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Visual Prediction of Driver Behavior in Shared Road Areas

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***Abstract*—We propose a framework to analyze and predict vehicles behavior within shared road segments like intersections or at narrow passages. The system first identifies critical *interaction regions* based on topological knowledge. It then checks possible colliding trajectories from the current state of vehicles in the scene, defined by overlapping occupation times in road segments. For each possible interaction area, it analyzes the behavioral profile of both vehicles. Depending on right of way and (unpredictable) behavior parameters, different outcomes are expected and will be tested against input. The interaction between vehicles is analyzed over a short time horizon based on an initial action from one vehicle and the reaction by the other. The vehicle to yield most often performs the first action and the response of the opponent vehicle is measured after a reaction time. The observed reaction is classified by attention, if there was a reaction at all, and the collaboration of the opponent vehicle, whether it helps to resolve the situation or hinders it. The output is a classification of behavior of involved vehicles in terms of active participation in the interaction and assertiveness of driving style in terms of collaborative or disruptive behavior. The additional knowledge is used to refine the prediction of intention and outcome of a scene, which is then compared to the current status to catch unexpected behavior.**

The applicability of the concept and ideas of the approach is validated on scenarios from the recent Intersection Drone (inD) data set.

I. Introduction

Urban traffic scenarios still pose a challenge for autonomous vehicles, as safe maneuvering needs to consider more factors than well-understood highway applications. This is mainly due to far more shared spaces as intersections and narrow passages where interactions with other traffic participants occur, especially oncoming traffic. In these scenarios, predictable actions of a vehicle are essential for perceived safety and trust in the vehicle, as a study finds 41% of drivers do not trust autonomous vehicle systems [1]. Inside urban areas the fatality rate for the driver and passengers is lower than outside, still more drivers and passengers die in accidents than pedestrians (60/40 ratio in the EU) [2]. According to the NHTSA, 36% of accidents happen at intersections with around 150.000 accidents in the US happening due to misjudgment of behavior [3]. An algorithm is to be found to reduce the severity of the problem by identifying interactions and classifying decisions of road users to help predict future behavior. Currently first experimental cars include safety mechanisms for intersections, mainly relying on safe passage times with large time gaps to securely pass. However, they do not infer any intention to collaborate in an encounter which could be used for better understanding of an outcome and could lead to more natural driving behavior for an autonomous vehicle.

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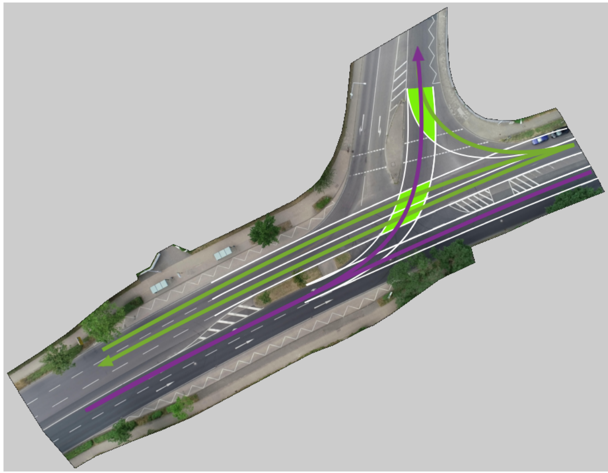

Fig. 1. Trajectories of two vehicles interacting with each other. At start position, all trajectories are feasible. Over time, vehicle from the left slows down to let oncoming traffic pass before turning left. Highlighted *interaction areas* (green) based on topology and *resource competition* analysis, actual trajectories highlighted by arrow. Scenario 00, vehicles 314 & 316

Problems for this inference come different sources which may influence the overall scenario:

1. Topology is fixed at a current scenario, but very individual for each intersection. Right of way situations may be predefined but may be changed currently.

2. Aggressiveness in an encounter plays a major role in an interaction as it may change the situation completely.

3. Drivers influence each other by behavior and react to changes in behavior to try to achieve seamless interaction.

4. Early prediction is based on small and noisy measurements which impacts prediction of behavior.

5. Observed behavior may match different outcomes first, differences may become obvious late.

As vehicles are bound to the road surface, there has been a lot of research about intentions, also in intersections. Doshi et al. [4] did a thorough comparison of approaches which have been extended substantially in the last few years.

Problems with these approaches arise because predictions are often purely based on current (or possible future) trajectory, which enables an autonomous vehicle to maneuver between vehicles, but does not consider behavioral feedback between drivers. For a human driver, the prediction of another vehicle's intention is not only defined by visual and topological clues as seeing turn signals or driving in a specific lane. Experienced drivers also take include approaching speeds, "perceived aggressiveness" of a driver and possibilities to avoid interactions altogether by changing the velocity and/or path slightly.

