Deception for Advantage in Connected and Automated Vehicle Decision-Making Games*

Hangyu Li[1], Heye Huang[1,†], Xiaotong Sun[2], and Xiaopeng Li[1]

***Abstract*— Connected and Automated Vehicles (CAVs) have the potential to enhance traffic safety and efficiency. In contrast, aligning both vehicles' utility with system-level interests in scenarios with conflicting road rights is challenging, hindering cooperative driving. This paper advocates a game theory model, which strategically incorporates deceptive information within incomplete information vehicle games, operating under the premise of imprecise perceptions. The equilibria derived reveal that CAVs can exploit deceptive strategies, not only gaining advantages that undermine the utility of the other vehicle in the game but also posing hazards to the overall benefits of the transportation system. Vast experiments were conducted, simulating diverse inbound traffic conditions at an intersection, validating the detrimental impact on efficiency and safety resulting from CAVs with perception uncertainties, and employing deceptive maneuvers within connected and automated transportation systems. Finally, the paper proposes feasible solutions and potential countermeasures to address the adverse consequences of deception in connected and automated transportation systems. It concludes by calling for integrating these insights into future research endeavors and pursuing to fully realize the potential and expectations of CAVs in enhancing the whole traffic performance.**

I. Introduction

Autonomy and connection are two important directions of future intelligent vehicle development [1], [2]. Connected and Automated Vehicles (CAVs) can communicate with other traffic participants, sharing perception and control information [3], [4]. This ability enables intelligent vehicles to have a perception ability beyond their own range, as well as to understand the intentions of other vehicles, which has the potential to achieve cooperative driving [5]. Despite ongoing debate regarding the societal benefits of Autonomous Vehicles (AVs) as compared to Human-Driven Vehicles (HDVs) [6], CAVs are widely acknowledged for their potential to enhance traffic safety, energy efficiency, and mobility significantly. This is attributed to their theoretical capability to eliminate human errors and facilitate cooperative operations.

Some traffic scenarios have been deeply explored, such as cooperative car-following [7]. Multiple adverse issues, such as perception noise, physical errors, and communication delays in CACC, have been considerably addressed [8]. However, even with perfect communication, CAV also have the potential to become unprecedented disruptors in the future owing to their vulnerability to cyber threats, hacking, and misinformation [9]. Their use by various entities could lead to deceptive practices aimed at seeking selfish or harmful objectives, especially in complex scenarios like intersections [10], on-ramps [11], and merging lanes. These scenarios, unlike CACC, present conflicting utilities, complicating optimal strategies. Negotiation-based game theory has effectively addressed issues. However, vehicle interactions are not always harmonious and cooperative, especially when the interests of different vehicles clash or local optima conflict with overall benefits, making competition inevitable. Vehicles may use deceptive strategies in various scenarios, prompting other vehicles to become confused and adjust their strategies, thereby gaining advantages, as shown in Fig. 1.

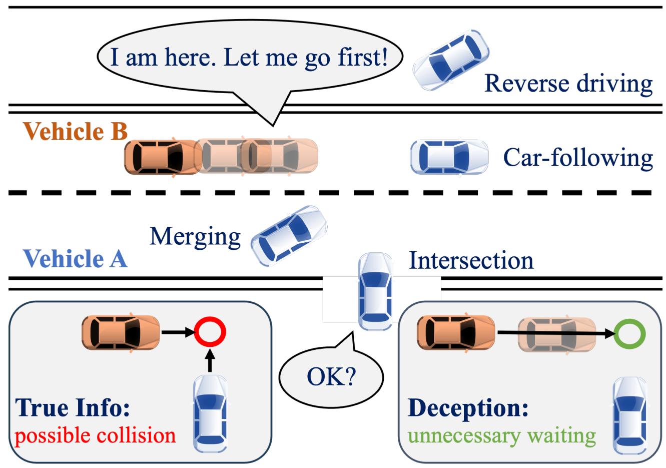

Fig. 1. CAV deception behavior in typical conflicting scenarios.

Without vehicle connectivity, decisions rely solely on single-vehicle perception. Inter-vehicle communication allows for decision-making based on shared signals and observations, highlighting the importance of balancing trust and deception. Deception modeling in real-world conflicts is complex, with game-theoretic and learning-driven methods being the primary approaches in existing literature [12]. Game theory is critical for analyzing decision-making in interactive conflicts involving AVs [13]. It studies deception in games where actions or outcomes are reported to other players, often through signaling games where signals can be honest, deceptive, or absent. In multi-vehicle conflicts, sig-

*This paper is based upon work supported by the U.S. National Science Foundation under Grant No.2313578.

†Corresponding author, email: hhuang468@wisc.edu

[1]Hangyu Li, Heye Huang, and Xiaopeng Li are with the Department of Civil & Environmental Engineering, University of Wisconsin-Madison, Madison, United States.

[2]Xiaotong Sun is with the Intelligent Transportation Thrust, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China and the Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, Hong Kong SAR, China.

naling games model defensive deceptions aimed at misleading attackers [14]. Carroll et al.[15] employed deceptive signaling games to study network defense, focusing on scenarios where attackers discern system types, forcing defenders to send signals, deceptive or genuine. Their findings suggest deception as a strategic equilibrium for defenders, often more effective than truthful signals. Yavin et al. [16] investigated pursuer-evader deception, analyzing strategies based on player positions and distances, with the evader disrupting signals to the pursuer. The goal was to identify the most effective pursuit strategies against misleading or incomplete information. Modeling interactive decision conflict through game theory can clarify multi-agent interactions through mathematical proofs and simulation analyses, improving decision-making transparency and application transferability [17]. However, the complexity and uncertainty of networks and game theory's reliance on common sense assumptions present challenges in real-world applications.

