This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIE.2018.2840530, IEEE Transactions on Industrial Electronics

Decision-Making Framework for Autonomous Driving at Road Intersections: Safeguarding Against Collision, Overly Conservative Behavior, and Violation Vehicles

Samyeul Noh, *Member, IEEE*

***Abstract*—In this paper, we propose a decision-making framework for autonomous driving at road intersections that determines appropriate maneuvers for an autonomous vehicle to navigate an intersection safely and efficiently (regarding *making progress*), even in the face of violation vehicles — one of the most challenging tasks in the domain of autonomous vehicles. The proposed framework uses a digital map to predict future paths of observed vehicles and then uses the predicted future paths to identify potential threats (vehicles) and collision areas, regardless of whether observed vehicles are obeying traffic rules at the intersection. Next, under an independent and distributed reasoning structure, it systematically, reliably, and robustly assesses the potential threats, even under incomplete and uncertain noise data, by way of a threat measure, Bayesian networks, and time window filtering. It then uses this information to determine appropriate maneuvers for the autonomous vehicle to navigate the intersection safely and efficiently. We have tested and evaluated the proposed framework through in-vehicle testing on a closed urban test road under traffic conditions inclusive of non-violation and violation vehicles. In-vehicle testing results show the performance of the proposed framework to be sufficiently reliable for autonomous driving at intersections regarding reliability, robustness, safety, and efficiency.**

***Index Terms*—Autonomous driving, collision avoidance, decision-making, road intersections, violation vehicles.**

I. Introduction

FOR us to succeed in bringing autonomous vehicles (AVs) to public roads, we need to be confident AVs can safely and efficiently (regarding *making progress*) navigate road intersections — a significant part of any modern traffic network. Unfortunately, intersections are both complex and dangerous. Moreover, 40 percent of all road injury accidents occur at intersections [1]–[3], 96 percent of which are attributed to driver error (examples of which include misinterpretation, inattention, and traffic rule violation) [4]–[6]. Therefore, we need to safeguard AVs against collision and incidences of driver error — specifically, traffic rule violation, which often causes severe accidents [7]. Second to this is the need to safeguard AVs from being overly conservative regarding safety. An overly conservative approach to safety is counterproductive to achieving driving efficiency and can lead to traffic accidents, delays, and deadlock [8]. For example, when there exists a violation vehicle (that is, a vehicle in violation of traffic rules) or a potential threat within an intersection, an AV need not necessarily stop immediately at the first sign of danger. If the safety of the AV can be guaranteed, then it would be more efficient of the AV to proceed as far as is possible regarding safety. In summary, AVs need to avoid both collision, even in the face of violation vehicles, and being overly conservative regarding safety.

In this work, we seek to address the problem of how an AV is to navigate an intersection safely without being overly conservative regarding safety, even in the face of violation vehicles, which is one of the most challenging problems in the domain of AVs. To this end, we propose a decision-making framework for autonomous driving at intersections that determines appropriate maneuvers for an AV to navigate a given traffic situation at an intersection safely and efficiently, regardless of whether observed vehicles are obeying traffic rules at the intersection. The proposed framework consists of three main modules: situation awareness, situation assessment, and maneuver decision. Through the situation awareness module (see Section III), it (a) uses a detailed, precise digital map to predict at the lane level all possible future motion paths of all observed vehicles, (b) identifies physical areas on the intersection where predicted future motion paths of observed vehicles intersect with the global path of the AV and classifies them as *potential collision areas* (CAs), (c) identifies *potential threats* — specifically, those observed vehicles that have a predicted future motion path set to intersect with the global path of the AV — and classifies them as *relevant vehicles*, and (d) establishes *vehicle-to-vehicle collision relations* (V2V-CRs) with the identified relevant vehicles. Through the situation assessment module (see Section IV), it utilizes (a) an independent and distributed reasoning structure to efficiently and systematically assess the given traffic situation, (b) a threat

Manuscript received December 24, 2017; revised March 19, 2018 and April 19, 2018; accepted May 14, 2018. This work was supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIT) [B0101-16-0134, Development of Decision-Making/Control Technology of Vehicle/Driver Cooperative and Autonomous Driving System(Co-Pilot) Based on ICT] and [2017-0-00046, Basic Technology for Extracting High-level Information from Multiple Sources Data based on Intelligent Analysis].

Samyeul Noh is with the Creative Contents Research Division, Electronics and Telecommunications Research Institute, Daejeon 34129, Rep. of Korea (e-mail: samuel@etri.re.kr).

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measure and Bayesian networks to reliably assess relevant vehicles regarding the possibility of collision, even under uncertain noise data, and (c) time window filtering to robustly assess relevant vehicles by filtering out incompletely estimated reasoning results caused by incomplete and uncertain noise data pertaining to vehicle tracking. Through the maneuver decision module (see Section V), it (a) classifies the reliably and robustly estimated reasoning results of the situation assessment module according to whether the results are currently affecting autonomous driving and (b) determines appropriate maneuvers for the AV to navigate the intersection safely and efficiently, based on the classified reasoning results, the state of the AV on the given road network concerning the identified CAs, intersection types, and traffic signals.

We have extensively tested and evaluated the proposed framework through in-vehicle testing on a closed urban test road under traffic conditions inclusive of non-violation and violation vehicles. In-vehicle testing results show the performance of the proposed framework to be sufficiently reliable for autonomous driving at intersections regarding reliability and robustness, even under incomplete and uncertain noise data, and safety and efficiency, even under traffic conditions involving violation vehicles.

II. Related Work

Researchers in the field of autonomous driving are facing the challenge of creating a decision-making framework for autonomous driving at intersections capable of detecting dangerous situations and instructing an AV to react accordingly to avoid incident. To overcome this challenge, they are working toward ensuring such a framework can predict the likely evolution of a traffic situation, assess how dangerous that future situation might be, and instruct an AV to react accordingly to avoid incident.

However, the existing literature mostly focuses on motion prediction, threat assessment, or decision-making problems, but not all three in combination. Moreover, there is little research on solving decision-making problems for autonomous driving at intersections regarding both safety and efficiency in the face of violation vehicles.

In the field of motion prediction, there exist two main approaches to the prediction of a future motion of a vehicle: physics-based approach [9], [10] and maneuver-based approach [11]–[17]. The physics-based approach derives a future motion of a vehicle by an interpretation of the laws of physics and is the most commonly used motion model for trajectory prediction and threat estimation in the context of road safety. Nevertheless, it is limited to short-term motion prediction since it is only concerned with low-level motion properties. Therefore, it is unable to anticipate any change in the motion of a vehicle caused by the execution of a maneuver such as “turning left” or “turning right.” Consequently, researchers have turned to various maneuver-based approaches to motion prediction; for example, prototype trajectory–based approach [11], [12], maneuver intention estimation–based approach [13], [14], and precise, detailed digital map–based approach [15]–[17]. Such maneuver-based approaches predict a future motion of a vehicle based on the maneuver that a driver intends to perform. Therefore, future motions derived from such approaches are more relevant and reliable in the long term in comparison to those derived from the physics-based approach.

