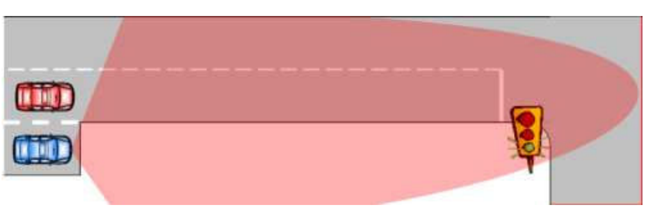

Fig. 2. Schematic layout of the experiment. Normal traffic passes a parked test vehicle during an approach to a traffic light. The test vehicle records the dynamic object data of the passing traffic.

on each object as the Kalman Filter is set up, which also supports the tracking algorithms. The downside of this setup is that a relatively straight road is needed for the last $100\,m$ of the approach to the crossing for non-occluded view, thus limiting the kind of crossings that can be monitored. Drivers are assumed to drive at least as fast on straight roads as on curvy roads. Since mainly upper bounds of the velocities during normal driving are interesting for ADAS, the types of crossings that can be monitored can be expected to be the most problematic ones.

Comparisons have shown that cars drive with a slightly reduced velocity when following a leading car when approaching a red light compared to cars that arrive at the intersection first. Since leading cars are the ones of particular interest for driver assistant systems, only those have been included in this work. For every car, the corresponding timestamp at which the light changed from green to orange has been manually marked during the data collection, and vehicles were clustered into groups depending on their relative position to the crossing at that timestamp. For each object, metadata such as object class and weather condition has been collected.

C. Validation of the Experimental Setup

In order to validate the velocity estimates of the tracking algorithms for the described setup, the experiment has been simulated on a closed test track with a second test car, and the tracking results have been compared to an onboard RTK GPS measurement of the moving vehicle. The RTK GPS sensor measures its position with $10\,Hz$ and accuracy in the cm-level, and also does a Doppler-measurement of its velocity.

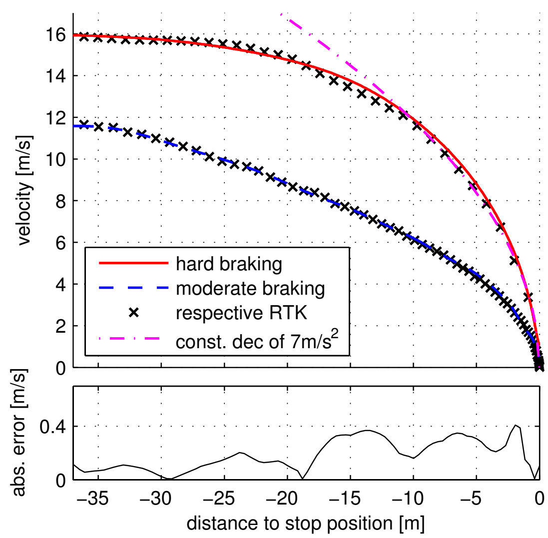

Fig. 3. Validation of laser scanner data acquisition vs. velocity estimation of a RTK GPS sensor as reference system. Top: A hard and a moderate braking maneuver is measured with the laser scanner and compared to the RTK GPS measurement of the braking vehicle. Bottom: Maximum absolute error during the hard braking maneuver. The error during the moderate braking maneuver is considerably smaller.

Fig. 3 illustrates the object velocity over the distance to the final stop position. Shown are a moderate and a hard breaking maneuver, recorded from the vehicle with the laser scanner and postprocessed tracking and with the RTK GPS sensor. The hard braking maneuver corresponds roughly to a braking with a constant deceleration of $7\,\frac{m}{s^2}$ during the last phase. The results show that the velocity estimation of the laser scanner based tracking and RTK GPS measured object movement are almost identical. At the bottom of Fig. 3 the absolute error during the hard braking maneuver is shown. Even during that maneuver the maximum deviations do not exceed $0.4\,\frac{m}{s}$. During more moderate braking maneuvers, the error is even considerably smaller, so that it can be concluded that very accurate velocity estimations can be achieved with the laser scanner based object tracking.