Recent studies have integrated learning-based defensive deception techniques, such as machine learning (ML) and reinforcement learning (RL), for creating decoys and fabricating information to mislead attackers [18]. ML-based approaches offer improved predictions about attackers or create highly similar deceptive objects using extensive available data [19]. Nadeem et al. [20] employed machine learning algorithms to train on historical network attack data in software-defined networks, developing high-quality honeypots. This ML-based method aims to identify potential malicious connections and attack destinations. Furthermore, RL has been applied to study defensive deception games. Utilizing RL or Deep RL [21], its reward function is employed to formulate players' utility functions, enabling agents to determine optimal strategies similar to other attack-defense games. In RL-based game formulations, players employ RL to ascertain optimal strategy, where the RL reward function considers gains and losses based on the player's beliefs about the opponent's actions. Nguyen et al. [22] proposed an embedded RL-based online deception method, considering the dynamic alteration of attacker strategies and tactics in response to defensive actions while maintaining a balance between availability and security. Learning-based methods address insufficient interaction between a single attacker and defender, extending to multi-agent interaction processes. At the same time, the accuracy of learning-based deception techniques depends on the availability of data on the interaction processes of conflicting agents. In practice, such data is often inaccessible to defenders, significantly limiting the training and exploration of learning-based approaches.

In the intricate decision-making games of CAVs, the strategic use of deceptive information can have profound effects. Considering imprecise vehicle perceptions, this paper strategically incorporates deceptive information into CAV interactions at unprotected intersections. Key contributions include:

1) Utilizing game theory, analyze the effect of incomplete information, in scenarios of perception uncertainty, cooperative connection, and deception on CAV decision-making games, emphasizing the negative impact of deception on overall traffic.

2) Highlight how CAVs with societal attributes and human-like deceptive behaviors aim to maximize their utility, ultimately leading to deviation from optimal actions by all traffic participants.

3) Simulation experiments show that deception by a CAV harms system benefits, even worse than AV solely decision-making scenarios, and emphasize the need for robust strategies to mitigate the adverse effects of deceptive tactics.

The remaining part of this paper is arranged as follows. Section II describes the focused scenario and the game theory behind it. In Section III, we analyzed the impact of perception error, connectivity, and deceptive behavior on the game and its equilibria. In addition, Section IV introduces the simulation experiments and discussions on the results. Finally, Section V concludes the paper.

II. Scenario and Model

Our research focuses on the scenario where two vehicles compete for the right to pass through the same roadblock, typically occurring at an unprotected signal-free intersection, as shown in Fig. 2.

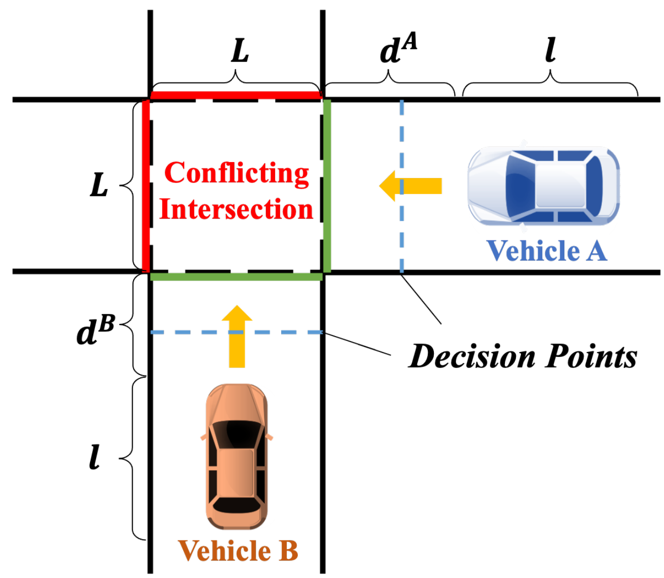

Fig. 2. A typical conflicting intersection where two vehicles compete for passing. That they do not give way to each other can lead to unsafe collisions.

To eliminate interference and focus on the main issue, we assume that both road approaches have the same grades and width (L). The two CAVs participating in the game are consistent in size (length l), power mobility, perception ability, etc., except for their strategies. The actual distances between the vehicle heads and the entrances of the intersection are d^A (for vehicle A) and d^B (for vehicle B), respectively.

We use a single decision process to represent the game between two CAVs. This allows us to avoid planning complex speed changes and precise acceleration control. The currently popular reservation-based intersection management strategy for multiple vehicles also has a similar approach [23], but without consideration of deception. Each approach has a decision point with the same distance (see Fig. 2) from the intersection, similar to the decision point set by FHWA for human drivers in MUTCD, where each incoming CAV makes a single decision when it reaches.

Two decisions (Σ) can be planned for each vehicle ($N = \{A, B\}$), keeping speed to pass or slowing down to yield:

$$\Sigma^A = \{pass,\ yield\} \tag{1a}$$
$$\Sigma^B = \{pass,\ yield\} \tag{1b}$$

We consider both safety and efficiency in the game payoffs:

$$U = S + E \tag{2a}$$
$$S = \begin{cases} 0, & \textit{risk-free} \\ -R, & \textit{risky} \end{cases} \tag{2b}$$
$$E = \frac{x}{v} - t_c \tag{2c}$$

The utility (U) of each agent consists of two parts. S stands for safety, which gives a large negative number representing a penalty ($-R$) to each vehicle causing a collision risk (i.e., two CAVs occupying a conflict block simultaneously). On the other hand, the gap between the expected time of entering the intersection (x/v) and the actual time of entering the intersection (t_c) at speed v is employed as the efficiency term (E) in utility.

Similar to a simple chicken game, this game will produce four different playoffs, as shown in Table I.