In the field of threat assessment, there exist two main approaches to threat assessment: deterministic approach [18], [19] and probabilistic approach [20]–[26]. The deterministic approach utilizes a rule-based expert system capable of estimating the possibility of collision as a binary prediction by way of various threat measures [27] such as time-to-collision (TTC), time-to-brake, time-to-steer, time headway, and deceleration to safety time. The approach has been used in various collision mitigation systems since it is both simple and computationally efficient; however, it is not capable of explicitly modeling the uncertainties of its input data. Consequently, researchers have turned to various probabilistic approaches to threat assessment such as fuzzy logic [20], [21], Markov processes [22], [23], and Bayesian networks [24]–[26]. Such probabilistic approaches not only utilize a probabilistic description of temporal and spatial relationships between vehicles, but also incorporate input-data uncertainties into threat assessment. In fact, this manuscript is motivated by the research of Schubert [24]–[26]; in particular, his well-established Bayesian approach, which is suitable for dealing with uncertain measurements and requires only a moderate number of hyper-parameters. Unfortunately, this approach is limited to a very constrained highway scenario: changing or keeping to the current lane while driving on a highway.

Recently, researchers have proposed several solutions for decision-making regarding autonomous driving at intersections, including using cooperative communications [28]–[31] and estimation of driver intention [32]–[36]. Decision-making frameworks based on cooperative communications, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, provide reliable solutions for autonomous driving at intersections regarding road safety and traffic efficiency under the assumption that all vehicles possess V2V or V2I communication capability. However, such communication technology is not yet widespread, and thus such frameworks cannot be employed in the immediate short-term. Decision-making frameworks based on estimation of driver intention provide reliable predictions of long-term motion and risk. Also, they can predict traffic violations by comparing estimated driver intention with driver expectation. However, driver intention can only ever be classified within a predefined set of considered driver intentions such as “turning left,” “turning right,” and “going straight.” Therefore, such decision-making frameworks are not applicable to all types of intersection. Moreover, they are often overly conservative regarding safety or unreliable regarding collision avoidance, since they neither consider temporal and spatial relationships between vehicles nor identify CAs between the AV and potential threats.

Perhaps the best-known AV is the Google self-driving car. At a green light at a signalized intersection, the Google self-driving car is programmed to pause for a brief period prior to crossing the intersection [37]. In doing so, it increases its likelihood of avoiding collision with a violation vehicle. In

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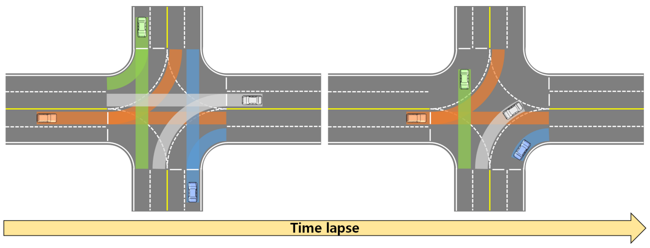


Fig. 1. Future motion prediction of vehicles at an intersection through the projection of the vehicles onto a detailed, precise digital map.

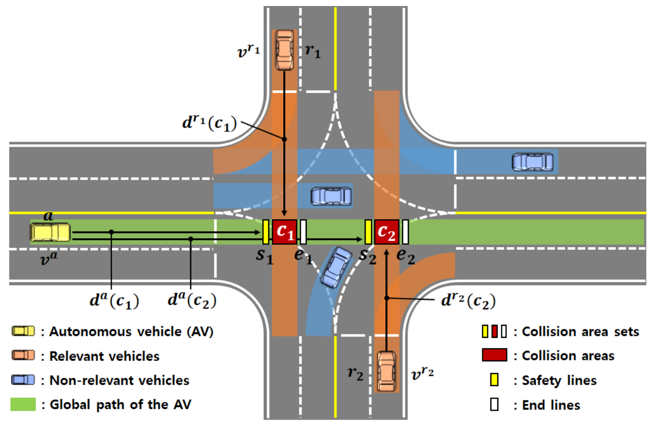


Fig. 2. Potential threat identification. The proposed framework simultaneously identifies relevant vehicles (that is, potential threats) r_1 and r_2 and CAs c_1 and c_2. It then establishes V2V-CRs between the AV and relevant vehicles.

contrast, at a stop line at an unsignalized intersection, it is programmed to move forward a short distance in an act of intent prior to crossing the intersection [38]. In doing so, it increases its likelihood of avoiding inefficient driving. Despite these capabilities, it is unable to avoid both collision with violation vehicles and overly conservative behavior. For example, in the case of a green light at a signalized intersection, if there exists no violation vehicle, it is overly conservative of the Google self-driving car to pause for a brief period prior to crossing the intersection. Also, Google self-driving cars have been reported to be involved in intersection-related accidents with violation vehicles [39], [40].

In summary, researchers need to ensure decision-making frameworks for autonomous driving at intersections can guarantee collision avoidance — even in the face of violation vehicles — without compromising on efficiency.

III. Situation Awareness

In this section, we describe the situation awareness module. For a given traffic situation at an intersection, regardless of whether observed vehicles are obeying traffic rules at the intersection, this module predicts at the lane level all possible future motion paths of all observed vehicles and identifies potential threats.

A. Future Motion Prediction of Vehicles

In the literature, conventionally, the prediction of a future motion of a vehicle is derived from an interpretation of the vehicle's kinematics and dynamics [41]. However, in the literature, it is assumed that the motion patterns of a vehicle can be identified in advance since a road network is a structured environment [16], [17]; for example, they can be extracted from a digital map by identifying all possible maneuvers at a given location on a road network.

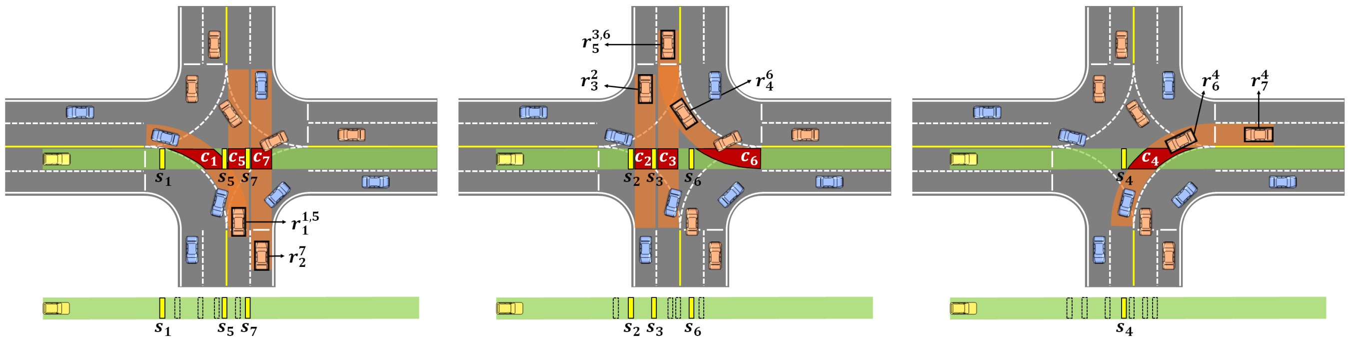
In this work, the proposed framework uses a detailed, precise digital map to predict at the lane level all possible future motion paths (hereafter referred to as "future paths") of all observed vehicles. The contextual information contained in such a map (that is, geometrical and topological characteristics of an intersection) gives a useful indication of what each observed vehicle intends to perform. Thus, through the projection of observed vehicles onto a detailed, precise digital map (see Fig. 1), the proposed framework can determine a finite set of future paths for each observed vehicle. Should an observed vehicle be located within an intersection, the proposed framework will additionally consider the vehicle's heading when determining a finite set of future paths for the vehicle, because of the characteristics of intersections; that is, paths can separate, cross, or join within an intersection. Since the proposed framework predicts at the lane level all possible future paths of all observed vehicles, it can be used with any intersection; that is, it can be considered a generic framework.

