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Rule-Based Decision-Making System for Autonomous Vehicles at Intersections with Mixed Traffic Environment

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***Abstract*— Before autonomous vehicles are widely spread, they will share the roads with non-autonomous cars. Furthermore, to ensure functional safety of the self-driving cars, the cause of decision-making and control algorithms' failure must be precisely identified. Rule-based methods are promising solutions due to their transparency and comprehensibility. In this paper, a rule-based decision-making system for autonomous vehicles solving a challenge of complex intersection with mixed driving environment is proposed. The system is designed to prioritize road safety and avoid collision with other road users at any cost. The proposed algorithm relies only on available on-board perception and localization sensors, allowing the automated car to operate among human-driven vehicle and without vehicle-to-vehicle communication technology. The system is validated in a simulation study on cross-intersection, where the ego vehicle deals with multiple cars arriving from different sides of the road. The results demonstrate algorithm's robustness and effectiveness under multiple scenarios, when neither intention nor trajectory of other traffic participants is known. Thus, the proposed solution is also potentially applicable to other types of intersections with different traffic rules.**

I. INTRODUCTION

Rapidly evolving autonomous vehicle (AV) and intelligent transportation technologies are set to significantly change the way of human and goods transportation. In addition to comfort and efficiency, AVs provide a vital improvement in traffic safety. Furthermore, the technology will allow people to dedicate their time to more pleasant activities instead of driving in traffic congestion. Yet, the first AVs will collaborate with human-driven vehicles. Thus, development of a decision-making system (DMS), which mimics experienced human driver and allows AV's to coexist together with non-AVs in mixed ecosystem, poses a great challenge.

The learning-based algorithms that rely on quality data tend to be efficient in DMS design. These algorithms, however, induce problems for practical application, because they serve as a black box. Therefore, they are challenged with functional safety compatibility. Rule-based (RB) methods, despite being more complicated, are transparent and clearly defined by set of rules and equations, meaning that the reasons for system failure can be easily observed and even eliminated in advance [1].

An intersection crossing is one of the most challenging tasks for AV. Among the most popular automation methods to tackle this problem are RB, optimization, hybrid, and machine learning [2]. These solutions, though, rely on connected and pure AV traffics. Hence, a DMS supported by modern infrastructure and reliable for given traffic conditions (i.e., for contemporary mixed traffic environment), which is concurrently intelligible for safety provision, is still missing.

Many scholars focused on solving intersection crossing for heterogeneous traffic. One approach is to predict the intention of other non-AVs [3], [4]. An integrated behavioral anticipation and DMS that models behavior for AV and nearby non-AV was developed in [5]. Proposed in [6] AV DMS tends to predict uncertain behavior of surrounding road users. A prediction model of the stochastic occupancy of the road by other human drivers for safety of planned paths of an AV with respect to the movement of other traffic participants was developed in [7]. A logistic regression model was introduced to get the probabilities of other vehicles' intentions [8], [9]. Samyeul Noh described a framework, which uses a digital map to predict future paths of observed vehicles [10]. With an assumption that the path of each vehicle at intersection is known, a combination of optimal control and model-based heuristics was studied in [11]. In [12], the authors proposed a game-theoretic DMS policy of multiple AVs at an unsignalized intersection assuming that every vehicle knows which way each other car is planning to use. Drivers' intention prediction effort, however, includes a number of indispensable limitations. Firstly, in reality the vehicles do not move independently from each other: especially at the intersections, where vehicle's maneuvers strongly depend on another traffic participants. Secondly, they are described by strictly deterministic representation of time. Thirdly, due to uncertainty of the data and models the approaches suffer from reliable real-time risk estimation of a traffic situation. Finally, these methods experience several challenges related to computational burden, verification and validation, safety, and many others.

Recurrent neural networks combined with a mixture density network were applied to AV at an intersection [13]. In [14], the AV DMS relies on an information (i.e., position, speed, and turning intention) from other manually driven traffic members. A human-like DMS was built up from human drivers recordings in [15]. Still, the main drawback of these solutions is their dependence on either preliminary collected data or a strong assumption that the required information for efficient algorithm implementation is tracked in real time (i.e., for interconnected vehicles and infrastructure).