Our approach is designed to minimize this gap of knowledge and prediction by combining base topology and scene outcome prediction by measurements of reactions to small changes introduced by one of the vehicles. Depending on the reaction, the willingness to keep or change the kind of given situation is predicted and behavioral parameters classified. Base analysis of a scene tells whoever goes first, depending on difference of arrival times and right of way. Arrival times are calculated for an interaction area around the intersection point of trajectories. The first vehicle introduces a small change in its arrival time and then waits for a reaction. The type of response classifies behavior parameters of the other vehicle, leading to a better understanding of actively modifying a scenario and intention to cooperate with the first vehicle.

The paper is structured as follows. Section II presents the related work. In section III, we present our approach from initial base knowledge and interaction identification based on difference of Time to Arrival (ΔTTA). The actions and reactions develop in the derivative TTA', where changes can be see more clearly. The measured behavior refines the predicted outcome. In section IV, we present a validation of the approach based on real-world examples from the *Intersection Drone (inD)* dataset. We conclude with a review of our approach and discuss the future work.

II. Related Work

Road users' intention prediction has been researched broadly in different aspects as it is especially relevant for autonomous driving. Simulation environments as SUMO[5] include different approaches for simulation and have individual models for following, lane changes and intersections. These methods, as for example the Intelligent Driver Model (IDM), are often used in driver intention estimation. These can be enriched by action models as in [6] or tailored to fit intersection models better using velocity profiles [7], both showing promising results. Another approach are data-driven models using aggregated real world data. One of these is called DESIRE[8], a deep learning approach for interaction-awareness which includes multiple possible paths of vehicles to learn. The main downside is the sheer magnitude of samples needed for a completely learned world. Bayesian networks as in [9] use conditional probability tables to infer drivers intentions at intersections, but are limited to output rather limited information. In [10], a deep learning network is used to infer behavior to improve performance of Bayesian networks for prediction in urban settings. Another approach is to use LSTMs for intention prediction at intersections as shown by [11].

Direct inference of vehicle motion from optical flow has been performed by [12] to predict interactions at intersections and also considers multiple paths, but the time horizon is very short as it relies on visible action. A good overview of multiple current approaches is found in [13] with aspects of intentions and performed actions for motion planning.

Driver intention in merging scenarios was analyzed by [14] which featured dynamics to estimate behavioral parameters and outcome with a more global overview of *tactical driver behavior prediction* in [4].

In this paper, Time to Arrival (TTA) is used; it is based on the concept of Time To Collision (TTC) first introduced by Hayward [15] in 1972 directly from image data. Further research by Lee [16] has extended knowledge of accepted time gaps between vehicles and braking parameters.

In a previous work [17], we proposed an approach for vehicle-pedestrian interaction prediction which focuses on *interaction areas* at which an interaction likely will take place and analyzes temporal evolution. The topological analysis is adapted here for motorized traffic. However, there was no analysis of mutual influences on behavior and classification of behavioral parameters.

III. Approach

The approach consists of three phases: Phase one identifies possible interactions and a logical map of possible outcomes in a scenario. Here, static road topology is read from a map beforehand, enabling the search for possible trajectories of vehicles in the scene. Overlapping lane paths show possible interaction areas and are combined with information about Time to Arrival (TTA) and right-of way situation to create a map of possible trajectories and outcomes of each interaction. It is described in chapters III-A to III-B.

In phase two, one vehicle initiates a stimulus/behavior change to the scenario. It depends on legal and behavioral parameters such as right of way and aggressiveness of the driver. In most cases, the yielding vehicle acts first, as it is legally bound to first try to avoid a collision by changing behavior (mainly velocity). It is described in chapter III-C.

In phase three, the reaction of the opponent vehicle is awaited. It is measured first after a fixed reaction time and then reevaluated over a time period if changes occurs. The driver may be neutral or ignorant of the stimulus, which is handled by a classification as such after additional time. Based on the classified reaction type, a prediction about future behavior is done and compared against the actual evolution of the scenario. This phase is described in chapters III-D to III-E.

Figure 2 gives an overview of the three phases of a typical situation in terms of ΔTTA, which is the time gap between vehicles at the interaction area.

1. A vehicle approaches a yield sign and detects a vehicle being too close to safely pass in front.

2. It starts braking as a *stimulus*, pushing the time difference in favor of the other vehicle. The change is noticed by the other vehicle at reaction time t_{react}.

3. After $t_{measure}$, the behavior of the other vehicle is analyzed for expressed reaction. The other vehicle can ignore the first vehicle for a neutral/ignorant outcome or actively change the situation by accelerating (collaborative) or (mistakenly) brake for a critical disruptive behavior.