In Fig. 1, finite sets of future paths are shown for the given observed vehicles as the vehicles progress through the given intersection. The proposed framework uses such finite sets to identify potential threats.

B. Potential Threat Identification

Throughout a given traffic situation at an intersection, the proposed framework is aware of all possible future paths of all observed vehicles. Since its primary aim is to avoid both collision and being overly conservative regarding safety, it only concerns itself with those future paths that intersect with the global path of the AV. In doing so, it simultaneously identifies relevant vehicles and CAs. Once it has identified such vehicles, it then establishes a V2V-CR between the AV and each such vehicle. Next, it classifies any remaining vehicles as *non-relevant vehicles*; since it considers such vehicles not to pose a potential threat to the AV, it does not assess them — a computationally efficient approach. Subsequently, it assesses only relevant vehicles concerning the possibility of collision, in a systematic, reliable, and robust manner.

An example of potential threat identification at an intersection is illustrated in Fig. 2. In Fig. 2, the yellow, orange, and blue vehicles represent an AV, relevant vehicles, and non-relevant vehicles, respectively. Also, the AV and relevant vehicles are denoted by a and r_i, respectively, where i represents a unique vehicle track ID number. The red areas represent areas within the intersection where possible future paths of relevant vehicles intersect with the global path of the AV; the proposed framework classifies such areas as CAs. Each CA c_k has an associated safety line s_k and an associated end line e_k — these lines form a set, and such sets are used by the maneuver decision module to determine appropriate maneuvers for the AV to avoid being overly conservative regarding safety. The proposed framework arranges the CAs c_k in order of distance



(a) (b) (c)

Fig. 3. Independent and distributed reasoning structure for intersections: (a) the case of relevant vehicles assigned to IRAs α_1, α_5, and α_7, (b) the case of relevant vehicles assigned to IRAs α_2, α_3, and α_6, and (c) the case of relevant vehicles assigned to IRA α_4. CCAs and their respective safety lines are denoted by c_k and s_k, respectively, where k denotes an arranged order.

to the AV by way of their respective safety lines s_k; that is, k denotes an arranged order. The distances along the road curvature from a (the AV) to CA c_k and from the relevant vehicle r_i to CA c_k are denoted by $d^a(c_k)$ and $d^{r_i}(c_k)$, respectively. The velocities of a (the AV) and relevant vehicles r_i are denoted by v^a and v^{r_i}, respectively.

IV. Situation Assessment

In this section, we describe the situation assessment module. This module uses an independent and distributed reasoning structure to assess a given traffic situation at an intersection efficiently and systematically. Under the said structure, independent reasoning agents (IRAs) reliably and robustly assess relevant vehicles by way of a threat measure and Bayesian networks (reliability), and time window filtering (robustness), even under incomplete and uncertain noise data.

A. Independent and Distributed Reasoning Structure

Under the independent and distributed reasoning structure, relevant vehicles are grouped according to CA; that is, those relevant vehicles that have a common collision area (CCA) form a group. Each group is then assigned an IRA; the primary roles of an IRA are (a) to analyze those temporal and spatial relationships that exist between the AV and those relevant vehicles to which the IRA is assigned and (b) to reliably and robustly assess the relevant vehicles to which the IRA is assigned, even under incomplete and uncertain noise data. Each IRA infers a threat level for each relevant vehicle within its assigned group by way of a threat measure and Bayesian networks, while considering any uncertainties (see Sections IV-B and IV-C). Then, each IRA determines the most imminent threat from among the relevant vehicles within its assigned group; that is, the relevant vehicle having the highest probability value corresponding to the threat level "dangerous." Each IRA then uses the inferred threat level of the most imminent threat within its assigned group as the threat level for the current traffic situation. Since each IRA has an associated CCA, each CCA carries a threat level for the current traffic situation. The inferred threat levels associated with the CCAs are then used by the maneuver decision module to determine appropriate maneuvers for the AV to avoid collision. However, the proposed framework must first filter out incompletely estimated reasoning results (generated by the IRAs) caused by incomplete and uncertain noise data pertaining to vehicle tracking — this is achieved using time window filtering (see Section IV-D).

We illustrate an instance of the independent and distributed reasoning structure for intersections in Fig. 3. In the case of Fig. 3, the said structure has grouped the known relevant vehicles according to CA, which has resulted in the identification of seven CCAs $\{c_1, \cdots, c_7\}$. The said structure has then assigned seven IRAs $\{\alpha_1, \cdots, \alpha_7\}$ accordingly; that is, α_1 to c_1; α_2 to c_2; α_3 to c_3; and so on. In Fig. 3a, we have highlighted two relevant vehicles, $r_1^{1,5}$ and r_2^7: the former is assigned by the said structure to IRAs α_1 and α_5 associated with CCAs c_1 and c_5, and the latter is assigned by the said structure to IRA α_7 associated with CCA c_7. Here, we note that r_i^k represents a relevant vehicle assigned to IRA α_k and not a relevant vehicle assigned to CCA c_k. Also, we note that a relevant vehicle can be assigned to one or more IRAs. Similarly, in Figs. 3b and 3c, the highlighted relevant vehicles are assigned by the said structure to IRAs and correspondingly denoted by r_3^2, r_4^6, and $r_5^{3,6}$, and r_6^4 and r_7^4, respectively.

B. Threat Measure

Many collision mitigation systems use TTC as a criterion to assess "potential threats" in a given traffic situation since it is representative of both speed difference and spatial proximity [42]. However, in this work, we utilize a criterion called time-to-enter (TTE) to assess relevant vehicles in a given traffic situation at an intersection [43]. For a relevant vehicle r_i^k associated with CA c_k, TTE is defined as the time it takes r_i^k to reach c_k from its current position at its current speed. To avoid collisions within CAs, we modify the TTE criterion by introducing a constraint that limits the TTE value to zero when r_i^k is located within its associated c_k. The formula for our modified version of TTE is defined as follows:

$$y_t^{r_i^k}(c_k) = \begin{cases} \frac{d_t^{r_i^k}(c_k)}{v_t^{r_i^k}}, & \text{for} \quad v_t^{r_i^k} > 0,\ d_t^{r_i^k}(c_k) > 0 \\ 0, & \text{for} \quad d_t^{r_i^k}(c_k) \leq 0 \\ +\infty, & \text{for} \quad \text{otherwise} \end{cases} \tag{1}$$

where $y_t^{r_i^k}(c_k)$, a random variable, represents the modified TTE value of relevant vehicle r_i^k for CA c_k at time t. The distance to CA c_k from the current position of relevant vehicle r_i^k along the road curvature at time t is denoted by $d_t^{r_i^k}(c_k)$. The velocity of relevant vehicle r_i^k at time t is denoted by $v_t^{r_i^k}$.

C. Probabilistic Reasoning based on Bayesian Networks

The primary challenge regarding situation assessment for AVs is to assess "potential threats" in a given traffic situation reliably and robustly, even under incomplete and uncertain noise data. To tackle uncertainties, we utilize Bayesian networks [24], [44] to reliably assess relevant vehicles (that is, potential threats) in a given traffic situation at an intersection, even under uncertain noise data. For a relevant vehicle, we define three threat levels in relation to the modified TTE, each of which represents a degree of an overall level of threat regarding the possibility of collision, as follows:

$$z \in Z = \{\underline{\text{D}}\text{angerous}, \underline{\text{A}}\text{ttentive}, \underline{\text{S}}\text{afe}\} = \{\text{D}, \text{A}, \text{S}\} \tag{2}$$

where z, a random variable, represents the threat level of a relevant vehicle or the threat level for a given traffic situation.