Promising methods are based on a set of logical rules representing expert's knowledge [2], e.g., computational intelligence algorithms [16] and [17]. An intersection maneu-

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ver for an AV was proposed to break down to a set of four primary situations, in which every case contains the required information to execute the whole maneuver [18]. In [19], a method to model the state space of an ego AV in a semantic way was proposed. A hybrid method, which includes a knowledge on scenario state combined with a RB was applied to determine actions of an AV in [20]. An ontology-based DMS was introduced in [21] and [22] with the assumption that other vehicle's intended driving direction is observable. Finally, another noticeable RB solution for AV's DMS at unprotected crosswalk was delivered in [23]. Still these methods were demonstrated only for simple scenarios. In most of the cases an AV engaged with a single human-operated vehicle. Therefore, the robustness to complex traffic environment, such as sealing with multiple vehicle approaching an intersection from various directions, was not stressed.

In this paper, a DMS for AV on cross-intersection with mixed traffic participants is introduced. The system is completed with RB approach prioritizing road safety and designed to mitigate traffic accident at any cost. The algorithm allows for tracking multiple vehicles at the same time, thus, solving an intersection crossing maneuver step-by-step in a human-driver-like nature without utilizing preliminary collected data set. Thus, precisely defined rules may be investigated on system safety. Furthermore, taking into account limitations of the related works, the DMS proposed in this paper is characterized by:

- The proposed algorithm consists of two parts: a policy for interacting with a single other vehicle, and a general policy for multiple vehicles that combines multiple individual policies making it easily adaptable to other types of intersections and any number of other vehicles.
- The method does not depend on prediction of other vehicles' intentions nor on vehicle-to-vehicle or vehicle-to-infrastructure communication, and other vehicles are observed with available on-board perception and localization sensors.
- The AV completes unprotected left turn maneuver at cross intersection with multiple other vehicles approaching from different directions simultaneously.
- For complexity, other vehicles drive on a main road, hence, the ego AV should give way to all cars before completing the maneuver.

The paper is structured as follows. The problem statement is delivered in the next Section. Section III is dedicated to the proposed RB DMS. Simulation environment and experiment results are presented in Section IV. The paper is concluded in Section V.

II. PROBLEM STATEMENT

In this paper, a scenario, where vehicles arrive at a cross-intersection from each legs at the same time is considered. The goal of the ego vehicle is to complete a desired maneuver not causing a collision with other non-AVs. Furthermore, the AV must drive obeying all traffic rules and accomplish the task without unnecessary delays. Finally, it shall not disturb other vehicles' intentions, which are not known to the AV.

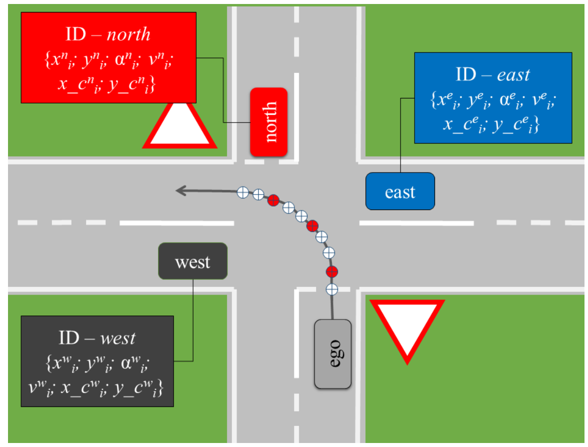


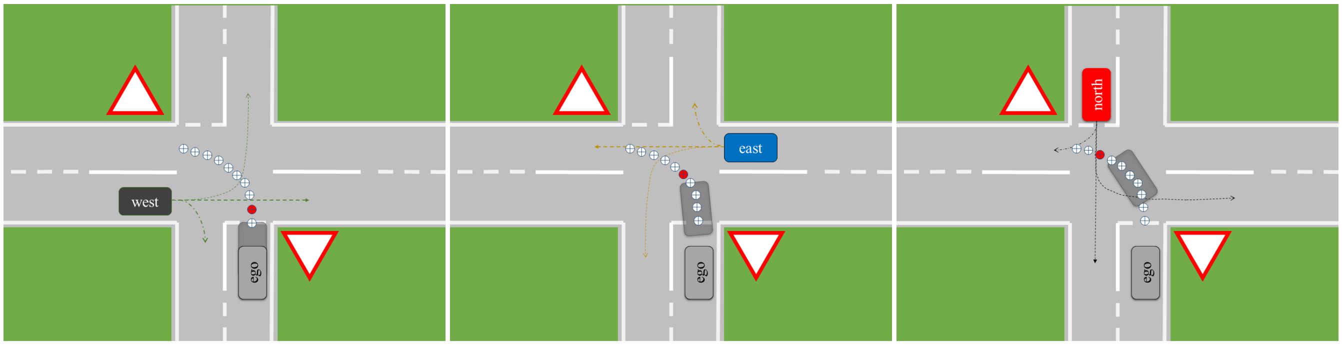
Fig. 1: A cross-intersection with three cars, N_i^{west}, N_i^{east}, N_i^{north}, approaching from multiple directions. Ego AV, N^{ego}, is coming from the south.