This separation enables the algorithm to pick a long-term high-level outcome at the very beginning from initial status and then classify driver's behavior profile at an early stage of

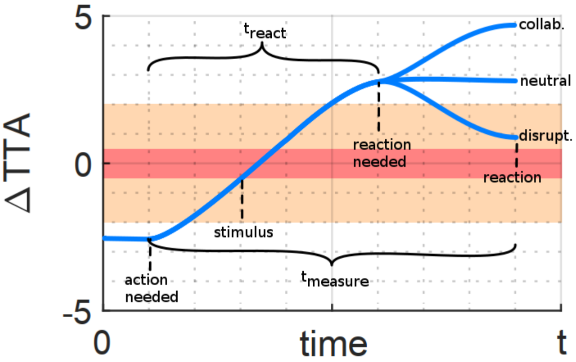

Fig. 2. Schematic three-phase approach: 1. An interaction situation is detected ($|\Delta TTA| < 10$). The first vehicle wants to go second ($\Delta TTA > 2$). 2. It brakes, pushing ΔTTA positive. 3. The other vehicle can react multiple ways, the behavior is measured after a reaction time at $t_{measure}$. The reaction is determined by the difference of change in ΔTTA caused by the first and second vehicle.

interaction, so that the outcome is refined and future behavior predicted more accurately.

This approach initial guess relies on previous work [17] from which interaction areas and TTA-wise thinking was used but extends further into the domain of a challenge of actions and reactions between the two drivers to determine behavior types in an interaction.

A. Identifying an interaction

At the beginning of planning, a static road map with topology information is needed. It includes lane numbers, turn options from each lane and all yield information for intersections with state-wide common laws included for otherwise undefined intersections.

Vehicles are usually bound to the road surface, so planned movement is following the road network and turning into other streets to get to a target position. Based on this information, a map of interaction areas as shown in Figure 3 is created locally where possible trajectories of vehicles may overlap. For each vehicle in a scene, the time to arrival to a reachable interaction area is calculated by

$$TTA = \frac{d}{\overline{v_0}} \tag{1}$$

in which d is the distance to the intersection point and $\overline{v_0}$ is the average of the expected velocity profile described in chapter III-A2.

For each pair of vehicles, ΔTTA for a common interaction area is calculated:

$$\Delta TTA = TTA_{veh_1} - TTA_{veh_2} = \begin{cases} < 0, & \text{veh1 first} \\ > 0, & \text{veh2 first} \end{cases} \tag{2}$$

An interaction is likely to happen with $|\Delta TTA| \leq 2s$ and possible with $|\Delta TTA| \leq 10s$.

1) Influences of topology: Figure 4 lists the three main yield situations between vehicles which may be encountered:
Right of way, yield or defined time-wise.
The first two are self-explanatory and often regulated by signs, the third is found at narrow passages as one-lane bridges or

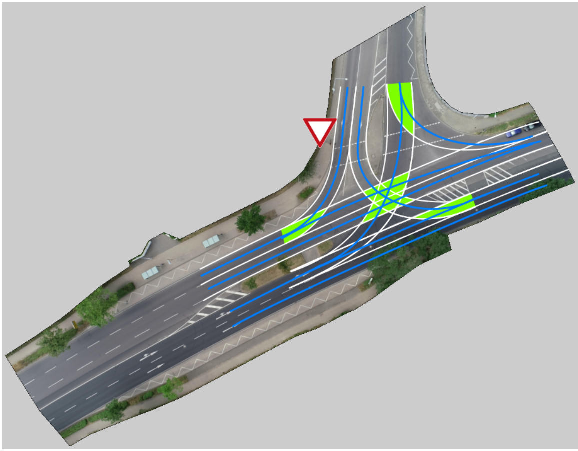

Fig. 3. Scenario 00/01 of inD data set: Set of all legal pathways (blue) with possible interaction/collision areas between two vehicles (green). Vehicles from top have to yield to other traffic.

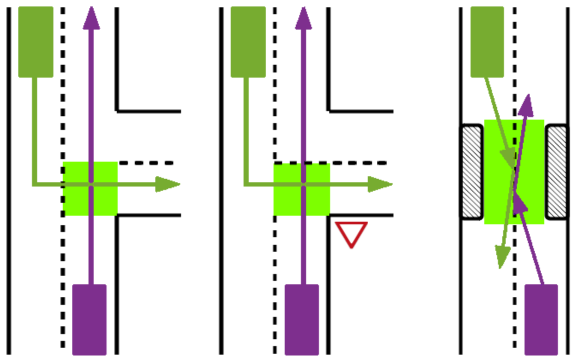

Fig. 4. Schematic overview of three yield situations from the first vehicle's perspective: LTR: Having right of way, yield to other vehicle, first to come. First vehicle in purple, other vehicle in green.