A likelihood function for the modified TTE value under the condition of a relevant vehicle's threat level requires the definitions of two thresholds, $\overline{y}^{\text{D}}$ and $\overline{y}^{\text{A}}$. These two thresholds can be used to parameterize the situation assessment; we assigned values of 4.0s and 7.0s to $\overline{y}^{\text{D}}$ and $\overline{y}^{\text{A}}$, respectively, based on both international standards for safety [45], [46] and vehicle tracking performance [47]. Also, a measure of uncertainty, denoted by $\sigma_y^{r_i^k}$, is used in the construction of the likelihood function to consider the uncertainties of the modified TTE value for relevant vehicle r_i^k.

The likelihood function for the modified TTE value under the condition of a relevant vehicle's threat level within each IRA can be now defined as follows:

$$p(y_t^{r_i^k} \mid z = \text{D}) \propto \begin{cases} \exp(-\frac{(y_t^{r_i^k} - \overline{y}^{\text{D}})^2}{2\sigma_{y_t}^{r_i^k\,2}}), & \text{for} \quad y_t^{r_i^k} > \overline{y}^{\text{D}} \\ 1, & \text{for} \quad \text{otherwise} \end{cases} \tag{3}$$

$$p(y_t^{r_i^k} \mid z = \text{A}) \propto \begin{cases} \exp(-\frac{(y_t^{r_i^k} - \overline{y}^{\text{A}})^2}{2\sigma_{y_t}^{r_i^k\,2}}), & \text{for} \quad y_t^{r_i^k} > \overline{y}^{\text{A}} \\ \exp(-\frac{(y_t^{r_i^k} - \overline{y}^{\text{D}})^2}{2\sigma_{y_t}^{r_i^k\,2}}), & \text{for} \quad y_t^{r_i^k} < \overline{y}^{\text{D}} \\ 1, & \text{for} \quad \text{otherwise} \end{cases} \tag{4}$$

$$p(y_t^{r_i^k} \mid z = \text{S}) \propto \begin{cases} \exp(-\frac{(y_t^{r_i^k} - \overline{y}^{\text{A}})^2}{2\sigma_{y_t}^{r_i^k\,2}}), & \text{for} \quad y_t^{r_i^k} < \overline{y}^{\text{A}} \\ 1, & \text{for} \quad \text{otherwise} \end{cases} \tag{5}$$

where $\overline{y}^{\text{D}}$ and $\overline{y}^{\text{A}}$ represent the thresholds of the modified TTE value for the "dangerous" and "attentive" threat levels, respectively. The uncertainty of the modified TTE value for relevant vehicle r_i^k at time t is denoted by $\sigma_{y_t}^{r_i^k}$.

Under the assumption that a prior probability mass function of the threat level of a relevant vehicle, $P(z)$, follows a uniform distribution, a probability distribution of the threat level of such a relevant vehicle for a given modified TTE value can be determined using Bayes' theorem, as follows:

$$P(z_t^{r_i^k} \mid y_t^{r_i^k}) = \frac{p(y_t^{r_i^k} \mid z)}{\sum_{j=1}^{N_Z} p(y_t^{r_i^k} \mid Z(j))} \tag{6}$$

where $P(z_t^{r_i^k} \mid y_t^{r_i^k})$ represents a probability distribution of the threat level of relevant vehicle r_i^k for the given modified TTE value $y_t^{r_i^k}$ at time t. The jth element of set Z is denoted by $Z(j)$. The parameter N_Z represents the number of threat levels in Z.

An inferred threat level for a relevant vehicle can be then determined by an argument that maximizes the probabilities arising from the aforementioned probability distribution of the threat level, as follows:

$$\hat{z}_t^{r_i^k} = \arg\max_{z_t^{r_i^k}} P(z_t^{r_i^k} \mid y_t^{r_i^k}) \in Z \tag{7}$$

where $\hat{z}_t^{r_i^k}$ represents an inferred threat level for relevant vehicle r_i^k at time t.

D. Robust Assessment based on Time Window Filtering

For each IRA, a probability distribution of the threat level for the current traffic situation associated with its CCA is determined by considering only the result of the probability distribution of the threat level of the most imminent threat from among the relevant vehicles within its assigned group, as follows:

$$P(z_t^{\alpha_k}) = P(z_t^{r_{\text{m}}^k} \mid y_t^{r_{\text{m}}^k}) \tag{8}$$

where $P(z_t^{\alpha_k})$ represents the probability distribution of the threat level for the current traffic situation associated with the CCA of IRA α_k at time t. The probability distribution of the threat level of the most imminent threat r_{m}^k from among all relevant vehicles assigned to IRA α_k at time t is denoted by $P(z_t^{r_{\text{m}}^k} \mid y_t^{r_{\text{m}}^k})$.

An inferred threat level for the current traffic situation associated with the CCA of each IRA can now be determined by way of an argument that maximizes the probabilities arising from the aforementioned probability distribution of the threat level, as follows:

$$\hat{z}_t^{\alpha_k} = \arg\max_{z_t^{\alpha_k}} P(z_t^{\alpha_k}) \in Z \tag{9}$$

where $\hat{z}_t^{\alpha_k}$ represents an inferred threat level for the current traffic situation associated with the CCA of IRA α_k at time t.

For AVs to determine safe and dependable maneuvers in traffic situations, the capability to robustly assess "potential threats" in a given traffic situation, even under incomplete noise data, is required. In this work, we use a time window filter to filter out incompletely estimated reasoning results (generated by the IRAs) caused by incomplete and uncertain noise data pertaining to vehicle tracking; for example, when false vehicles are detected or true vehicles are sometimes missed, within a given time window. Examples of time window filtering are illustrated in Fig. 4.

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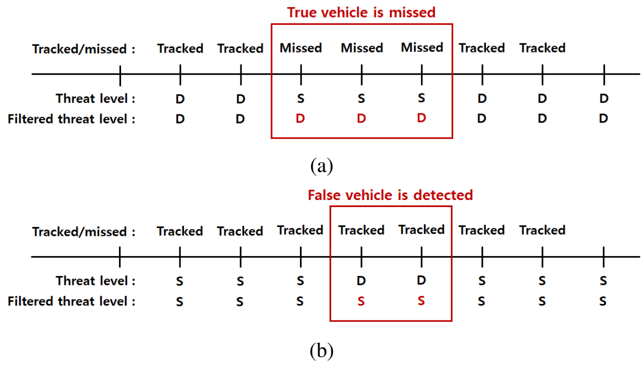

Fig. 4. Examples of time window filtering: (a) false negative cases and (b) false positive cases.

V. Maneuver Decision

In this section, we describe the maneuver decision module. This module determines appropriate maneuvers that ensure an AV avoids both collision and being overly conservative regarding safety, based on traffic signals, intersection types, the current state of the AV on the road network concerning the identified CAs, and the reliably and robustly inferred threat levels from IRAs. The said maneuvers are determined through the following three steps: *entry*, *update*, and *decision* (see Algorithm 1).