III. Data Evaluation

Fig. 4 depicts the data base for all vehicles consisting of about 270 separate objects approaching a traffic light in an urban area with a speed limit of just under $14\,\frac{m}{s}$ $(50\,\frac{km}{h})$. Statistical tests have shown that the velocity distribution of different drivers approaching an intersection is not a normal distribution. In the case where a vehicle is supposed to stop it can be assumed that the higher a vehicle's velocity approaching an intersection is, the higher the potential for a dangerous situation as a harsher braking maneuver is required to stop and yield. The meaning of "high" velocity here is to be taken relative to the distance to the crossing. Even a moderate but constant velocity becomes "high" at some distance, as stopping at the intersection becomes more difficult. Therefore, it is usually of interest for driver assistant systems to know which part of the sample lies below some velocity/distance threshold curve, which is exactly what quantiles express. The 1-quantile $Q_{1.}$ corresponds to the envelope curve, the 0.5-quantile $Q_{.5}$ corresponds to the median.

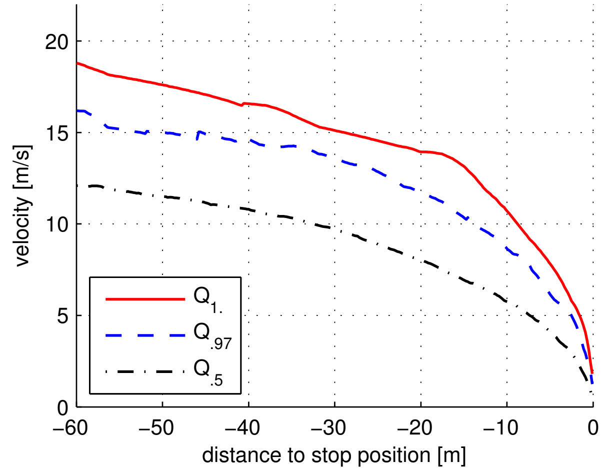

Fig. 5. Distance/velocity graph of envelope curve, $Q_{.97}$ quantile, and median of all measured objects approaching a red light. The velocity level of the quantiles decreases rapidly at the upper end, meaning that there are only a few sporty drivers compared to a vast majority of normal and careful drivers.

Fig. 5 shows the envelope curve of all approaches as a solid red line. Comparison of the envelope to the median (black dash-dotted line) reveals a big difference between the behavior of "sporty" and "normal" drivers. The divergence between the envelope curve and the $Q_{.97}$ curve (blue dashed line) however shows that there are only a few sporty drivers that push the envelope towards high velocities.

It is interesting to investigate how braking maneuvers are influenced by the distance of the vehicle to the traffic lights when the lights turn from green to orange, Fig. 6. Obviously, the drivers that are already close to the lights have no other

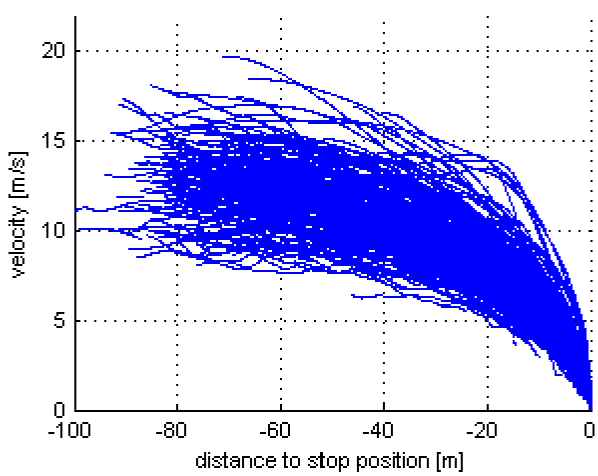

Fig. 4. Distance/velocity graph of all measured objects during the last $100\,m$ of the approach to the traffic lights. Notable is the high variance in velocity of the approaching vehicles, ranging from around $8\,\frac{m}{s^2}$ for extremely careful drivers to almost $20\,\frac{m}{s^2}$ for very sporty drivers at a distance of $70\,m$ to the intersection. The allowed speed limit was $14\,\frac{m}{s^2}$.