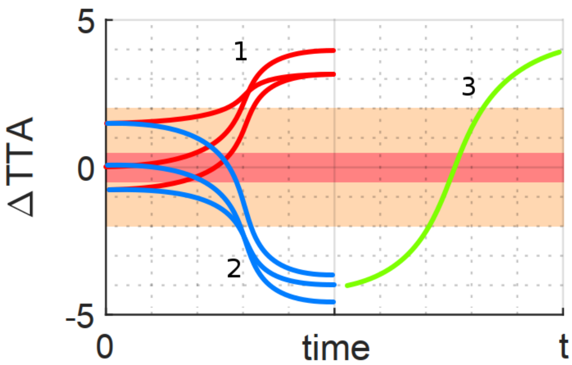

Fig. 5. Schematic temporal evolutions for different outcomes of an interaction from a vehicle's perspective: 1/2: Passing behind/in front the other vehicle from different start values. 3: Sharp braking to let a vehicle pass, especially in yield situations.

at four-way stops. In latter cases, usually the vehicle arriving first has the right of way.

2) Velocity profile: Topology also influences an expected initial velocity profile v_0. For (nearly) straight roads, the vehicles are set in a constant velocity model v or may accelerate to $0 < v < v_{maxAllowed} + 5m/s$ which includes speeding 11mph/18km/h over the limit. For vehicles speeding faster, a conservative approach of "don't pass in front" should be implemented, as not to come into the path of a dangerous driver. According to statistics by the UK government[18], this includes only 6-7% of cars/LCVs on 30mph roads, so it seems applicable as a threshold. For cornering, the theoretical maximum velocity of a vehicle is defined by NHTSA for level surfaces is

$$v_{max} = \sqrt{\frac{g \cdot \mu_{lat}}{\rho}} \tag{3}$$

with g being the gravity, ρ the road curvature and μ_{lat} the maximum side friction between the wheels and the ground.

However, this is the absolute maximum value a vehicle can physically corner and not useful for estimation. Another approach is to take the planned top speed of a corner, which should be below 15mph or 6.7m/s according to NACTO[19]. The velocity profile v_0 is set to decelerate at a constant rate b from velocity v and arrive at cornering speed:

$$b = \frac{v - 6.7}{d_{corner}/v} \tag{4}$$

with d_{corner} being the distance to the beginning of the intersection and following through with a fixed value of 6.7m/s.

3) Safe passing distances: To account for occupation time, input noise and safe clearance distance between vehicles, a buffer is kept between two vehicles.

$$|\Delta TTA| \leq \begin{cases} 0.5s, & \text{collision} \\ 2.0s & \text{close call} \end{cases} \tag{5}$$

of which the first needs to be avoided at all cost. Close calls are unsafe maneuvers to be avoided but may occur in measurements.

The actual value of ΔTTA when the first party arrives at the interaction area is an indicator for level of perceived security/risk acceptance. Real data seems to show dependencies on traffic situation, initial velocity and driver's skill. Further research is needed for improved values, as it seems that vehicles with yield signs tend to wait longer.

B. Expected and possible outcomes

Figure 4 shows the three different scenarios mentioned, possible outcomes in the domain of ΔTTA are shown in Figure 5.

For all situations, $|\Delta TTA| \leq 2s$, so an interaction is needed to keep a safe passing distance between vehicles. Expected velocity profiles of vehicles are defined as v_{0veh1} and v_{0veh2}

The expected outcome for the first two scenarios is the lawful yield of the respective vehicle. In the third option, both parties need to agree on an outcome.

In the first scenario, the first vehicle has right of way, so a temporal evolution and outcome of type 2 is expected, the other vehicle probably will wait.

The middle scenario has a yield sign for the first vehicle, so the natural behavior is outcome 1 or even 3 for a defensive driver as merging sharply at a yield sign can be insecure. The initially expected outcome is similar to before, with the other vehicle going first.

For the third situation, both parties need to agree on who goes first, as they both may arrive at the interaction area at the same time. Depending on levels of passive or aggressive behavior, one vehicle will need to let the other pass, so either behavior 1 or 2 is seen. In this case, the outcome does not define a vehicle to go first yet, it has to be chosen later. This approach is limited and would be very complex for all possible scenarios, so it is generalized to a tow-step action/stimulus by one vehicle and the reaction of the other vehicle in the next sections.

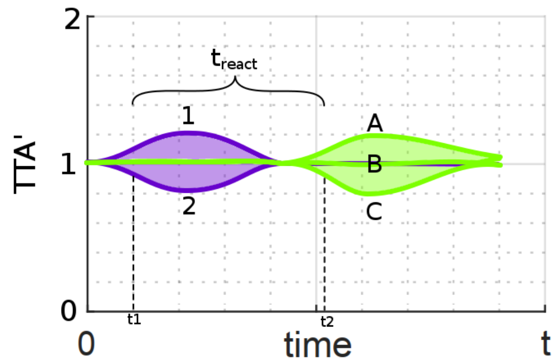

Fig. 6. Schematic example of a stimulus of the first vehicle (purple) and reaction by the other vehicle (green). First applies a change to its own TTA at t1 by reaching the intersection area faster/slower (1/2). The other vehicle may react at t2 by changing its TTA to earlier/same/later (A/B/C). The reaction time is measured between the two changes. No change (B) is set after a reaction time of 2s has passed.