1) Entry: The entry step determines whether the AV is to stop or proceed through an intersection and is based on the recognized traffic signal result l_t from a vision sensor fitted to the AV; the intersection type T from the detailed, precise digital map; and "dilemma zone check" (Algorithm 1, lines 2–11). The recognized traffic signal result l_t for the traffic signal associated with the global path of the AV takes one of three possible values: G, Y, or R, where G represents "green light," Y represents "yellow light," and R represents "red light." The intersection type T takes one of two possible values: S or U, where S represents "signalized intersection" and U represents "unsignalized intersection." A dilemma zone — an area prior to the stop line of an intersection in which drivers and AVs encounter a dilemma regarding whether to stop or proceed through the intersection when the signal turns from green to yellow — is denoted by $\overline{y}^{\text{aDZs}} < y_t^a(\text{I}) < \overline{y}^{\text{aDZe}}$, where $y_t^a(\text{I})$ represents the time it takes the AV to reach the intersection and $\overline{y}^{\text{aDZs}}$ and $\overline{y}^{\text{aDZe}}$ represent the thresholds associated with the start and end points of the dilemma zone, respectively.

2) Update: The update step performs two roles: First, it removes from the IRA set $\mathcal{A}$ those IRAs whose reasoning results no longer affect autonomous driving — by this, we mean that the reasoning result of an IRA is said to affect autonomous driving no longer once the AV is known to have proceeded two-thirds of the way through the associated CCA (lines 13–16). Second, it then extracts from the IRA set $\mathcal{A}$ those IRAs whose reasoning results indicate either "dangerous" or "attentive" (that is, those whose reasoning results are currently affecting autonomous driving) — these are placed in a new IRA set, set $\mathcal{B}$ (lines 17–18), where they are used to determine an appropriate maneuver for the AV to safely and efficiently navigate the intersection through the

Algorithm 1 Maneuver decision

Input: Traffic signals l_t, intersection types T, inferred threat levels $\hat{z}_t^{\alpha_k}$, safety lines s_k, and end lines e_k for each IRA $\alpha_k \in \mathcal{A}$.
Output: An appropriately determined maneuver.

1: // 1. Entry step
2: **while** $T =$ S and $l_t \neq$ G **do**
3:     **if** $l_t =$ R **then**
4:         **return** Stop to the intersection
5:     **else**
6:         **if** $y_t^a(\text{I}) \geq \overline{y}^{\text{aDZe}}$ **then**
7:             **return** Stop to the intersection
8:         **else if** $\overline{y}^{\text{aDZs}} < y_t^a(\text{I}) < \overline{y}^{\text{aDZe}}$ **then**
9:             **return** E-stop to the intersection
10:         **else**
11:             **break**
12: // 2. Update step
13: **for all** $\alpha_k \in \mathcal{A}$ **do**
14:     **if** $\frac{1}{3}d_t^a(s_k) + \frac{2}{3}d_t^a(e_k) \leq 0$ **then**
15:         $\alpha_k \notin \mathcal{A}$
16:         **continue**
17:     **if** $\hat{z}_t^{\alpha_k} =$ D or A **then**
18:         $\alpha_k \in \mathcal{B}$
19: // 3. Decision step
20: **if** $\mathcal{A} = \emptyset$ **then**
21:     **return** Cross the intersection without stopping
22: **for all** $\alpha_k \in \mathcal{B}$ **do**
23:     **if** $d_t^a(s_k) > 0$ **then**
24:         **if** $y_t^a(s_k) \geq \overline{y}^{\text{aUS}}$ **then**
25:             **return** Stop to s_k
26:         **else if** $y_t^a(s_k) \geq \overline{y}^{\text{aIS}}$ **then**
27:             **return** E-stop to s_k
28:         **else**
29:             **if** $\hat{z}_t^{\alpha_k} =$ D and $v^a \leq \overline{v}$ **then**
30:                 **return** E-stop immediately
31:     **else**
32:         **if** $\hat{z}_t^{\alpha_k} =$ D and $v^a \leq \overline{v}$ **then**
33:             **return** E-stop immediately
34: **return** Proceed to the end of the intersection

decision step. We note here that in the case where there no longer exist any relevant vehicles associated with a CCA and the AV has yet to proceed two-thirds of the way through the CCA, then the reasoning results of the associated IRA are said to be still affecting autonomous driving. In such a case, the associated IRA is inferring a threat level of "safe" for the current traffic situation based on a TTE value of infinity for the CCA, and will continue to do so until the AV proceeds two-thirds of the way through the CCA.

3) Decision: The decision step determines an appropriate maneuver for the AV to navigate a given traffic situation at an intersection safely and efficiently. In this step, if set $\mathcal{A}$ is empty, then the maneuver decision module concludes that there are no potential threats to consider. Thus, the module determines a maneuver to cross the considered intersection without stopping (lines 20–21). Similarly, if set $\mathcal{B}$ is empty but set $\mathcal{A}$ is not, then the module determines a maneuver to proceed to the end of the considered intersection (line 34). Otherwise, the module determines a maneuver based on the current state of the AV on the road network concerning the identified CAs and the reliably and robustly inferred threat levels from the IRAs in set $\mathcal{B}$ (lines 22–34). If the AV exists before the safety line s_k associated with $\alpha_k \in \mathcal{B}$, then the

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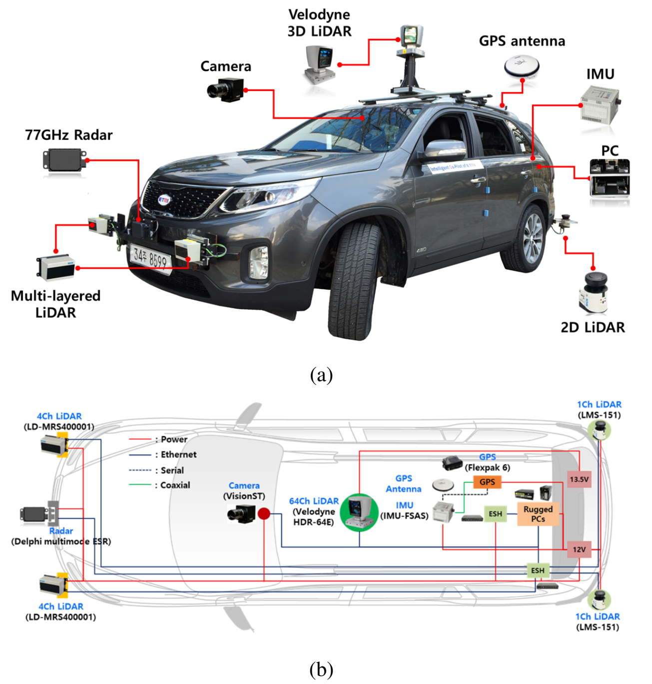

Fig. 5. Experimental vehicle configuration: (a) hardware platform and (b) sensor configuration.

module determines one of the following five maneuvers: "stop normally to the safety line s_k," "stop urgently to the safety line s_k," "stop immediately," "proceed to the next safety line if the next IRA exists in set $\mathcal{B}$," or "proceed to the end of the intersection" (lines 23–30, 34). In lines 23–30 of Algorithm 1, $\overline{y}^{\mathrm{aUS}}$ and $\overline{y}^{\mathrm{aIS}}$ represent the thresholds of the modified TTE of the AV for "urgent stop" and "immediate stop" situations, respectively. By "urgent stop," we mean a situation where the AV needs to stop urgently to the safety line s_k to avoid collision. By "immediate stop," we mean a situation where the AV needs to stop immediately to avoid collision. Here, $\overline{v}$ represents the upper limit of the AV's speed for "immediate stop." If the AV exists within the CCA associated with $\alpha_k \in \mathcal{B}$, then the module determines one of the following three maneuvers: "stop immediately," "proceed to the next safety line if the next IRA exists in set $\mathcal{B}$," or "proceed to the end of the intersection" (lines 31–34).