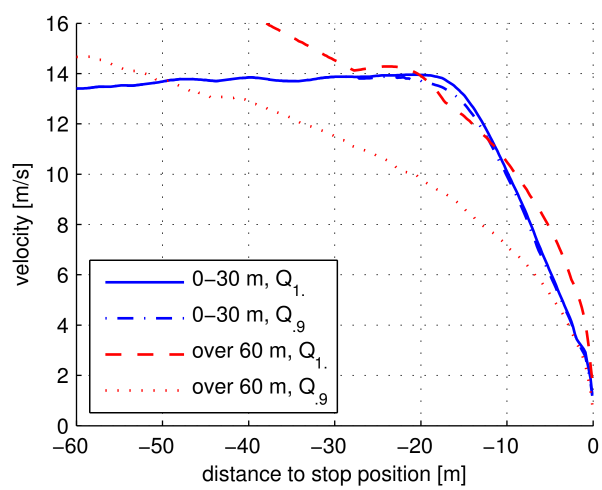

Fig. 6. Braking maneuver depending on the distance of the cars to the lights on switch to orange. Even when approaching the red light from far away, some drivers choose a sporty trajectory, so a sporty approach is not always forced by a suddenly changing light surprising the driver.

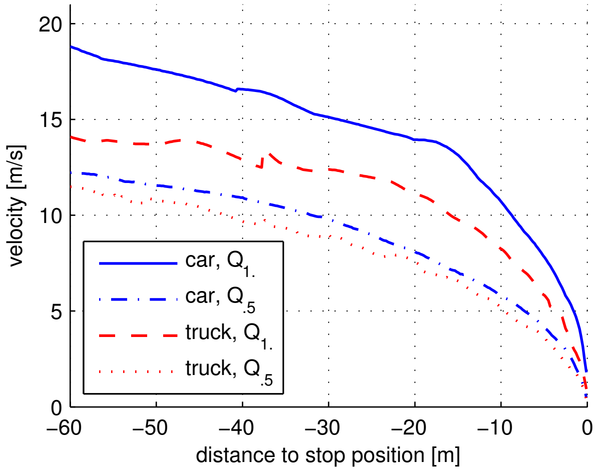

Fig. 7. Comparison of cars and trucks. An average approach of a car and a truck is very similar, while a sporty truck driver still chooses a more conservative trajectory than a sporty car driver.

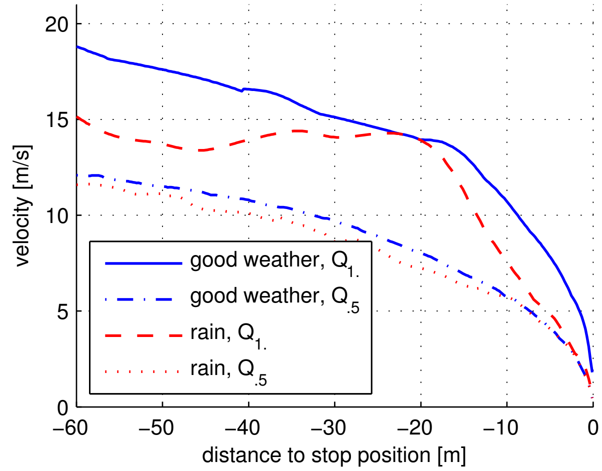

Fig. 8. Driving behavior in good weather conditions and rain. Rainy weather conditions do not stop some drivers to perform a rather hard breaking maneuver. Data analysis has shown that the sporty driver on the envelope curve in rainy conditions was not surprised by a suddenly changing light, as the light changed to red when the driver was still at a distance of more than $60\,m$.

choice but to do a hard braking maneuver if they decide to stop (blue curves). As expected, the vast majority of drivers that are still far away from the lights do a moderate braking maneuver (red dotted curve). Still, there are some drivers that approach even a red light in a very sporty way (red dashed curve), which has to be taken into account when designing advanced driver assistant systems.