The environment contains a set of agents $\mathcal{N} = \{N^{ego},\ N_0,\ ...,\ N_I\}$, with $I \in \mathbb{N}_0$ and the ego AV - N^{ego}. Every other non-AV N_i, with $i \in \{0,\ ...,\ I\}$, and with $i = 0$ meaning that the car does not belong to the intersection area, has a set of observed parameters $\mathcal{P} = \{p^0,\ ...,\ p^J\}$, with $J \in \mathbb{N}_0$, $p^j = \{x^j;\ y^j;\ \alpha^j;\ v^j;\ x\_c^j;\ y\_c^j\}$, and with $j \in \{0,\ ...,\ J\}$ defining a number of intersection legs (i.e., in our case study $j \in \{west,\ east,\ north\}$). Variables $x^j,\ y^j,\ \alpha^j,\ v^j,\ x\_c^j,\ y\_c^j \in \mathbb{R}^2$ are relative to the ego AV dynamic x and y coordinates, angle position, velocity, and static x_c and y_c coordinates of the potential cross point with the ego AV at the intersection. Each non-AV drives with speed $v_i^j(t) \in [0,\ v_{max})$ for time $t \in [0,\ \infty)$. The parameters of the ego AV $p^{ego} = \{x^{ego};\ y^{ego};\ v^{ego};\ \mathcal{W}\}$, with $ego \in \mathbb{N}_0$, and with $x^{ego},\ y^{ego},\ v^{ego} \in \mathbb{R}^2$ being AV's x and y coordinates and velocity. The ego vehicle N^{ego} contains a set of waypoints $\mathcal{W} = \{w_0^x,\ w_0^y,\ ...,\ w_M^x,\ w_M^y\}$, with $M \in \mathbb{N}_0$, and $m \in \{0,\ ...,\ M\}$, and $w_m^x,\ w_m^y \in \mathbb{R}^2$ being global x and y coordinates of the ego AV's route planned before the journey.

The AV behaves in accordance to a set of actions $egoAction = [Drive,\ Brake]$. The simplified DMS rule for N^{ego} velocity v^{ego} is defined as follows:

$$v^{ego} = \begin{cases} v_{speed\_limit} & \text{if } egoAction = Drive \\ 0 & \text{if } egoAction = Brake \end{cases} \quad (1)$$

where system's contribution is to decelerate the AV, when the collision hazard situation appears. Otherwise, the control holds speed of the vehicle fixed by the speed limit of the road segment v_{speed_limit}. The task of the DMS is to execute $Brake$ command before the collision occurs and at the same time allowing the ego AV to complete the route defined by the set of waypoints $\mathcal{W}$ as fast as feasible, yet not exceeding the v_{speed_limit}. It must be mentioned that the introduced



(a) (b) (c)

Fig. 2: Stopping waypoint at an intersection before potential conflict with approaching non-AV: (a) ego versus N_1^{west}; (b) ego versus N_1^{east}; (c) ego versus N_1^{north}.

DMS does not solve the continuous output of the vehicle deceleration.

The studied scene is denoted in Fig. 1 for $i = 1$ and $j = (west,\ east,\ north)$. The ego's N^{ego} intention is to perform left turn maneuver. Therefore, according to the intersection traffic rules the AV must give a road to all approaching road users from *west*, *east*, and *north* directions. For simplicity only one non-AV comes from each side of the road, however, the traffic can be also much more dense. For this, the AV utilizes information about the environment $\mathcal{N}$, and extracts required parameters $\mathcal{P}$ from the available sensors: distance, speed and angle position relative to the vehicles observed in front. The DMS is also based on static information about the intersection geometry, AV's set of waypoints, which it follows to reach its final destination, and traffic rules of the intersection. Moreover, the number of existing dynamic objects is required, including their velocities and geometric locations. The angle position is useful to determine the direction a non-AV drives from (i.e., west, east or north).