TABLE I
NORMAL-FORM GAME PLAYOFFS OF TWO AGENT CAVS COMPETING FOR THE RIGHT OF WAY AT AN INTERSECTION.

(U^A, U^B)	A: Pass	A: Yield
B: Pass	$(-R, -R)$	$(\frac{d^A}{v} - \frac{L+d^B+l}{v}, 0)$
B: Yield	$(0, \frac{d^B}{v} - \frac{L+d^A+l}{v})$	$(-D, -D)$

In a conflict, there is a restriction on the difference of distances between the two vehicles and the entrances of the intersection (see (3)), which ensures the negativity of E.

$$|d^A - d^B| < L + l \tag{3}$$

When both CAVs choose to pass, each vehicle enters the intersection at the same speed v, which does not cause a delay. However, the presence of two vehicles at a conflicting intersection can lead to a significant collision risk. Therefore, both agents receive a large negative utility as penalties for this outcome.

Alternatively, when vehicle A chooses to pass and vehicle B decides to yield, there will be no delay and no safety risk for passing through the intersection, leading to a zero utility for vehicle A. On the other hand, vehicle B has to wait until vehicle A drives entirely out of the intersection, which results in a time delay ($\frac{d^B}{v} - \frac{L+d^A+l}{v}$), though no safety penalty is given to it. Oppositely, when vehicle A decides to give way to vehicle B, it suffers from a time delay ($\frac{d^A}{v} - \frac{L+d^B+l}{v}$) but no safety penalty either.

The special situation is when both agents decide to yield. In order to maintain the completeness of the game model, a moderate negative number ($-D$) is given to both CAVs as the playoff. The total utility of the intersection ($U^{tot} = U^A + U^B$) will be much greater than the penalty for collision risk but less than the shortest delay time for decisive decision-making, shown as (4). It may be subject to change in different situations.

$$-R \ll -2D < -\frac{L + l - |d^A - d^B|}{v} \tag{4}$$

This yield decision by both CAVs resulted in further gameplay closer to the intersection and at lower speeds, causing delays for both sides. However, we will not further discuss and design the playoff for this situation in detail, and the reasons will be explained in the following sections.

III. Game Analysis

For CAV decision-making in an ideal situation, interacting vehicles know ego and each other's precise and accurate positions. Control can be implemented through specific traffic rules, such as *first come, first go*, the same as human traffic regulations. Even more precise and targeted planning and control can be conducted, which is also the potential of CAV to improve the traffic system. However, the gap between reality and ideals makes it necessary to consider situations beyond. For example, [24] considers the driver's irrational behavior. Our work regards the imprecise observation of intelligent connected vehicles and focuses on analyzing the deceptive behavior in response.

In this section, we will rely on the game model we proposed in Section II to analyze pure or mixed strategies in ideal, imprecisely perceptual, cooperatively connecting, and deceptively competing scenarios, as well as the impact of these equilibria on the safety and efficiency of the entire intersection. The comparison of the decision-making process between four situations is presented in Fig. 3. This analysis considers the variations in the information perceived and received by the interacting vehicles, Vehicle A and Vehicle B, under different circumstances. Factors such as the completeness and accuracy of the information will influence the strategies these vehicles adopt to maximize their benefits. Consequently, this leads to divergent impacts on the overall traffic system.

A. Ideal situation

In an ideal situation, both vehicles at the intersection know each other's exact locations. Moreover, the locations of decision points are also perceived by both CAVs. Each has complete information of whether the other has completed the decision and the specific choice. Therefore, for the vehicle that makes the decision first, there are two options (pass or yield), and we will analyze them by sequence.

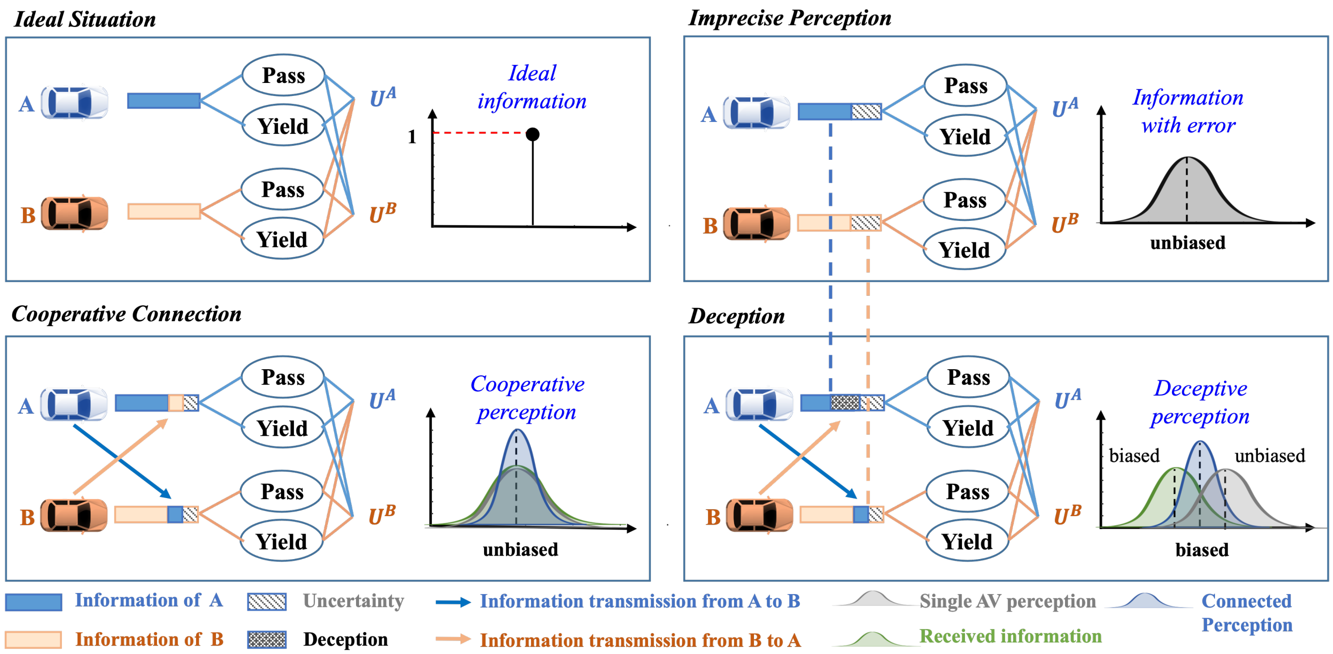

Fig. 3. The game process comparison of four situations with two conflicting CAVs. Specifically, this paper considers the ideal, imprecise perception, cooperative connection, and deception scenarios.