VI. Experimental Results

To validate the feasibility of the proposed framework for autonomous driving at intersections, in this section, we present experimental results based on two representative test cases: signalized and unsignalized intersections. The experiments were conducted through in-vehicle testing on a closed urban test road under traffic conditions inclusive of non-violation and violation vehicles (that is, vehicles in violation of traffic rules). A detailed video of our experiments of autonomous driving at intersections is available at https://youtu.be/h7ExZ040wyk.

A. Experimental Vehicle Configuration

The experimental (ego) vehicle has several sensors to estimate its pose and perceive its environment. A NovAtel virtual reference station–aided GPS is attached to the roof to estimate the vehicle's pose. The GPS is combined with IMar IMU to provide enhanced real-time kinematic performance. A 77GHz long- and mid-range Delphi multi-mode ESR Radar attached to the front bumper, two multi-layered LD-MRS LiDARs attached to the front edge, two 2D SICK LMS LiDARs attached to the rear edge, and a 3D Velodyne HDL-64 LiDAR attached to the roof are used to detect and track surrounding vehicles. A vision sensor (camera) attached to the center of the windshield is used to detect traffic signals. The ego vehicle configuration including its hardware platform and sensor configuration is illustrated in Fig. 5.

B. Qualitative Analysis

The pictures shown in Figs. 6 and 7 illustrate results of the proposed decision-making framework for autonomous driving at intersections for the two considered test cases: signalized and unsignalized intersections, respectively. In these pictures, the gray lines represent map data from the detailed, precise digital map; the white and green rectangles represent crosswalks — white rectangles indicate the portion of a crosswalk that is on the road and green rectangles indicate the portion of a crosswalk that is on a sidewalk; the brown car represents the ego vehicle; the green line represents the global path of the ego vehicle; the blue rectangles represent the trajectory of the ego vehicle; and the red, yellow, green, and black convex polygons on the road represent observed objects (vehicles, pedestrians, and "unknown"). In this paper, we focus only on vehicles. Among the observed vehicles, the red, yellow, and green colored convex polygons represent relevant vehicles. The black colored convex polygons represent non-relevant vehicles. A relevant vehicle's color corresponds to the inferred threat level for the relevant vehicle regarding the possibility of collision — "red" corresponds to "dangerous," "yellow" corresponds to "attentive," and "green" corresponds to "safe." The colored bars above a relevant vehicle represent probabilities corresponding to the three predefined threat levels — once again, "red" corresponds to "dangerous," "yellow" corresponds to "attentive," and "green" corresponds to "safe." An arrow on each observed object represents both a heading and a classification — a white arrow indicates that the observed object concerned has been classified as "unknown," and a blue arrow indicates that the observed object concerned has been classified as either "vehicle" or "pedestrian." The white messages below each observed object represent the track types, unique vehicle track IDs, and speeds of the observed objects concerned. Each image is representative of the front view of the ego vehicle. Each whiteboard represents the current traffic situation while highlighting relevant vehicles assigned to set $\mathcal{B}$ and associated safety lines in yellow.

1) Test Case I: Test Case I is designed to test whether the ego vehicle can safely and efficiently navigate signalized intersections involving violation vehicles. Experimental results of autonomous driving in the case of Test Case I are illustrated in Fig. 6. In Fig. 6a, the ego vehicle stops normally to the safety line s_1 associated with Track ID 180 to avoid not only collision with Track ID 180 (whose inferred threat level reads

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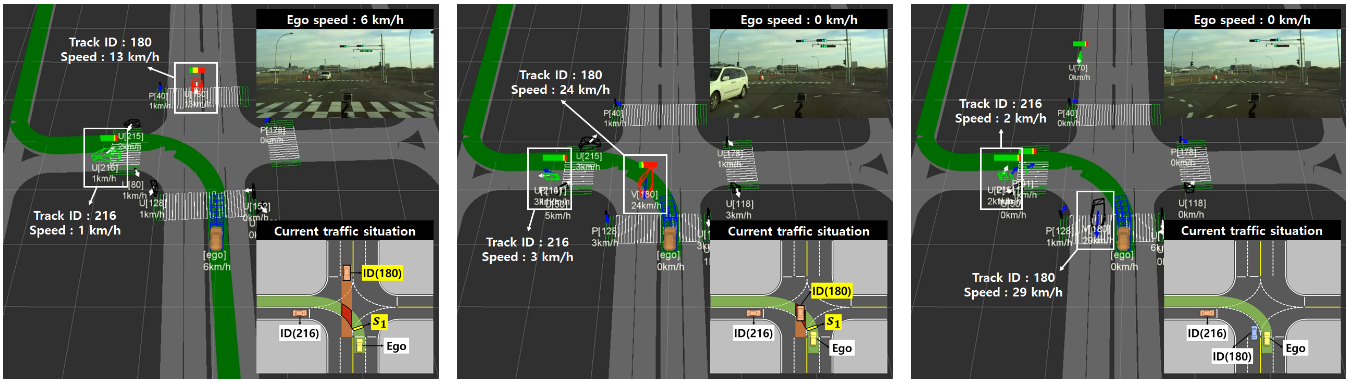
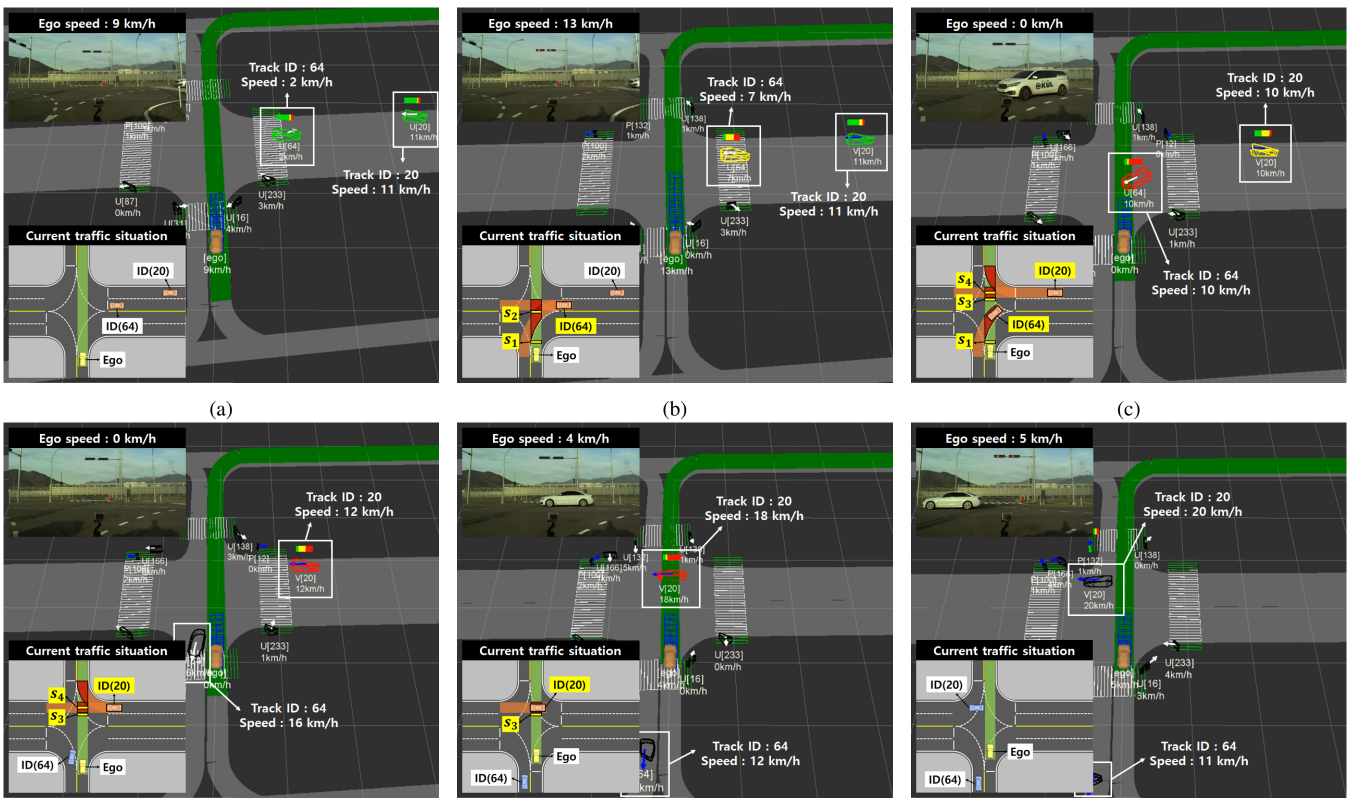