From a human driver's point of view, it is not efficient to stay in front of the "Give Way" traffic sign without entering the intersection until all other traffic participants leave the road. The most realistic behavior is to let vehicles arriving from the *west* and *east* pass first. Then drive in the middle of the intersection allowing the *north* vehicle to complete its maneuver. The ego AV must also ensure that it will neither block the way for other cars nor cause a collision with them. When all these constraints are matched, the ego vehicle may finish the unprotected left turn maneuver.

Remark 1: the described solution assumes that (a) all vehicles entering the intersection drive according to the traffic rules; (b) no sensor failures occur; (c) the information about the intersection (e.g., dimensions and traffic rules) is available and accurate.

III. DECISION-MAKING SYSTEM

A. System Description

The DMS is designed to complete the left turn avoiding collision with other vehicles at a cross-intersection. A local planning trajectory algorithm is applied to generate a set of waypoints passing through the intersection. In this paper, the A^* search algorithm is used. Foremost, the data about an intersection is essential, because it gives the AV a location of a waypoint passing through the intersection $\{x\_c_i^j,\ y\_c_i^j\}$, where the AV has a potential conflict with other vehicles.

The DMS consists of a general policy potentially applicable to any other intersection shape, and of a sub-policies, which are true for different actors N_i located at the intersection. The ego AV decides its action for each vehicle coming from any side of an intersection separately. Further, these acts are combined together and executed in an order creating a general policy for intersection crossing. Moreover, outside of the general and sub-policies, the AV mitigates collision with any object appearing in front of it.

Right before entering the intersection, the AV identifies surrounding vehicles. Using the information about the intersection and its own route, the AV labels the position of potential conflict locations with other vehicles. In Fig. 2, these critical waypoints are highlighted with red color and are shown for each human driven vehicle separately. For example, the collision point with a car coming from *west* is right before AV's intersection entrance (Fig. 2a). It means that the AV may drive no further than this place not to endanger *west* car's trajectory despite the direction of *west's* heading. Possible directions of each intersection participant is also derived in Fig. 2. The same idea applies to other vehicles driving from *east* or *north*. The AV knows *a priori* the potential collision locations from the list of its waypoints. These locations are also marked with red for *east* and *north* vehicles in Fig. 2b and Fig. 2c, respectively. Thus, the AV may continue driving and stop before the red waypoint (its stopping position is shown as transparent car in Fig. 2).

B. General Policy for Intersection Crossing

A general policy for various intersection types crossing is introduced in Algorithm 1. The main idea is to receive the action command to $Drive$ from each observed vehicle at the intersection i from every intersection leg j. The algorithm scans the policy starting from the first p_i^j, who has a set of

Algorithm 1: General policy for i vehicle and j intersection leg

Data: List of observed vehicles $\mathcal{N}$; measured parameters of the observed vehicles $\mathcal{P}$; ego AV's parameters including route waypoints p^{ego}; intersection geometry; intersection rules.
Result: Longitudinal behaviour for AV

$ego \leftarrow Drive$;
while N^{ego} *is at intersecition* **do**
  for j *in* $\{west,\ east,\ north,\ ...\}$ **do**
    while $x^{ego},\ y^{ego} \neq x\_c^j,\ y\_c^j$ **do**
      $v^{ego} \leftarrow v_{speed\_limit}$;
      for i *in* $\mathcal{N}$ **do**
        $egoAction \leftarrow SubPolicy(p_i^j;\ p^{ego})$;
        if *egoAction = Brake* **then**
          $v^{ego} \leftarrow 0$;