C. Initial stimulus

As for different cases (having right of way, yielding or undefined), different analyses of curvatures would be needed, further analysis is set in TTA' of each vehicle to see the individual behavior more clearly - compare the simplification in Figures 5 to 6.

$$TTA' = \frac{TTA(t) - TTA(t + \Delta t)}{\Delta t} \tag{6}$$

It expresses a change in velocity by means of change to the Time to Arrival per time step (compared to the expected velocity profile v_0).

$$TTA' = \begin{cases} < 1, & \text{vehicle slows down} \\ = 1, & \text{expected velocity} \\ > 1, & \text{vehicle accelerates} \end{cases} \tag{7}$$

It is an indicator if a vehicle actively changes behavior to change its TTA, thus changing the interaction.

In each interaction situation, one of the vehicles is the first to react. For an autonomous vehicle, it should be able to first introduce a stimulus to the interaction, a small but noticeable change to its own arrival time.

In Figure 6, the purple first vehicle has two options to choose as initial action: It may either accelerate/keep momentum/take a shorter route to be at the intersection earlier (1) or slow down to be there later, often to signalize a yield situation (2). In terms of TTA', these actions increase or decrease the value. For a vehicle with right of way, the option "keep the anticipated velocity profile" is possible, but discarded here, as the stimulus would then begin with the other vehicle initiating a stimulus and the first vehicle possibly reacting to it (or staying neutral).

1) Stimuli for autonomous vehicles: For an autonomous vehicle it will be necessary to pick the most favorable option for both outcome and action to signalize its decision to the other vehicle. Based on the current data set, human drivers show different behavior patterns in real scenarios. There is a need for predefined behavior patterns which to expect from an autonomous vehicle for it to be perceived as driving safe but "naturally". These may include active or even assertive behavior in certain situations, as strict passive behavior is safe for the passengers but also takes longer to reach a destination. In some scenarios as in Scenario 5 (Figure 12) the early clearing of the intersection enables a smoother ride compared to coming to a full stop to wait for traffic.

D. Measuring the reaction to behavior

Behavior parameters are defined as

$$B_{veh} = \begin{cases} passive, active \\ collaborative, neutral, disruptive \end{cases} \quad (8)$$

where the initial values are $B_{veh} = [passive, neutral]$.

To determine the will of collaboration, the reaction $\Delta TTA'$ of the other driver is measured after a time period $T_{react} = 1s$. This time is needed as the driver first needs to register that the first vehicle has changed behavior and then also needs to have time to react as intended. If no reaction is visible there, reaction is awaited for another second in intervals of 0.1s. If still no change seen, the reaction is defined as $B_2 = [passive, neutral]$.

$$\Delta TTA'_{veh} = TTA'_{veh}(t_1 + t_{react}) - TTA'_{veh}(t_1) \quad (9)$$

In Figure 6, three reactions are shown to a stimulus: active acceleration, passive neutral and active deceleration. Active behavior can be a collaborative or disruptive option.

$$B_{veh} = \begin{cases} collab., & s(TTA'_2 - 1) \neq s(TTA'_1 - 1) \\ neutral, & (TTA'_2) \approx 1 \\ disruptive, & s(TTA'_2 - 1) = s(TTA'_1 - 1) \end{cases} \quad (10)$$

With s being the sign/signum function. $TTA' - 1$ is used because at expected velocity real TTA evolves exactly the same as expected TTA from v_0, so the neutral gradient of the function is 1.

The collaborative option is changing TTA'_2 in the opposite direction of TTA'_1, as it means reaching the interaction area faster when the other is slowing down or vice versa. In terms of ΔTTA, both vehicles push in the same direction, usually to widen the time gap between them, virtually agreeing on an outcome (which may be different than the initial one).

Disruptive behavior is defined if the reaction is in the same direction as the stimulus with $TTA'_2 \approx TTA'_2$, so the ΔTTA stays the same. As long as ΔTTA does not approach zero at TTA, no additional reaction is needed but may be considered.

In Figure 6, collaborative behavior are pairs 1A and 2C, disruptive 1C and 2A.

In the real world, this behavior is intuitive for a human driver: Changes in TTA are clear signals of a driver trying to pass or yield in a situation, a human assumes that a driver will drive according to the law and will only intervene if the situation seems unusual and/or critical. This is exactly the case when disruptive or incorrect behavior is observed, either by an inattentive driver (playing on the phone or similar) or by reckless driving.