1) case 1: The first vehicle decides to pass. The utility of the second decision-making vehicle choosing to yield is higher than that of choosing to pass ($-R < -\frac{L+l-|d^A-d^B|}{v}$). Therefore, giving way to the leading vehicle is its dominant strategy.

2) case 2: The first vehicle decides to yield. This time, oppositely, the utility of the second decision-making vehicle choosing to pass is higher ($-D < 0$). Therefore, when the other CAV gives way, the ego vehicle should not hesitate to continue passing through the intersection.

Considering the above two cases, due to the unique dominant strategy for the other agent, the vehicle that makes the decision first will choose to pass to gain more excellent utility ($-\frac{L+l+|d^A-d^B|}{v} < 0$). The whole process can be seen in Fig. 4.

Therefore, the ideal equilibrium is one of the two pure strategy Nash equilibria of the chicken game shown in Table I (depending on which agent makes the decision first). This can also maximize the overall efficiency of intersections ($U^{tot}_{max} = -\frac{L+l-|d^A-d^B|}{v}$). In addition, the pure strategy equilibrium complies with the *first come, first go* traffic regulation, facilitating integration into HDVs and mixed traffic.

B. Perception uncertainty

Automated vehicle (AV) collects surrounding information through sensors to achieve self-localization and traffic participants' observation to assist decision-making. However, due to the imperfection of sensors, there is inherent uncertainty in the observation, which has led to multiple accidents involving AVs. This calls for enhancing the reliability and accuracy of these sensor systems to mitigate risks and improve the overall safety of AVs [25].

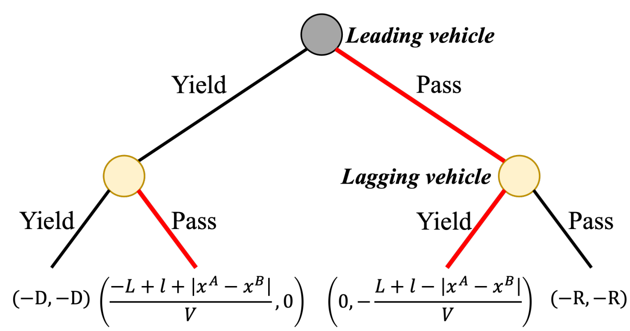

Fig. 4. The ideal game process of two conflicting vehicles at an intersection. Dominant strategies of each sub-game are marked by red lines.

As the detection and measurement of the other vehicle is not entirely precise, AVs make decisions with uncertainty. In our game theory model, compared to the ideal situation, AVs making decisions with perceived uncertainty in reality forms an incomplete information game, as shown in Fig. 5.

We first consider the leading vehicle. Due to the fact that the vehicle making decisions afterward is currently driving normally, based on the ego vehicle's observation, this vehicle is believed to have completed the decision and decided to pass with a certain probability ($p \in (0, 0.5)$). The complementary probability ($1-p$) suggests that it has not made a dicision yet.

1) case 1: The lagging vehicle is believed to pass. If the other vehicle is observed to complete a *pass* decision, the ego vehicle should choose a dominant strategy of *yield*. It is a local Nash Equilibrium generated from the chicken game in the ideal situation with complete information (see Table I).

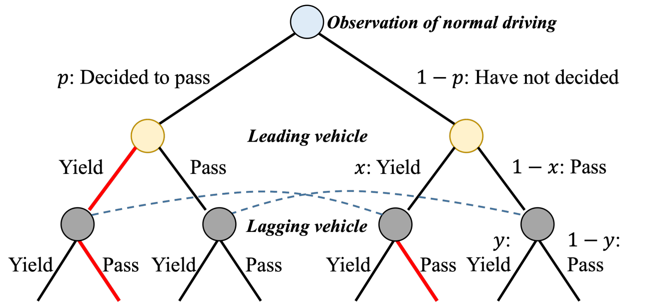

Fig. 5. The incomplete information game of two conflicting AVs at an intersection. The uncertainty of observation results in the decision-making vehicle not knowing whether the opponent, who is driving normally, has decided to pass or has yet to make a choice.

2) case 2: The lagging AV is considered undecided yet. If the ego vehicle believes a delayed decision from the other, it will need to consider the vehicle's perception error and decision-making. No pure strategy equilibrium can be expected. We then assume that the ego AV takes a mixed strategy with a certain probability (x) of choosing to yield while the complementary probability ($1-x$) of choosing to pass.

Therefore, for the vehicle that makes the decision first, based on its perception ability and analysis of the other vehicle, the probabilities of choosing to yield and pass are:

$$\frac{\Sigma^1 = pass}{\Sigma^1} = (1-p)(1-x) \tag{5a}$$

$$\frac{\Sigma^1 = yield}{\Sigma^1} = p + (1-p)x \tag{5b}$$

Considering the second decision-making AV, although there are perception uncertainties in distance and localization, it can accurately understand the yield intention based on the observed vehicle's deceleration behavior. Consequently, if the first AV opts to yield, the game reverts to a complete information state, prompting the second AV to adopt passing as its dominant strategy.