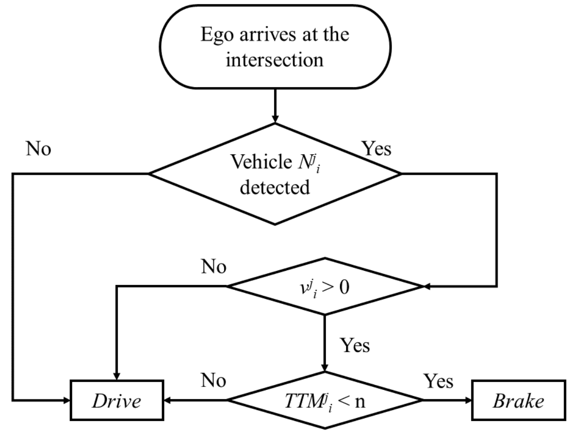


Fig. 3: Decision-making system flowchart for a single non-AV N_i^j ($SubPolicy(\cdot)$).

conflicting waypoints $\{x\_c^j;\ y\_c^j\}$ closer to the ego AV. It starts from the most critical one $j = west$ and ends with $j = north$ in our case study. The ego AV must receive a command, which allows to drive ahead, from each individual policy. Whenever any of these policies outputs $Brake$ command, the AV immediately stops. Otherwise, the AV drives until the designated point, and waits there for the next single policy driving permission from other leg of the intersection. For example, if there is no vehicle in the west (i.e., for N_i^j $j = west$ and $i = 0$), the $SubPolicy$ outputs $Drive$ command. However, it is only allowed to drive until the next stopping waypoint, which conflicts with the next vehicle, N_i^{east}. Before AV continues forward, it checks the policy from all vehicles in the east N_i^{east} and then in the north N_i^{north} (Algorithm 1). Moreover, it is important to note that each individual policy $Brake$ command allows to drive until the conflict waypoint at the intersection.

In short, the ego AV must obtain $Drive$ command from each conflicting side of the road. It prioritizes policy request depending on emerging conflict with other vehicle. Hence, a human-like reasoning is modeled, when human driver would first of all make sure that the road from *west* is safe to drive, than from *east*, and finally from *north* in accordance to the given traffic rules.

In addition to general intersection policy, the algorithm includes also a collision avoidance safety measure. It is applied not only at the intersection, but also driving on other road segments regardless of the traffic rules. This safety aspect demands AV to stop by any means if any object (i.e., static or dynamic) is in a short distance in front of it. Thus, even if the DMS decides to drive forward (e.g., when traffic rules do not oblige to give way to other non-AVs), the ego AV will stop in front of the object ahead. Hence, the potential collision will be avoided, when another car mistakenly or willfully did not give a road to the AV.

C. Policy for Single Human-Driven Vehicles

The AV may continue driving until a conflict waypoint at the intersection (i.e., a waypoint from the list of waypoints followed by the AV, where it can cross with non-AV trajectory) depending on the vehicles' side of entering the intersection (i.e., $x^{ego},\ y^{ego} \neq x\_c^j,\ y\_c^j$ in Algorithm 1). The AV shall wait before the conflict waypoint and continue its route after other non-AV passes the hazardous location and if the road ahead is free. Nevertheless, before the AV decides whether to yield or continue driving, it must analyze each human driven car's state individually, because, for instance, if the car is too far, or not driving (i.e., $v_i^j = 0$), it does not make sense for the AV to wait for this vehicle to pass. Hence, an individual policy is derived for each conflicting car. In Fig. 3, the sub-policy flowchart for a single human-driven vehicle is presented.

The ego AV scans the environment, and receives p_i^j containing distance, relative speed and angle position of an observed vehicle utilizing on-board sensors (e.g., radar). First, it detects, if the vehicle is present at an intersection or not. If the latter is true, the AV may continue driving as no conflicting car exists. However, if the car N_i^j is approaching the intersection, the AV must identify its speed. If the vehicle stands still, the AV continues driving due to received $Drive$ command. Otherwise, the AV calculates a time-to-merge (TTM) parameter between N_i^j and conflict waypoint from AV's $\mathcal{W}$. The TTM must not exceed a fixed threshold n and is calculated as:

$$TTM_i^j = \frac{d_i^j}{v_i^j}, \tag{2}$$

where d_i^j and v_i^j are the distance between conflict waypoint and a vehicle, and velocity of the vehicle, accordingly.

At this phase, the trajectory of the non-AV is not crucial. Calculated TTM also ascertains, if the conflicting car moves closer or away from the red waypoint. Hence, rapidly growing TTM means that the non-AV drives away from the collision point (e.g., by turning right instead of driving straight) and ego AV may continue following planned trajectory.