E. Prediction and Reevaluation

The two-step function of stimulus and reaction enables the algorithm to predict the most probable outcome as the two initial actions are assumed to be kept valid for the rest of the scene. The outcome is only changed if the vehicle will have enough time clearance to pass in front, with $\Delta TTA(TTA_{min}) > 2s$, calculated as:

$$\Delta TTA(C) = \Delta TTA + \Delta TTA' \cdot min(TTA_2, TTA_1) \quad (11)$$

With $C = min(TTA_2, TTA_1)$ - the moment of the first vehicle to arrive. This guarantees that the gap is large enough from both vehicles perspective for a vehicle to pass in front of the other.

Nevertheless, the predicted outcome needs to be reevaluated if situations change unexpectedly. This may include just incorrect prediction: The other vehicle may mot intend to take the planned path at all but go for other options in the scene. An example would be for a yielding vehicle to slow down for oncoming traffic but the other vehicle slowing down too for a right turn. Due to these cases, it is necessary to include more than one interaction area for analysis. In the above case, if all possible interactions are considered, the velocity profile v_0 for the interaction of a right turn would turn out to match better than going straight, making this interaction more probable.

IV. RESULTS

This chapter is split into two parts: First, the underlying map and scenario data is explained. Then, analysis of outcomes in chosen scenarios is performed.

A. Test Environment

For verification, a test environment with a suitable amount of suitable examples is necessary with different situations and different behavior and outcomes.

1) Databases: Although many data sets are available for research, steady intersection data is quite rare or deprecated. Data sets recorded on-board are often unavailable in total as *Cityscapes*[20] or feature just rather short segments with few interactions as *KITTI*[21]. Moreover, camera setups with ground truth focus towards the front which e.g. means an interaction behind or to the side of the vehicle is not visible in-camera.

a) InD data set: The Intersection Drone data set [22] is quite new and has several benefits such as unobstructed data from above where multiple intersections are covered several times with accurate labeling and continuous data. This allows for early and reliable knowledge about traffic, not limited the one test vehicle which just needs to be in the perfect spot to see an interaction. Each vehicle can be defined as the first vehicle and the scene defined from its view. This also eliminates unusual behavior towards a strange looking vehicle with sensors mounted everywhere. Also different driver types are modeled each time, covering more test cases. The data set includes the track data itself and added meta data for each track which includes lane definitions for both real and virtual lane markings. Latter are the tracks e.g. a turning vehicle should stay in without them being painted visibly on the street.

b) OpenStreetMap: Topology information is extracted from OpenStreetMap [23] around the GPS coordinates found in the meta data of each data set. For this setup information about right of way rules are extracted, loosely based on Filippidis [24].

c) Velocity profiles: Velocity profiles are determined as stated in chapter III-A2. Here, the whole scenario is classified by start and goal positions of vehicles, creating velocity profiles for corners, which are then normalized for the initial speed of vehicles to create v_0 profiles e.g. for going straight or turning left/right. By this, a vehicle with a velocity v at any position can be assigned a "standard" profile until further knowledge is gained.

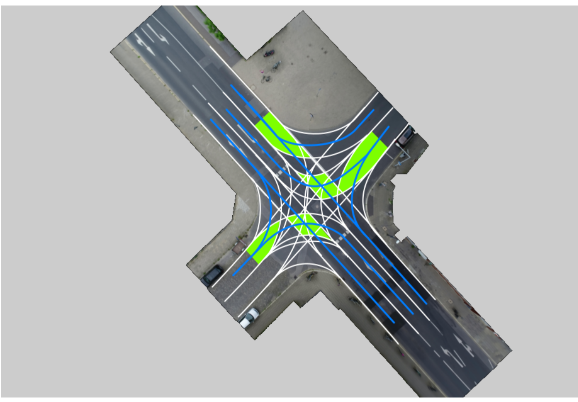

Fig. 7. Scenario 08 of inD data set: Set of all legal lanes for driving (defined by lane markings or virtual boundaries) in white. Subset of all possible pathways in blue for vehicles with possible interaction areas between these in green, defined by overlapping lanes to be occupied by both vehicles.

d) Trajectory extraction: The creators of the inD data set include thorough information about each vehicle as center position, heading and velocity. These are then synchronized with topology data for lane estimation and to predict possible velocity profiles for different intended goals.

B. Chosen scenarios

For validation, five examples of applicability have been chosen. First, two examples show typical yielding behavior at an intersection, coming to a full stop. One example shows active interaction between two vehicles where the yielding vehicle just slows down but does not stop at the intersection. One example shows behavior when the yielding vehicle realizes that the other vehicle will turn and thus not interfere anymore. The last example shows active collaboration via acceleration of the other vehicle.