When the second vehicle is making decisions, and the first vehicle is driving normally, based on the symmetry of equal perception ability, the probability of determining that the first vehicle has made a *pass* decision is $1-p$.

Similarly, it can be assumed that the lagging AV takes a mixed strategy with a certain probability (y) of choosing to yield, while the complementary probability ($1-y$) of choosing to pass, under the condition of believing the first AV undecided. Therefore, the probabilities of the second vehicle choosing to yield and pass are:

$$\frac{\Sigma^2 = pass}{\Sigma^2} = p(1-y) \tag{6a}$$

$$\frac{\Sigma^2 = yield}{\Sigma^2} = 1 - p + py \tag{6b}$$

Therefore, under such circumstances, the optimal strategy for the lagging vehicle is to:

$$\arg\max_y \left\{ \begin{array}{l} -\dfrac{L+l-|d^A-d^B|}{v} y \\ +(1-p)(1-x)(-R)(1-y) \end{array} \right\} \tag{7}$$

By solving this, we get:

$$y = 0, \; if \; x > 1 - \frac{L+l-|d^A-d^B|}{vR(1-p)} \tag{8a}$$

$$y = 1, \; if \; x < 1 - \frac{L+l-|d^A-d^B|}{vR(1-p)} \tag{8b}$$

$$y \in [0,1], \; if \; x = 1 - \frac{L+l-|d^A-d^B|}{vR(1-p)} \tag{8c}$$

On the other hand, for the vehicle making decisions first, the optimal strategy is to:

$$\arg\max_x \left\{ \begin{array}{l} -\dfrac{L+l+|d^A-d^B|}{v} x \\ +p(1-y)(-R)(1-x) \end{array} \right\} \tag{9}$$

By solving this, we get:

$$x = 0, \; if \; y > 1 - \frac{L+l+|d^A-d^B|}{vRp} \tag{10a}$$

$$x = 1, \; if \; y < 1 - \frac{L+l+|d^A-d^B|}{vRp} \tag{10b}$$

$$x \in [0,1], \; if \; y = 1 - \frac{L+l+|d^A-d^B|}{vRp} \tag{10c}$$

The game equilibria under perception errors can be derived by combining (8) and (10). When the observation is precise, and there is a clear gap between two vehicles ($p < \frac{L+l+|d^A-d^B|}{vR}$), there exists an equilibrium that $(x=0, y=1)$, which is consistent with the *first come, first go* rule in ideal situations.

As perception precision decreases or the distance between two vehicles narrows (i.e. making a vague picture of who leads and who falls behind) ($p \geq \frac{L+l+|d^A-d^B|}{vR}$), one more pure strategy equilibrium $(x=1, y=0)$ and a mixed strategy equilibrium ($x = 1 - \frac{L+l-|d^A-d^B|}{vR(1-p)}, y = 1 - \frac{L+l+|d^A-d^B|}{vRp}$) will show up. Due to the increased probability of being penalized for safety issues, vehicles that make decisions first tend to make a more conservative choice, and pure strategy equilibrium will dominate. As for the mixed strategy, $x \approx 1$ makes it similar to the pure yield strategy, preventing it from passing the intersection without deceleration.

AV can have more confidence in the perception results when the sensor precision is high enough over a threshold due to the tiny probability of being penalized by collision. In most cases, the leading AV decides to pass and only yields when the other agent is perceived as leading. This leads to a total utility of the intersection between optimal and second-optimal, as a transition from a perfect situation to an imprecisely perceived situation:

$$U_{sec}^{tot} = -\frac{L+l+|d^A-d^B|}{v} < U_{max}^{tot} \tag{11}$$

AV can have more confidence in the perception results when the sensor precision is high enough over a threshold due to the tiny probability of being penalized by collision. In most cases, the leading AV decides to pass and only yields when the other agent is perceived as leading. This leads to a total utility of the intersection between optimal and second-optimal as a transition from a perfect situation to an imprecisely perceived situation:

$$U_{sec}^{tot} < U_{av}^{tot} < U_{max}^{tot} \tag{12a}$$

$$U_{av}^{tot} = \max\left\{U_{sec}^{tot}, U_{tr}^{tot}(p)\right\} \tag{12b}$$

$$\begin{aligned} U_{tr}^{tot}(p) = &- p(1-p)R - p\frac{L+l+|d^A-d^B|}{v} \\ &- (1-p)^2\frac{L+l-|d^A-d^B|}{v} \end{aligned} \tag{12c}$$

Taking a conservative strategy to avoid conflict actively also conforms to our observation of most automated vehicles operating on the road nowadays. However, it can be seen that this caused by perception uncertainty harms the utility of the leading vehicle and leads to a decrease in overall benefits in efficiency and safety.

C. Connectivity and deception

CAVs enhance AVs' capabilities via cooperative perception, decision-making, and control. Collaborative CAVs can not only compensate for a single vehicle's sensor blind spots through multi-view information but also improve precision in observing the same object through information fusion. Taking distance measurement as an example, two vehicles with the same perception ability make two independent and shared observations of the same vehicle's position, which reduces the variance while maintaining unbiasedness:

$$\mu_{co}^{avg} = \frac{\mu^A+\mu^B}{2} = \mu^A = \mu^B \tag{13a}$$

$$(\sigma_{co}^{avg})^2 = \frac{\left(\sigma^A\right)^2+\left(\sigma^B\right)^2}{4} = \frac{\left(\sigma^A\right)^2}{2} = \frac{\left(\sigma^B\right)^2}{2} \tag{13b}$$

Therefore, the cooperative perception can reduce the probability of misjudging the decision-making status of the other agent ($p_{co} < p$). For vehicles that make decisions first, a smaller p_{co} leads to more choices of *pass* when the other agent's decision status cannot be determined, which is a pure strategy of $(x=0, y=1)$.