The threshold n allows for understanding, if the ego AV has enough time to pass before the non-AV. Hence, this final measure decides whether to stop and yield, or complete the maneuver with no risk. The value is found with trial and error. The same DMS flowchart (Fig. 3) in fact is true for each human driven car that the ego AV meets at the intersection. The approaching direction is significant. Hence, the ego AV requests driving allowance from each N_i^j vehicle.

IV. RESULTS

A. Simulation Environment and Scene Description

To validate proposed DMS an open source CARLA (0.9.8) simulator was used [24]. It allows for testing various complex scenes (i.e., under different weather and road conditions, traffic density, etc.) also including multiple ego vehicles at the same time. The software is especially popular for testing autonomous driving algorithms.

On a lateral and longitudinal low level control a proportional-differential-integrative regulator is used. Lateral controller's task is to minimize the error between the center line of the vehicle and line connecting generated trajectory waypoints of the route. The longitudinal regulator is responsible for driving with a speed limit defined by the road segment: it minimizes the error between AV's current velocity and speed limit. Considering the radius of the left turn maneuver, the longitudinal velocity of the AV at the intersection is limited to 25 km/h to ensure smooth and safe motion.

The scene of the intersection is complex due to multiple non-AV actors coming from different directions at the same time. The simulation environment was programmed in a way that all vehicles arrive at the intersection simultaneously. There were no traffic lights at the intersection. Hence, the cars must follow the defined intersection rules, namely *east-west* road from the ego AV reference is the main one. All other vehicles had a random destination, what means that the AV never knew, where these cars went. Various examples of the simulation experiments were compiled in a short video[1].

B. Ego AV with $East$ and $North$ Vehicles

This case study demonstrates how the AV crosses an intersection in a human-driver-like manner moving across the location step-by-step. The vehicle arriving from the *west* is located at the intersection, however, for the algorithm demonstration purpose it will not move. This allows to show an example, when the vehicle is detected at the intersection, however, does not enter it for unknown reasons. It will show that the ego AV continues its left turn maneuver without waiting for *west* non-AV to complete its path, because non-AV's speed is equal to zero (Fig. 3). Otherwise, the AV would stuck in front of the intersection not willing to drive ahead.

To ensure complexity, two other vehicles have trajectories, which cross with the AV's route. In particular, *east* vehicle

[1][Online]. Available: https://drive.google.com/drive/folders/1AJpb-7xgxyWUD_ntOjd-lTiAFZs6UgNn?usp=sharing

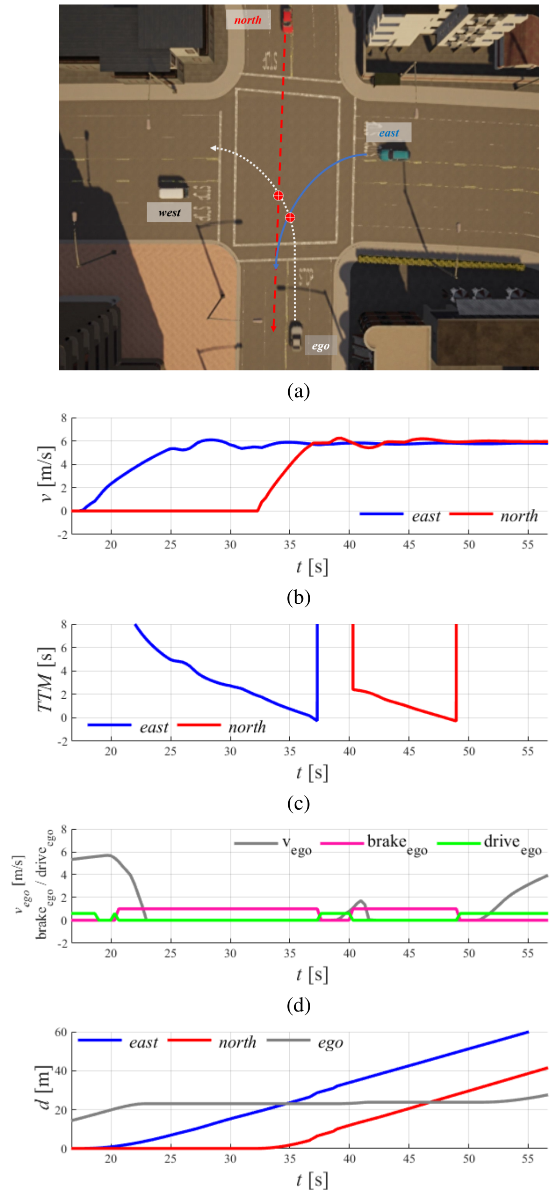


Fig. 4: Experimental results: (a) scene with each car's direction; (b) non-AV velocities; (c) non-AV times-to-collision; (d) ego AV's speed and pedals displacement; (e) vehicles' traveled distance.