As it can be seen from Fig. 7, trucks approach a red light on average only slightly slower than cars. However, there is a notable difference for the envelope curve between trucks and cars that shows that sporty truck drivers are on a lower velocity level than sporty car drivers. This information could be used by systems that are able to distinguish between several object classes [10].

Fig. 8 presents a comparison between driving behavior in good weather conditions as opposed to rainy weather, in which only around 15 drivers have been recorded. During the approach, the velocity in rainy conditions is on average slightly lower than in good weather conditions. Still, even in rainy conditions there are drivers that do very sporty approaches to a red light. The car that produced the envelope (red dashed) curve for rainy conditions was more than $60\,m$ away from the crossing when the light turned red, so the rapid braking maneuver was not caused by a suddenly changing light. Although the small number of drivers during rainy weather can not be statistically analyzed, this is a notable observation.

IV. Implications for Intersection Safety Systems

When designing warning strategies for intersection safety systems, avoiding false and thus irritating warnings is vital for user acceptance of the assistance system. To reduce faulty warnings, two conditions have to be met for a warning to be issued: An atypical driving behavior (either by the driver of the host vehicle or by other drivers) has to be recognized *and* this possibly faulty behavior must pose a direct threat to the host vehicle.

In order to check for the first condition, atypical driving behavior has to be differentiated from normal maneuvers. If the ADAS has the information that a car is supposed to stop and yield (e.g. via infrastructure-to-car communication [11]), one way of separating expected from exceptional behavior during the approach of the car is to define a limiting curve in the velocity/distance diagram, and claim that every maneuver above that limiting curve is an atypical driving behavior.

If an atypical driving behavior has been detected, it is still necessary to make sure that this behavior does in fact pose a threat to the host vehicle. This can be done by means of a collision risk assessment.

A. *Traffic Situation Misinterpretation of the Host Vehicle*

In this section, we are investigating a possible warning strategy for the case when the host vehicle does not brake when approaching an intersection where it has to yield (e.g. a red light or a stop sign). In this case, the misinterpretation always poses a direct threat to the host vehicle, so the predominant design variable for a decision to issue a warning is the limiting curve in the distance/velocity diagram. A reasonable choice for this limiting curve would be a last physically-possible warning point with the assumption of a constant maximum deceleration after a certain driver reaction time. In Fig. 9, an example approach of a vehicle with $15\,\frac{m}{s}$ ($54\,\frac{km}{h}$) is depicted. The general limiting curve of an emergency breaking for any velocity is assumed to result from a duly stop after a constant deceleration of $9\,\frac{m}{s^2}$ and a time delay of $1.5\,s$ which accounts for the human reaction time (typically a little more than $1\,s$) as well as a time delay in the braking system (assumed as a little less than $0.5\,s$). The vehicle crosses this limiting curve at around $35\,m$ away from the targeted stop position. After that,

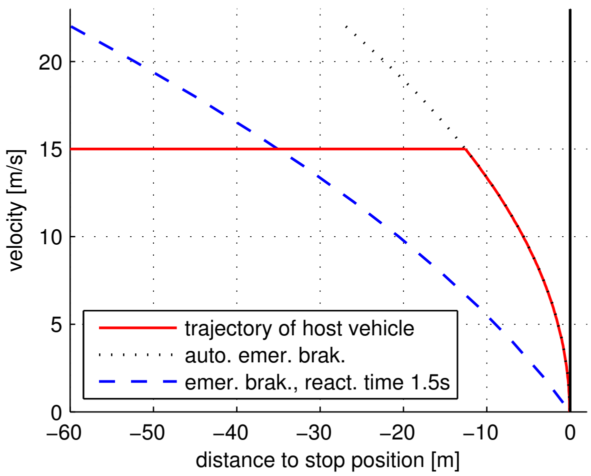

Fig. 9. Idealized warning strategy for a missed braking maneuver of the host vehicle at an intersection. A vehicle approaches with a constant velocity. When it hits the dashed curve of the last possible warning point, a warning is issued, and the vehicle brakes with full deceleration of $9\,\frac{m}{s^2}$ after a time delay of $1.5\,s$. So the dashed curve partitions the the graph in an area where a warning is still possible and one where it is too late.