Furthermore, if decision information can be shared beyond perception to achieve complete information, the game between two CAVs will tend towards an ideal situation. Only when the vehicle that makes the decision first observes the wrong relationship, even with the help of cooperative perception, will it choose the equilibrium strategy of yield (while the second vehicle would decide to pass, which is also the second optimal strategy for the overall intersection utility U_{sec}^{tot}). With such help, the total utility of the intersection will be closer to the ideal situation:

$$U_{tr}^{tot} < U_{co}^{tot} < U_{max}^{tot} \tag{14a}$$

$$\begin{aligned} U_{co}^{tot} = &- p_{co}\frac{L+l+|d^A-d^B|}{v} \\ &- (1-p_{co})\frac{L+l+|d^A-d^B|}{v} \end{aligned} \tag{14b}$$

From this, connectivity is effective and promising in eliminating the reduction of utility caused by single AV perception errors. However, under human-like autonomous driving decision-making development, we cannot expect every CAV to handle conflicts cooperatively. For the CAV falling behind, although the *first come, first go* strategy is beneficial for the overall traffic at the intersection, it pays all the cost and suffers from wait and delay. It likely sends incorrect leading messages through the V2V connectivity in a deceptive manner, prompting the leading vehicle to brake and yield.

1) case 1: Through cooperative decision-making. The most effective way is often the weakest to attack. Inspired by that *yield* is a dominant strategy for the lagging vehicle to avoid delays and improve efficiency, the lagging CAV will send information to the other CAV that the decision of *pass* has been made, thereby forcing the previously leading vehicle to yield and wait longer. This is a pure strategy Nash equilibrium in the chicken game (see Table I) with complete information, while the total utility is not optimal.

2) case 2: Through cooperative perception. Deviated location information can be transmitted to the other CAV, prompting it to yield. It is more difficult to distinguish from the normal perception than directly sharing incorrect decision-making status information. Compared to (13), such deception still improves the precision of perception but reduces the accuracy:

$$\mu_{de}^{avg} = \frac{\mu^A+\mu^B+bias}{2} = \mu_{co}^{avg} + \frac{bias}{2} \tag{15a}$$

$$\left(\sigma_{de}^{avg}\right)^2 = \frac{\left(\sigma^A\right)^2+\left(\sigma^B\right)^2}{4} = (\sigma_{co}^{avg})^2 \tag{15b}$$

From the comparison between cooperative and deceptive perception, we can obtain that under the attack of deceptive information, the probability of the leading vehicle making incorrect judgments on the decision-making status of the lagging vehicle has significantly increased ($p_{co} < p < p_{de}$).

A larger p_{de} has a less probability to satisfy the requirement of $p_{de} < \frac{L+l+|d^A-d^B|}{vR}$. Even if it can be met, this condition raises the probability of the first deciding vehicle yielding, subsequently diminishing the total utility of the intersection.

$$\begin{gathered} U_{sec}^{tot} \le U_{de}^{tot} < U_{av}^{tot} < U_{max}^{tot} \\ U_{de}^{tot} = \max\left\{U_{sec}^{tot}, U_{tr}^{tot}(p_{de})\right\} \end{gathered} \tag{16}$$

Due to the fact that CAVs will always deceive for advantage in a connected condition, hurting the overall utility of the intersection to even worse than AVs without connectivity, each CAV's belief in the other's decision-making status and

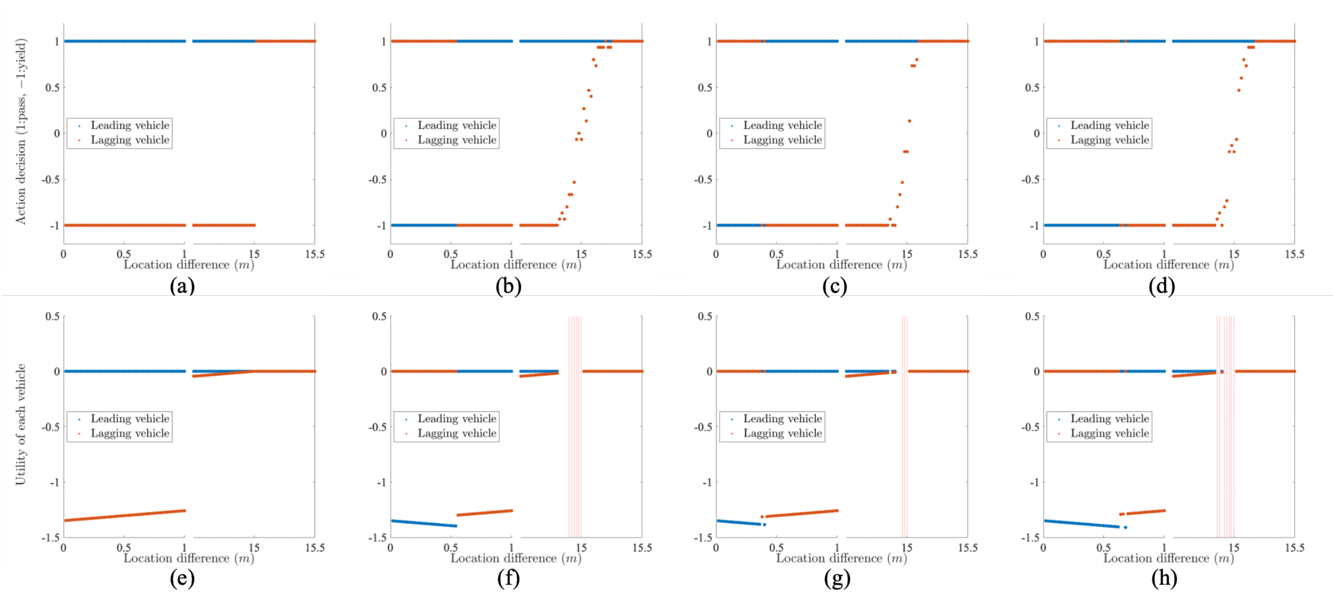

Fig. 6. From left to right, (a)-(d) show the decisions of both vehicles changing with true value gaps under ideal condition, imprecise perception, cooperation, and deception, respectively. Accordingly, (e)-(h) represent the utility of both vehicles under the corresponding decisions.