turns left, and *north* one drives straight. According to the intersection rules, the *east* car has a priority to drive first. Moreover, as ego vehicle makes a left turn, it must yield to the cars heading straight from *north*.

The scene is depicted in Fig. 4a. The *east* goes first following the blue solid line. Second goes the *north* pursuing the red dashed curve. The ego vehicle comes the last. Its trajectory is identified as white dotted way. There are two potential collision locations at the intersection marked as red nodes. According to the algorithm, the ego AV must stop before these waypoints, if conflict with human-operated vehicle is possible.

The first vehicle the AV focuses on is *east*. The simulation results presented in Fig. 4 only highlight the time, when the AV is at the intersection. Hence, upon entering the intersection, the AV observes positive speed of the *east* car (Fig. 4b, blue plot). At about 20 s of simulation time, the AV decides to decelerate by displacing the braking pedal (Fig. 4d, pink line). This behavior is due to TTM with *east* is below allowed threshold. The *north* also yields to the *east*.

At about 37 s, the *east* vehicle disappears from the ego car' observation range. It also symbolizes that the non-AV passed the potential collision location on ego's trajectory. The AV instantly decides to continue driving forward. However, the vehicle moves ahead for only few meters, because it detects another driving car from the *north* (Fig. 4b, red curve). The AV is only allowed to pass few meters ahead until it reaches the conflicting node with the *north* non-AV. Thus, the AV waits in the middle of the intersection until the last vehicle completes its maneuver.

In Fig. 4e, the traveled distances by each vehicle are plotted. During the period of ego AV yielding to the *east*, the distance of the AV is constant. Then, it travels few meters ahead until stopping in front of the crossing waypoint with *north*. there it waits for the latter car to clear the ego's route. At around 48s, when the TTM with *north* car is below allowed threshold (Fig. 4c, red line), the ego AV releases the brake pedal and applies the acceleration (Fig. 4d).

C. Ego AV with Three Vehicles from All Directions

To incorporate complexity in the algorithm verification, the next experiment considers three non-AVs driving from all intersection legs. In particular, the *west* car drives on a main road, its direction is straight. On the same road, but from the opposite direction arrives the *east* one, who tends to turn left. Hence, the latter gives way to the *west*. Another car approaches intersection from *north*, and goes straight giving way to the ones on the main road. Finally, the ego AV attends to complete the left turn. Therefore, according to the rules, it yields to all mentioned vehicles. The described simulation scene is presented in Fig. 5a.

In Fig. 5, the simulation results are introduced. Upon reaching the intersection the AV, first, concentrates on *west* car according to Algorithm 1. It identifies hazardous TTM with the *west* (Fig. 5c, black), and applies brakes at around 10 s (Fig. 5d, pink). At 17 s, the non-AV clears the intersection, and the ego AV has a small gap between the critical location with *east* vehicle. Hence, it drives ahead (Fig. 5d, green curve), and at around 19 s, the AV decelerates again due to TTM with *east* (Fig. 5c, blue).

In principle, the loop repeats (Algorithm 1) with the same logic as described in previous subsection, where the AV collaborates with both the *east* and the *north* cars. In fact, both non-AVs have the same routes as in previous example. The AV, in its turn, drives step-by-step until the safe locations, where it waits for vehicles from each directions to clear the intersection in course.