(a) (b) (c)

Fig. 6. Test Case I: signalized intersection involving violation vehicle. (a) Track ID 180, whose inferred threat level reads "dangerous," violates a red light. Track ID 216, whose inferred threat level reads "safe," stops and waits at its stop line of the intersection since its traffic light shows red; (b) Track ID 180, whose inferred threat level reads "dangerous," crosses the intersection while violating a red light. Track ID 216, whose inferred threat level reads "safe," is still stationary at its stop line of the intersection; and (c) Track ID 180 is considered as "non-relevant," and Track ID 216 is inferred as "safe."



(a) (b) (c)

(d) (e) (f)

Fig. 7. Test Case II: unsignalized intersection involving violation vehicles. (a) Track IDs 64 and 20 are both inferred as "safe." Track ID 64 stops and waits at its stop line of the intersection, and Track ID 20 approaches the intersection from a distance; (b) Track ID 64, whose inferred threat level reads "attentive," has started to cross the intersection, even though the ego vehicle was the first to enter the intersection. Track ID 20 is still inferred as "safe"; (c) Track ID 64, whose inferred threat level reads "dangerous," crosses the intersection, and Track ID 20, whose inferred threat level reads "attentive," is now nearing the intersection; (d) Track ID 64 is now considered as "non-relevant," and Track ID 20, whose inferred threat level reads "dangerous," is continuing to accelerate as it approaches the intersection; (e) Track ID 20, whose inferred threat level reads "dangerous," crosses the intersection at speed; and (f) Track ID 20 is now considered as "non-relevant."

"dangerous") but also being overly conservative regarding safety, regardless of whether its traffic light is still showing green. In this case, Track ID 180 has started to cross the intersection although its traffic light is showing red (that is, it is in the process of violating a traffic rule). Track ID 216, whose inferred threat level reads "safe," stops and waits at its stop line of the intersection since its traffic light is showing red. In Fig. 6b, the ego vehicle stops and waits at the safety line s_1 to avoid collision with Track ID 180 until Track ID 180 is inferred as "safe" or is considered as "non-relevant," regardless of whether its traffic light is still showing green. Track ID 180, whose inferred threat level reads "dangerous,"

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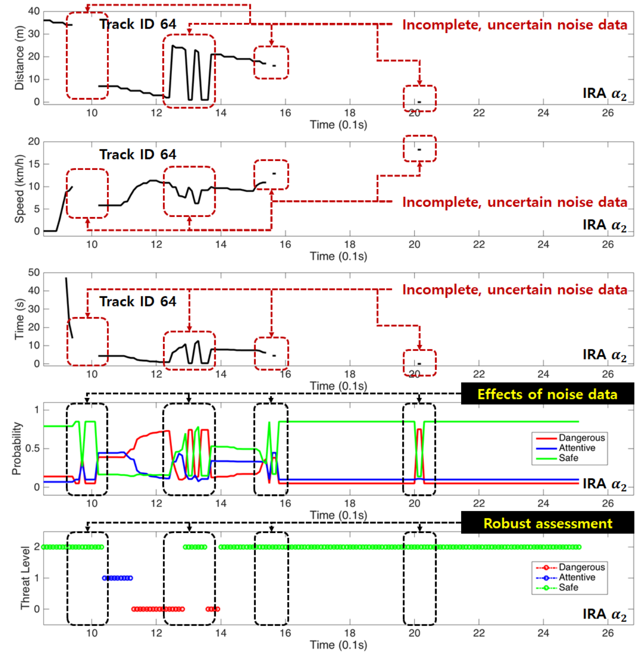
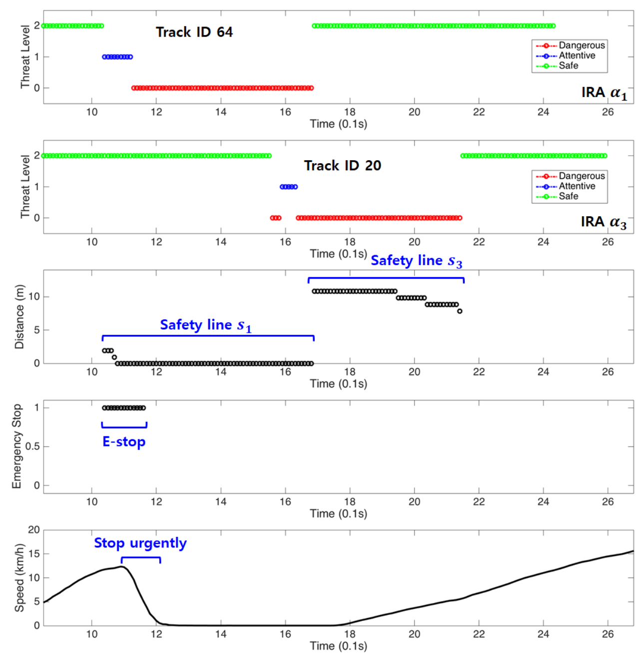
is crossing the intersection while violating a red light. Track ID 216, whose inferred threat level reads "safe," is still stationary at its stop line of the intersection. In Fig. 6c, since Track ID 180 is now considered as "non-relevant," Track ID 216 is still inferred as "safe," there are no further potential threats, and the traffic light corresponding to the ego vehicle is still showing green, the ego vehicle can now cross the intersection. If, however, the traffic light corresponding to the ego vehicle were to be showing red, then the proposed framework would instruct the ego vehicle to wait for the next green light. This is because if the traffic light changes to red when the ego vehicle still exists on or before the first crosswalk or stop line, then the ego vehicle waits for the next green light. On the other hand, if the traffic light changes to red when the ego vehicle has already passed the first crosswalk or stop line, then the ego vehicle passes through the intersection while flashing its emergency lights, provided it is safe to do so.