location information decreases to zero. This is in line with the characteristics of *cheap talk* games. As a result, each CAV relies only on the information it perceives, and the role of the vehicle-to-vehicle connectivity will be significantly reduced.

IV. Experiment

In this section, we introduce our simulation experiment to intuitively and quantitatively show the impact of vehicle perception uncertainty, connectivity, and deception on decision-making games at a conflicting intersection.

The parameters for the simulation experiments are listed in Table II.

TABLE II
PARAMETERS USED IN SIMULATION EXPERIMENTS.

Parameter	Value
Road width L	10 m
Vehicle length l	5 m
Vehicle speed v	40 km/h
Equivalent time for safety penalty R	10000 s
Delay caused by both yield D	2 s
Measurement error std σ	0.1m

A conflict will exist in this intersection when there is a $L+l=15m$ difference in distance between two vehicles and the intersection entrances. We consider the leading vehicle and cover situations where the lagging vehicle is $0\sim 20m$ behind. We repeated $N=30$ random trials for uncertain scenarios, and the average results are shown in Fig. 6.

In an ideal conflicting situation, the leading vehicle will always decide to pass while the lagging vehicle will give way out. And if the gap between them is larger than $15m$, both vehicles will choose to pass with the awareness of no conflict. The leading vehicle's utility keeps at zero while the lagging vehicle's utility linearly increases from zero distance to a larger gap (see Figure. 6 (a) and (e)).

In the presence of perception errors, the observation results of each vehicle are set to have a Gaussian error with a standard deviation of 0.1m. This makes the 95% confidence interval of the perception result around $\pm 0.2m$, consistent with the ability of cutting edge AVs [26]. When two vehicles are close, the leading vehicle cannot accurately determine the location relationship, leading to its active yield decision. This causes longer waiting times, resulting in a negative utility of the leading vehicle, and even worse, with the gap between increases. When the gap is large enough, and the probability of misjudgment is below the threshold, both vehicles will resume the *first come, first go* strategy. In addition, when the gap increases to around $15m$, the lagging vehicle will sway between pass and yield due to uncertainty, where conflicting traffic leads to a probability of collision accidents (see Figure. 6 (b) and (f)).

Cooperative perception can effectively compensate for decreased utility caused by perception errors. Smaller uncertainty helps to achieve a lower probability of misjudgment, thereby reducing the range of distance between two vehicles with which the leading vehicle will actively decide to yield and that of potential accidents (see Figure. 6 (c) and (g), with larger utility and lower collision probability).

However, transmitting deceptive information can reduce the system-level benefits. Location information with an offset of $0.2m$ is set to be transmitted from the lagging vehicle to the leading vehicle, causing a significant deviation in the leading vehicle's judgment of the location relationship between the two vehicles. As a result, deceptive information leads to the larger gap range with which the leading vehicle actively yields and a higher probability of collision at the critical gap of $15m$ (see Figure. 6 (d) and (h)).

V. Conclusion

In summary, this paper has introduced a game theoretical framework for analyzing CAV interactions, explicitly examining the repercussions of vehicle perception uncertainty and adversarial deception on the traffic system. The strategic use of CAVs' deception to optimize individual utility has been theoretically demonstrated to potentially compromise the efficiency and safety of the overall traffic system, particularly in conflicting intersections. This paradox highlights the inherent conflict between single-vehicle optimization and the broader system-wide benefits, weakening the advantages brought by vehicle-to-vehicle connectivity. In addition, extensive simulation experiments have been conducted to underscore the detrimental impact of such deceptive maneuvers.

Furthermore, we plan to delve into the decision-making process, exploring the equilibrium between signaling strategies and reception beliefs through signaling games. Expanding the scope to diverse scenarios will provide a more comprehensive understanding of how these characteristics impact macroscopic traffic networks. Moreover, ongoing real-world experiments are poised to validate our theoretical derivations.

Inspired by [27], future research is expected to leverage machine learning methods for accurately identifying irrational drivers and cooperative vehicles, thereby improving decision-making for CAVs. Even without intentional deception, addressing mechanisms to counteract similar behaviors can address problems like communication delays. Therefore, we advocate integrating considerations of incomplete information in CAV studies, employing verification mechanisms, recognition methods, robust control, and other strategies to mitigate the adverse effects on intelligent transportation systems.

References

[1] Prateek Bansal and Kara M Kockelman. Forecasting americans' long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice*, 95:49–63, 2017.

[2] DianGe Yang, Kun Jiang, Ding Zhao, ChunLei Yu, Zhong Cao, ShiChao Xie, ZhongYang Xiao, XinYu Jiao, SiJia Wang, and Kai Zhang. Intelligent and connected vehicles: Current status and future perspectives. *Science China Technological Sciences*, 61:1446–1471, 2018.

[3] Zachary MacHardy, Ashiq Khan, Kazuaki Obana, and Shigeru Iwashina. V2x access technologies: Regulation, research, and remaining challenges. *IEEE Communications Surveys & Tutorials*, 20(3):1858–1877, 2018.