In Fig. 5e, the traveled distances of the vehicle at the intersection are depicted. Three yielding steps of the AV are

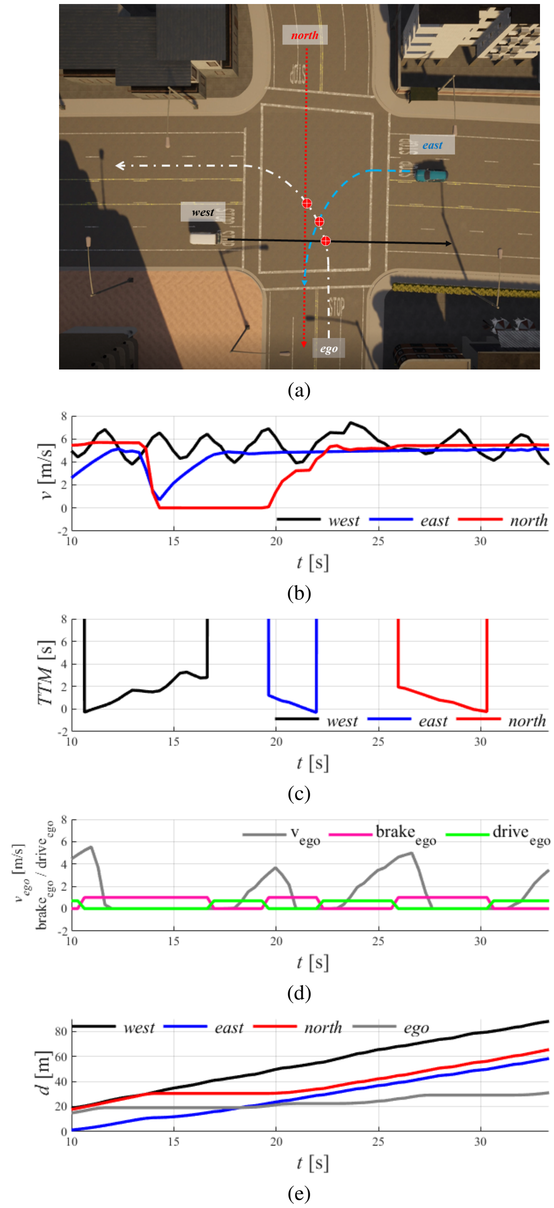


Fig. 5: Experimental results: (a) scene with each car's direction; (b) non-AV velocities; (c) non-AV times-to-collision; (d) ego AV's speed and pedals displacement; (e) vehicles' traveled distance.

clearly observed (i.e., gray curve). Consequently, ensuring safe left turn maneuver the ego AV completes the trajectory passing through the intersection. The system enables the AV to continuously cross the intersection not waiting for other vehicles to complete their trajectories. This is in fact similar to human driver performance, because people do not wait before the intersection entrance until the road is completely clear for driving. They tend to move step-by-step from one "safe" location to another.

D. Limitations

There are some obvious limitations of the proposed RB method. Foremost, the TTM thresholds for N_i^j vehicles are derived by trial and error. Hence, the optimal value is not ensured. Nevertheless, the current values may be accepted for RB system's demonstration purpose. Furthermore, the AV actuation signals are accepted as two constant variables for simplicity $\{Drive,\ Brake\}$. Their selection is only justified by maximum acceleration and deceleration rate allowance. In addition, despite noticeable actuation delay (Fig. 4d, Fig. 5d) vehicle dynamics are not considered in this simulation. Accordingly, in future works, the authors will focus on elimination of the limitations. Specifically, reinforcement learning approach will be investigated on finding optimal balance between safety, comfort and AV performance. The optimization criteria could be optimal TTM selection with continuous output signal.

V. CONCLUSIONS

In this paper, we introduced a rule-based decision making system for autonomous vehicles in mixed traffic environment at cross intersections. The DMS consists of two components: a general policy applicable to various intersection types and a sub-policy for coordinating interaction with a single other vehicle met at the intersection. The main concern of the proposed DMS is to ensure traffic safety. For that, the DMS tracks the motion of other vehicles and maintains that their TTM is within a safety threshold. The policy enables safe unprotected left turns step-by-step similar to human behavior. The simulation study demonstrated the robustness of the DMS to changing environment. As a conclusion, rule-based systems are efficient in ensuring safety in autonomous vehicles. In practice, however, the complexity of real traffic environments makes the manual design of the rule bases burdensome, bordering on infeasible. Machine learning methods such as imitation and reinforcement learning have lately shown great promise for handling the complexity, but they lack usually any safety guarantees. We see then the need to embed safety guarantees to the learning-based methods as the great open problem of the moment.

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