2) Test Case II: Test Case II is designed to test whether the ego vehicle can safely and efficiently navigate unsignalized intersections involving violation vehicles. Experimental results of autonomous driving in the case of Test Case II are illustrated in Fig. 7. In Fig. 7a, the ego vehicle proceeds to enter the intersection since Track IDs 64 and 20 are both inferred as "safe": Track ID 64 has stopped and is waiting at its stop line of the intersection, and Track ID 20 is approaching the intersection from a distance. In Fig. 7b, the ego vehicle stops urgently to the safety line s_1 associated with Track ID 64 to avoid collision with Track ID 64 since Track ID 64 is inferred as "attentive." Here, Track ID 64 begun to cross the intersection, even though the ego vehicle was the first to enter the intersection; Track ID 20 is still inferred as "safe." In Fig. 7c, the ego vehicle stops and waits at the safety line s_1 to avoid collision with Track ID 64 until Track ID 64 is inferred as "safe" or is considered as "non-relevant." Track ID 64, whose inferred threat level reads "dangerous," is crossing the intersection, and Track ID 20, whose inferred threat level reads "attentive," is now nearing the intersection. In Fig. 7d, the ego vehicle now begins to proceed through the intersection since Track ID 64 is considered as "non-relevant." However, it can only proceed to the safety line s_3 associated with Track ID 20 since Track ID 20 is inferred as "dangerous": Track ID 20 is continuing to accelerate as it approaches the intersection. In Fig. 7e, the ego vehicle proceeds to the safety line s_3 to avoid not only collision with Track ID 20 (whose inferred threat level reads "dangerous") but also being overly conservative regarding safety. In Fig. 7f, the ego vehicle can now proceed to the end of the intersection since there are no further potential threats: Track ID 20 is now considered as "non-relevant."



(a)



(b)

Fig. 8. Quantitative results for Test Case II: (a) reliably and robustly estimated reasoning results of IRA α_2 associated with CA c_2 under incomplete and uncertain noise data and (b) appropriately determined maneuvers that ensure the AV avoids both collision and being overly conservative regarding safety, based on traffic signals, intersection types, the state of the ego vehicle concerning the identified CAs, and the reliably and robustly estimated reasoning results of IRAs.

C. Quantitative Analysis

The plots described in Figs. 8a and 8b illustrate quantitative results in the case of Test Case II. Fig. 8a shows reliably and robustly estimated reasoning results under incomplete and uncertain noise data, whereas Fig. 8b shows appropriately determined maneuvers that ensure the AV avoids both collision and being overly conservative regarding safety.

In Fig. 8a, the first three plots represent traffic situations associated with IRA α_2 regarding distances of the most imminent threats to CCA c_2, speeds of the most imminent threats, and modified TTE values of the most imminent threats, respectively. The last two plots represent probabilistic reasoning results of IRA α_2. Here, the probabilities associated with the threat levels and the robustly inferred threat levels are visualized, respectively. During the experiments, incomplete and uncertain noise data occur often, as is evident by that shown in the first three plots. The incomplete noise data affects the probabilities associated with the threat levels, even though the proposed framework has considered the uncertainties of the data. However, the threat levels are inferred robustly by filtering out incompletely estimated probabilities associated with the threat levels, within the boundaries of time windows.

In Fig. 8b, the first two plots represent reliably and robustly inferred threat levels of IRAs α_1 and α_3, respectively. The third plot represents distances to the safety line associated with the first IRA in set $\mathcal{B}$. The fourth plot represents whether the emergency stop is triggered or not. The fifth plot represents speeds of the ego vehicle during autonomous driving at the intersection. During the experiments, the ego vehicle stops urgently to the safety line s_1 associated with IRA α_1 to avoid collision with Track ID 64 assigned to IRA α_1 since Track ID 64 is inferred as "attentive." In this case, Track ID 64 crosses the intersection even though the ego vehicle was the first to enter the intersection. The ego vehicle stops and waits at the safety line s_1 to avoid collision with Track ID 64 until the inferred threat level of IRA α_1 indicates "safe" (that is, Track ID 64 is considered as "non-relevant"). When the inferred threat level of IRA α_1 indicates "safe" and at the same time the inferred threat level of IRA α_3 indicates "dangerous," the ego vehicle proceeds to the safety line s_3 associated with IRA α_3 to avoid not only collision with Track ID 20 assigned to IRA α_3 but also being overly conservative regarding safety, instead of stopping and waiting at the safety line s_1 until the inferred threat level of IRA α_3 indicates "safe." Also, when the inferred threat level of IRA α_3 changes to "safe" (that is, Track ID 20 is considered as "non-relevant") before the ego vehicle reaches safety line s_3, the ego vehicle crosses the intersection without stopping at safety line s_3.

VII. Conclusion

The majority of current studies regarding autonomous driving at road intersections focus on motion prediction, threat assessment, or decision-making problems. In addition, they are overly conservative regarding safety, unable to guarantee safety in the face of violation vehicles, or inapplicable to all types of intersection.

In this work, we proposed a decision-making framework — consisting of situation awareness, situation assessment, and maneuver decision — that determines appropriate maneuvers for an autonomous vehicle (AV) to navigate an intersection safely and efficiently (regarding *making progress*), even in the face of violation vehicles. The proposed framework can be used with any type of intersection since it predicts at the lane level all possible future paths of all observed vehicles using a detailed, precise digital map. In addition, it can systematically, reliably, and robustly assess potential threats at an intersection, even under incomplete and uncertain noise data, by way of an independent and distributed reasoning structure, a threat measure, Bayesian networks, and time window filtering. Most notably, it can determine appropriate maneuvers that ensure the AV avoids not only collision but also being overly conservative regarding safety, even in the face of violation vehicles: it can ensure the AV avoids collision since it identifies potential threats and collision areas, regardless of whether observed vehicles are obeying traffic rules at the intersection, and it can ensure the AV avoids being overly conservative regarding safety since it instructs the AV to make progress whenever it is safe to do so — a feat made possible since the proposed framework considers temporal and spatial relationships between the AV and other vehicles and identifies potential collision areas.

Our experimental results show that the proposed framework provides a reliable performance for autonomous driving at intersections regarding reliability and robustness (even under incomplete and uncertain noise data) and safety and efficiency (even in the face of violation vehicles). Although the proposed framework provides a reliable performance for autonomous driving at intersections, decision-making for a dilemma zone at signalized intersections was not well analyzed. Future work should, therefore, include decision-making for a dilemma zone at signalized intersections once the performance of traffic signal detection can be guaranteed for long distances and lighting variations or once vehicle-to-infrastructure communication is made available. In addition, future work should explore an integration of estimation of driver intention for a better understanding of traffic situations and to improve the performance of decision-making.

Finally, the next big step for future work is to verify the proposed framework on public urban roads upon resolution of impending legal and insurance issues.

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Samyeul Noh received the B.S. degree in systems science from the School of Engineering Science, Osaka University, Osaka, Japan, in 2009 and the M.S. degree in electrical and computer engineering from University of California at San Diego, La Jolla, CA, USA, in 2012.

Since 2012, he has been a Researcher with the Creative Contents Research Division, Electronics and Telecommunications Research Institute, Daejeon, Rep. of Korea. His main fields of interest include autonomous driving systems, robotics, and deep learning. His research activities include data fusion, probabilistic reasoning, and decision-making for autonomous vehicles.