The Scenarios are vehicles X, Y with X to yield for Y:
1. $314, 316$ in scenario 00: X wants to turn left with Y from the opposite direction (Fig.1).
2. $254, 253$ in scenario 00: X comes from the top, turning right, Y comes from the right going straight.
3. $176, 181$ in scenario 00: as 3.
4. $160, 159$ in scenario 08: X comes from the bottom right, turning left with Y from opposite direction. (Fig. 7).
5. $176, 181$ in scenario 08: X comes from top left and wants to turn left, Y from opposite direction.

All examples are chosen that the first vehicle is the one to yield at the intersection in the initial configuration. This implies that it introduces a stimulus to the situation and awaits a reaction. With swapped vehicles, the initial reaction still is expected from the yielding vehicle as mentioned in chapter III-C and the vehicle with right of way is usually neutral at the beginning. For validation, these scenarios are also more interesting as having right of way because just ignoring the other vehicle is an accepted answer there.

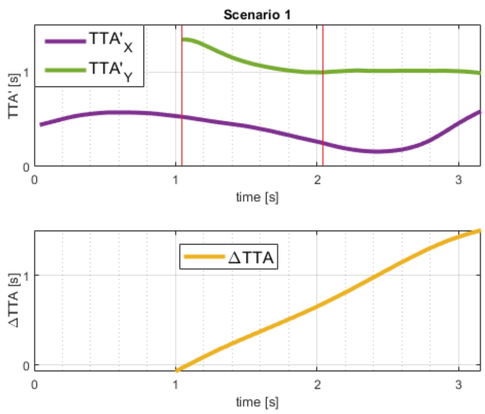

Fig. 8. Scenario 1, top: changes over time in TTA' for both vehicles, bottom: ΔTTA between the two vehicles. t1 and t2 highlighted in red.

Scenario 1 in Figure 8 is a typical scenario in traffic. At detection (t1), $\Delta TTA \approx 0$, so the expected outcome is Y to go first, as it has right of way. The first vehicle X decelerates sharply for the oncoming traffic as indicated by its low value $TTA' < 1$. Y accelerates a bit first, but it slows its acceleration and keeps a constant velocity from $t = 1.8s$ and on. It reaches the interaction area at $t = 3.18s$, the time gap being under 1.5s, a close call. The resulting parameters thus are $B_Y = [passive, neutral]$. The outcome is just as predicted at first.

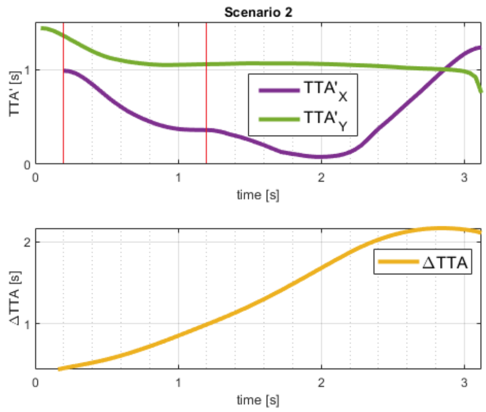

Fig. 9. Scenario 2, top: changes over time in TTA' for both vehicles, bottom: ΔTTA between the two vehicles. t1 and t2 highlighted in red.

The second scenario in Figure IV-B shows a typical "merge behind a vehicle" situation: The first driver sees a yield sign and an approaching vehicle. The driver brakes, as seen by the sharp decline of TTA' value. Here, TTA'_Y clearly is above one, so the other vehicle also accelerates, collaborating with the first vehicle with $B_Y = [active, collaborative]$. This enables X to slow down less, seen by the rise of TTA' after $t \approx 2.2s$. The outcome is as expected and $\Delta TTA(TTA_Y) > 2s$, so it is a safe passing when the first vehicle Y arrives at the interaction area.

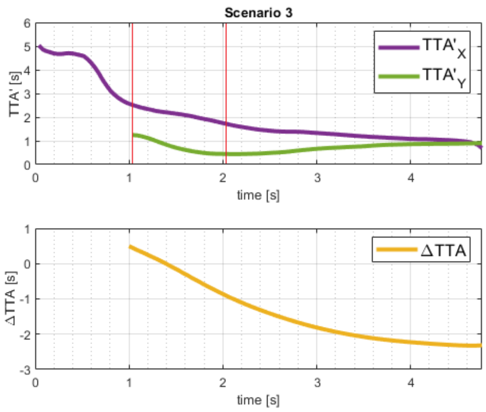

Fig. 10. Scenario 3, top: changes over time in TTA' for both vehicles, bottom: ΔTTA between the two vehicles. t1 and t2 highlighted in red.

In the third scenario (Figure 10), the first vehicle approaches a yield sign but decides to go before the other vehicle. Its interaction point is further down the road, as it has a "head start" in front of the other. It accelerates sharply and keeps accelerating over the whole period. With a $\Delta TTA \approx 0.5s$ it is not in favor of the interaction at the beginning but uses sharp acceleration for its own benefit. The reaction of the other vehicle is collaborative by slowing down to let the first vehicle merge in more easily, $TTA'_Y(t2) < 1$, both push ΔTTA in negative direction for the first vehicle to go first. Again, $B_Y = [active, collaborative]$.