it continues straight for $1.5\,s$ and then follows the trajectory of an automatic emergency braking. It must be emphasized that the curve of the emergency braking after a certain time delay is not a trajectory of a vehicle, but a limiting curve that partitions the two-dimensional state space into an area where a warning under the given assumptions is still possible and an area where this warning would come too late. In the area where the warning would be too late for collision avoidance, there is still potential for collision mitigation maneuvers.

In Fig. 10 the quantiles $Q_{1.}$, $Q_{.97}$, and $Q_{.5}$ are overlaid with the physically last possible warning point. From this figure it can be seen that during a typical approach, most vehicles that do in fact yield and do not pose a danger cross the limiting curve of the last possible warning point at some distance. No warning is to be issued in such a case, so the crossing of the limiting curve can not be taken as the sole criterium for a warning. Clearly, there is a need for additional constraints on the warning strategy to overcome the warning dilemma. One feasibly additional constrait could be put on the driver-induced pedal positions. Since in this case the warning is supposed to make the driver aware of a missed stopping and yielding responsibility, a warning is probably redundant if the driver is already in the braking process. Checking for a deceleration of the vehicle during the last meters before crossing the limit curve could be another possible way to overcome the warning dilemma. It can be seen on Fig. 10 that the velocity curves are decelerating when crossing the limit curve. It is still to be investigated if these measures are sufficient to lower the false alarm rate below acceptable thresholds. Adjusting the limiting curve to the type of driver could also increase the system performance, but induces further problems and should be avoided if somehow possible.

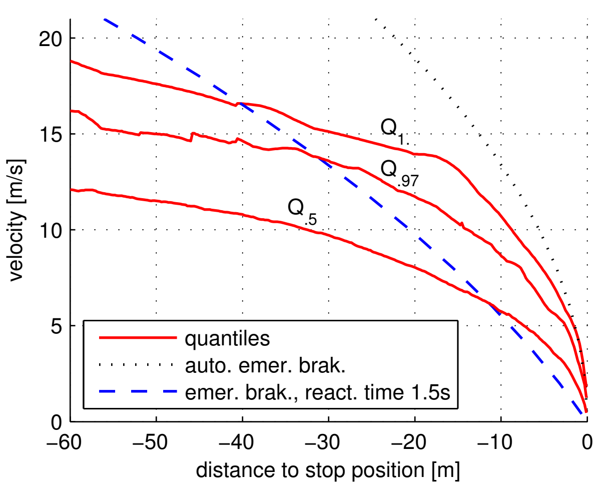

Fig. 10. Investigation of the warning dilemma for the given approach: Even normal drivers cross the last possible warning point at some distance during an approach. The last possible warning point can not be taken as the sole criterium for a warning to avoid false warnings.

B. Traffic Situation Misinterpretation of Another Road User

In a second test case, another road user's failure to yield to the host vehicle is examined. The scene in Fig. 11 shows a vehicle in red approaching an intersection. It is assumed that the host vehicle has an up-to-date high-level map of the intersection ([12], [13]) together with traffic regulations, and knows that the host vehicle has the right of way. Considered is the case when both vehicles are going straight. The host vehicle in blue might interfere with the other vehicle in the red conflict zone. Possible conflict zones can be computed in advance when approaching an intersection [2].