[4] Christoph Burger, Piotr F Orzechowski, Ömer Şahin Taş, and Christoph Stiller. Rating cooperative driving: A scheme for behavior assessment. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6. IEEE, 2017.

[5] Cristina Olaverri-Monreal, Pedro Gomes, Ricardo Fernandes, Fausto Vieira, and Michel Ferreira. The see-through system: A vanet-enabled assistant for overtaking maneuvers. In *2010 IEEE intelligent vehicles symposium*, pages 123–128. IEEE, 2010.

[6] Xiaobo Qu, Lingshu Zhong, Ziling Zeng, Huizhao Tu, and Xiaopeng Li. Automation and connectivity of electric vehicles: Energy boon or bane? *Cell Reports Physical Science*, 3(8), 2022.

[7] Shengbo Li, Keqiang Li, Rajesh Rajamani, and Jianqiang Wang. Model predictive multi-objective vehicular adaptive cruise control. *IEEE Transactions on control systems technology*, 19(3):556–566, 2010.

[8] Yang Zhou, Soyoung Ahn, Madhav Chitturi, and David A Noyce. Rolling horizon stochastic optimal control strategy for acc and cacc under uncertainty. *Transportation Research Part C: Emerging Technologies*, 83:61–76, 2017.

[9] Alexandros Nikitas, Simon Parkinson, and Mauro Vallati. The deceitful connected and autonomous vehicle: Defining the concept, contextualising its dimensions and proposing mitigation policies. *Transport policy*, 122:1–10, 2022.

[10] Peiqun Lin, Jiahui Liu, Peter J Jin, and Bin Ran. Autonomous vehicle-intersection coordination method in a connected vehicle environment. *IEEE Intelligent Transportation Systems Magazine*, 9(4):37–47, 2017.

[11] Jackeline Rios-Torres and Andreas A Malikopoulos. A survey on the coordination of connected and automated vehicles at intersections and merging at highway on-ramps. *IEEE Transactions on Intelligent Transportation Systems*, 18(5):1066–1077, 2016.

[12] Ziyuan Zhou, Guanjun Liu, and Ying Tang. Multi-agent reinforcement learning: Methods, applications, visionary prospects, and challenges. *arXiv preprint arXiv:2305.10091*, 2023.

[13] Richard J Sexton. The formation of cooperatives: a game-theoretic approach with implications for cooperative finance, decision making, and stability. *American Journal of Agricultural Economics*, 68(2):214–225, 1986.

[14] Jeffrey Pawlick, Edward Colbert, and Quanyan Zhu. Modeling and analysis of leaky deception using signaling games with evidence. *IEEE Transactions on Information Forensics and Security*, 14(7):1871–1886, 2018.

[15] Thomas E Carroll and Daniel Grosu. A game theoretic investigation of deception in network security. *Security and Communication Networks*, 4(10):1162–1172, 2011.

[16] Jeffrey Pawlick, Edward Colbert, and Quanyan Zhu. Analysis of leaky deception for network security using signaling games with evidence. In *Workshop Econ. Inf. Secur*, 2018.

[17] Charles Fox, Fanta Camara, Gustav Markkula, Richard Romano, Ruth Madigan, Natasha Merat, et al. When should the chicken cross the road?: Game theory for autonomous vehicle-human interactions. 2018.

[18] Mu Zhu, Ahmed H Anwar, Zelin Wan, Jin-Hee Cho, Charles A Kamhoua, and Munindar P Singh. A survey of defensive deception: Approaches using game theory and machine learning. *IEEE Communications Surveys & Tutorials*, 23(4):2460–2493, 2021.

[19] Yao Deng, Tiehua Zhang, Guannan Lou, Xi Zheng, Jiong Jin, and Qing-Long Han. Deep learning-based autonomous driving systems: A survey of attacks and defenses. *IEEE Transactions on Industrial Informatics*, 17(12):7897–7912, 2021.

[20] Muhammad Waqas Nadeem, Hock Guan Goh, and Aun. Toward secure software-defined networks using machine learning: A review, research challenges, and future directions. *Computer Systems Science & Engineering*, 47(2), 2023.

[21] Mu Zhu, Ahmed H Anwar, Zelin Wan, and Cho. Game-theoretic and machine learning-based approaches for defensive deception: A survey. *arXiv preprint arXiv:2101.10121*, 2021.

[22] Thanh Thi Nguyen and Vijay Janapa Reddi. Deep reinforcement learning for cyber security. *IEEE Transactions on Neural Networks and Learning Systems*, 2021.

[23] Kurt Dresner and Peter Stone. Multiagent traffic management: A reservation-based intersection control mechanism. In *Autonomous Agents and Multiagent Systems, International Joint Conference on*, volume 3, pages 530–537. IEEE Computer Society, 2004.

[24] Guanming Liu, Bin Xiao, and Daofei Li. Game-theory based driving decision algorithm for intersection scenarios considering driver irrationality. In *2020 4th CAA International Conference on Vehicular Control and Intelligence (CVCI)*, pages 747–752. IEEE, 2020.

[25] Jianqiang Wang, Heye Huang, Keqiang Li, and Jun Li. Towards the unified principles for level 5 autonomous vehicles. *Engineering*, 7(9):1313–1325, 2021.

[26] Tuopu Wen, Kun Jiang, Benny Wijaya, Hangyu Li, Mengmeng Yang, and Diange Yang. Tm 3 loc: Tightly-coupled monocular map matching for high precision vehicle localization. *IEEE Transactions on Intelligent Transportation Systems*, 23(11):20268–20281, 2022.

[27] Qianwen Li, Xiaopeng Li, Handong Yao, Zhaohui Liang, and Weijun Xie. Automated vehicle identification based on car-following data with machine learning. *IEEE Transactions on Intelligent Transportation Systems*, 2023.