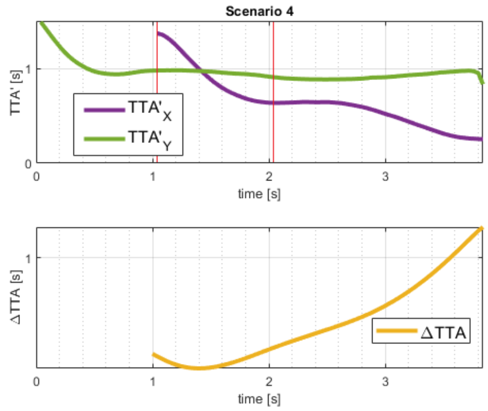

Fig. 11. Scenario 4, top: changes over time in TTA' for both vehicles, bottom: ΔTTA between the two vehicles. t1 and t2 highlighted in red.

The last two scenarios have similar start and end configurations but show different parameters of collaboration. In scenario 4 (Figure 11), the initial ΔTTA is close to zero, so an interaction needs to take place. The first vehicle brakes, but the other vehicle also decelerates with $TTA'_Y < 1$, so that the first vehicle needs to brake even sharper to let Y pass. ΔTTA just rises above one second in the end. The behavior parameters for Y thus are $B_Y = [active, disruptive]$.

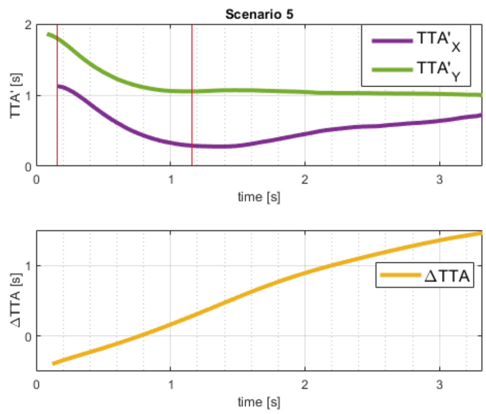

Fig. 12. Scenario 5, top: changes over time in TTA' for both vehicles, bottom: ΔTTA between the two vehicles. t1 and t2 highlighted in red.

In the last scenario (Figure 12), the initial $\Delta TTA \approx 0$ is similar to the one before, so the first vehicle starts braking. However, the other vehicle accelerates slightly for the whole time, so that the first vehicle can even slow down less than anticipated with a similar outcome. Here, the other vehicle has collaborated actively with the first vehicle for a correctly predicted behavior $B_Y = [active, collaborative]$.

V. CONCLUSIONS

The validation of the approach shows that the idea of the interdependence of actions and reactions between vehicles is feasible for prediction of drivers' intention and situation outcome. The first part of topology extraction is already useful for ADAS systems as these can just focus on intersection regions with other traffic together with possible paths in a scenario. Interactions are found early purely on ΔTTA knowledge, enabling countermeasures to avoid collision.

Our approach of a performed action and measurement of a possible reaction in terms of TTA' is feasible for more detailed prediction as intrinsic driving parameters can be estimated. Parametrization of drivers' intentions can then be used for refinement of the base assumptions of driving behavior (e.g. allowing shorter gaps or demanding longer gaps in certain situations).

For an autonomous system, this mechanism is very useful to assess possible smooth and comfortable trajectories through a scene as it may use perceived collaboration or disruption for its own planning. It does not need to rely on fixed time gap values to pass but may detect a collaborative driver to pass first at an intersection. It could speed up or slow down slightly at an intersection so that a yielding vehicle could pass more easily. This enables new ways of path planning and collaborative outcomes in a scenario.

As byproducts, analysis of possible paths is performed to match unexpected behavior to a better fitting trajectory which may no longer interfere with the first vehicle plans.

The validation was done on top view drone data, but a real vehicle could use LIDAR or stereo camera sensors for the same result, as only vehicles which see each other can interact as shown in the approach. Topological data (roads, lanes, interaction areas etc.) should be included in a HD map in the vehicle and could updated by onboard systems or communication devices as C2C/C2I/C2X.

Future analysis should include broader search for interactions, as the inD data set is currently unstructured by means of scenarios. This would diversify the very long scenes into categories of interactions which would improve availability for other approaches. The verification of the approach was performed on real driver's behavior. For an automated system, intrinsic logic for dealing with situations should be defined as mentioned in Chapter III-C1.

The availability of drones and high definition cameras will enable easier data set generation for more and diversified scenarios in the future.

The capability of the approach can be specialized by decreasing the necessary input to perform the task so that simpler and less expensive sensor systems could be used to determine a similar output.

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