Now it is assumed that both vehicles are staying in their respective traffic lanes, and that the dynamic state of the objects only changes in the longitudinal direction by a maximum assumed acceleration and deceleration. When simulating the objects for future timestamps, the object boxes expand in the longitudinal direction to a zone in which the vehicle is

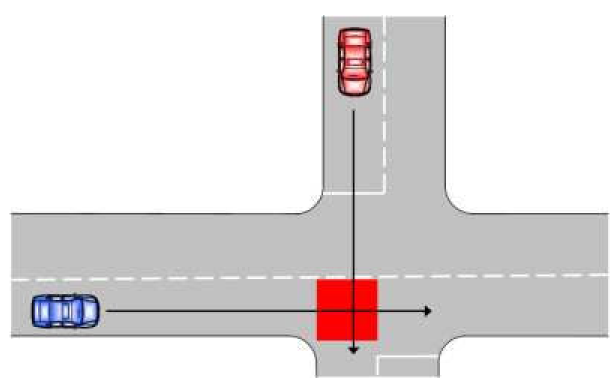

Fig. 11. Test case for failure to yield of another vehicle. The blue host vehicle (driving horizontally) is assumed to have the right of way, but the red vehicle (driving vertically) fails to yield. The red area is the pre-calculated conflict zone.

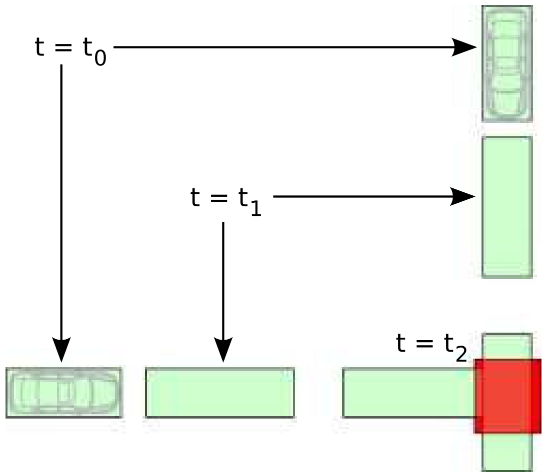

Fig. 12. Longitudinal expansion of object boxes. Drivers are assumed to stay in their respective lanes. Acceleration and deceleration maneuvers are modelled by an expansion of the object boxes in longitudinal direction. A possible crash occurs whenever these elongated boxes overlap.

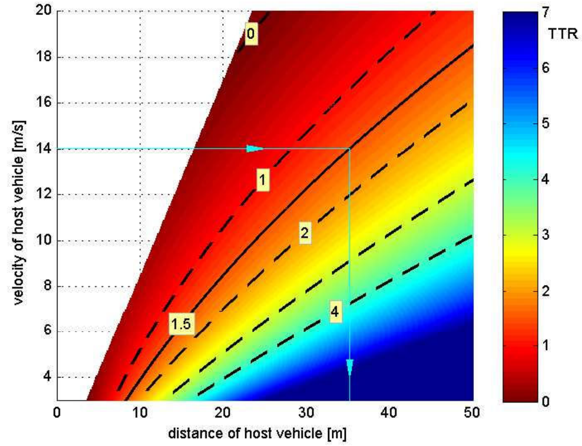

Fig. 13. Exemplary simulation run showing the *time to react* of a vehicle that is $10\,m$ away from the intersection when an atypical behavior is detected. The *time to react* (TTR) is dependent on the host vehicle's velocity and distance to the conflict zone as well as the other vehicle's position. The graph shows the areas where a warning would be feasible depending on the assumed driver reaction time. The cyan line shows that if the host vehicle approaches the intesection at $14\,\frac{m}{s}$, the warning must be issued at a distance of $35\,m$ to the conflict zone in order to allow for a collision avoidance maneuver.

contained under the assumptions mentioned above, Fig. 12. If the boxes of two vehicles at a certain timestamp overlap, a collision is possible. It is possible to take the amount of overlap normalized to the box sizes as a collision risk metric for that timestamp, but this metric of course highly depends on the assumptions made on maximum acceleration and deceleration.

In order to check if the other vehicle poses a danger to the host vehicle, it is only necessary to compute the timestamps of the earliest entry into and the latest exit (possibly never) out of the conflict zone for both vehicles. If the geometry of the intersection is known, no time resolution of the simulation is necessary, so this can be done extremely fast. If those time intervals overlap, the vehicle poses a potential threat to the host vehicle, and the first timestamp of overlap is the timestamp of the earliest possible collision.

As a consequence, if the time intervals overlap, the condition of posing a threat to the host vehicle is met. It still needs to be judged if the other vehicle behaves atypically for a warning to be justifiable. The measure of atypical behavior can once again be taken from the distance/velocity diagram, where a limiting curve that separates normal from atypical behavior has to be defined. To avoid false warnings, the chosen limiting curve has to be quite restrictive. The $Q_{1.}$ quantile of the driver data recording seems like a feasible choice.

The usefulness of such a system can be analyzed by looking at the time gap between the warning point and the earliest possible collision ("time to collision", TTC), or alternatively by the time gap that still remains for the driver of the host vehicle to react until a maximum braking maneuver has to be initiated in order to avoid the collision ("time to react", TTR). The latter can also be seen as the time gap between the warning timestamp and the beginning of an automatic emergency braking that would avoid the collision. A TTR that is lower than the assumed reaction time of the human driver shows that a warning will probably not enable the driver to avoid the collision, but could still be useful for collision mitigation maneuvers.

As a testcase, the maximum acceleration and deceleration of the host vehicle was chosen to be $1\,\frac{m}{s^2}$ and $-2\,\frac{m}{s^2}$ respectively, the parameters for the other vehicle were $1\,\frac{m}{s^2}$ and $-6\,\frac{m}{s^2}$. Vehicles sizes have been set to $2\,m$ width and $4.5\,m$ length. With the additional assumption of the other vehicle's atypical behavior being caught at the earliest possible point in time (the crossing of the limiting curve, so distance and velocity of the object are coupled), three variables characterize a situation: The host vehicle's velocity and distance to the conflict zone, and the distance to the conflict zone of the other vehicle.

Fig. 13 shows an example simulation run for a traffic situation where atypical behavior of the other vehicle is recognized $10\,m$ before it reaches the intersection. As the limiting curve was chosen to be the Q_1. quantile of the driver data recording, it can be seen from Fig. 5 that the other vehicle's velocity is around $11\,\frac{m}{s}$ in that case. The TTR is plotted as a function of the dynamic state of the host vehicle. The contour line where TTR equals $1.5\,s$ is of particular interest: Under the assumptions made about driver reaction delay and braking system time constant, the warning would be early enough to allow for a collision avoidance maneuver by the host vehicle's driver for all dynamic states below that line. On the line of TTR equal to $0\,s$, only an automatic emergency braking system would be able to avoid the collision, for states between those two lines a human driver could still do collision mitigation with a hard braking maneuver. For dynamic states above a TTR of $0\,s$, even an automatic emergency braking system could only do collision mitigation. The white area on the left of the figure is caused by the host vehicle leaving the conflict zone before the other vehicle reaches it. In the depicted example of a host vehicle that approaches with $14\,\frac{m}{s}$ (around $50\,\frac{km}{h}$), the warning needs to be issued at a distance of at least about $35\,m$ away from the conflict zone in order to assist the driver in avoiding the collision (cyan lines in Fig. 13). Given that the view at intersections is often occluded by obstacles, detection and tracking of such imperiling vehicles at an early stage is a hard task.

V. Conclusions

It has been shown by a comparison to RTK GPS measurements that a laser scanner based tracking algorithm is well suited for traffic recording and data acquisition of driver behavior. Approaches of ordinary drivers to a red traffic light have been collected and impacts of several influences on the driver have been analyzed. The resulting information of typical driver behavior when approaching an intersection has then been used to estimate whether warning systems for intersection safety can have the potential to avoid or at least mitigate collisions for two selected situations. It was shown that in general the warning dilemma is not negligible. For failure-to-yield situations by the host vehicle, the warning dilemma can possibly be overcome in many situations, rendering an assistant system useful. It is however hard for driver assistant systems to account for yielding failures by surrounding drivers at intersections, especially when the viewshed is occluded.

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