Safe, Efficient and Socially-Compatible Decision of Automated Vehicles: A Case Study of Unsignalized Intersection Driving

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Abstract
Safe and smooth interaction between other vehicles is one of the ultimate goals of driving automation. However, recent reports of demonstrative deployments of automated vehicles (AVs) indicate that AVs are still difficult to meet the expectation of other interacting drivers, which leads to several AV accidents involving human-driven vehicles (HVs) without the understanding about the dynamic interaction process. By investigating 4300 video clips of traffic accidents, it is found that the limited dynamic visual field of drivers is one leading factor in inter-vehicle interaction accidents. A game-theoretic decision algorithm considering social compatibility is proposed to handle the interaction with a human-driven truck at an unsignalized intersection. Starting from a probabilistic model for the visual field characteristics of truck drivers, social fitness and reciprocal altruism in the decision are incorporated in the game payoff design. Human-in-the-loop experiments are carried out, in which 24 subjects are invited to drive and interact with AVs deployed with the proposed algorithm and two comparison algorithms. Totally, 207 cases of intersection interactions are obtained and analyzed, which shows that the proposed decision-making algorithm can improve both safety and time efficiency, and make AV decisions more in line with the expectation of interacting human drivers. These findings can help inform the design of automated driving decision algorithms, to ensure that AVs can be safely and efficiently integrated into the human-dominated traffic.

Keywords Automated driving · Social compatibility · Game theory · Interactive driving · Unsignalized intersection

Abbreviations
AD  Automated driving
AEB  Automated emergency braking
AVs  Automated vehicles
EEG  Electroencephalogram
HVs  Human-driven vehicles
NE  Nash Equilibrium
RoW  Right of way
RSS  Responsibility sensitive strategy
SC  Social compatibility
TTA  Time to arrive

1 Introduction
Automated driving (AD) is evolving rapidly in recent years. By assisting human drivers in driving tasks, e.g., lane keeping and speed control, AD has achieved much success in commercialization. Further, the last five years have witnessed the rapid development of autonomous driving technology, e.g., RoboTaxi, which has attracted much attention from both the public and the research community. Although AD is often advertised as a safety and comfort feature in modern vehicles, the current AD technologies have still raised many safety concerns related to human factors [1]. Without resolving safety concerns and achieving stable driving performances, AD is still far away from winning wide trust from users [2–5]. As pointed out by Noy et al. [6], AD should be designed in accordance with cybernetics principles, i.e., by using a human-centric approach in technology development.

Such human-centric approach does not mean to consider only the human driver/passenger in AV, but also those traffic participants outside the AV cabin. In the foreseeable future, highly automated vehicles can hopefully share the
open roads with human-driven vehicles (HVs). Considering the infinite varieties of human driving behaviors, it is challenging for AVs to safely and efficiently interact with HVs in dynamic scenarios [7]. Concerns over the harmonious coexistence of AVs and HVs have been raised by both the academia and industry [8]. Public safety reports indicate that current AVs are driving in unexpected ways from human drivers’ point of view, which leads to traffic accidents. A road test report by Waymo also shows that the human driver is the critical factor in the interactions between AVs and HVs, posing a significant threat to AVs’ safety [9]. However, available driving decision-making algorithms have not sufficiently considered the interactions between AVs and HVs [10]. Therefore, there is an urgent need for research on decision-making of AVs in highly dynamic and interaction-intensive driving scenarios.

In current AV decision algorithms, there have been basically two ways to consider inter-vehicle interactions. A common way is to directly imitate the cooperation and interaction behaviors of human drivers. For example, Beaurocras et al. [11] obtained some reference speed profiles of specific styles based on human driving data clustering, which were used to achieve human-like driving in complex interactions. Chen et al. [12] proposed an imitation learning framework to design the driving policy for complex urban scenarios. Theoretically, given sufficient interaction data of human driving, such models can provide a satisfactory driving policy that considers social compatibility. However, the imitation-based methods are limited by the completeness of dataset, making them difficult to cope with the uncovered corner cases.

Another way is to make interactive decisions and planning based on predicting the interacting vehicle’s future behaviors [13–19]. For example, Sezer et al. [13] handled the interaction problem by predicting the interacting driver’s intents with uncertainties, while the parameters of the driver behavior model were selected intuitively, and the human decision mechanism was not considered. Menendez-Romero et al. [14] proposed a cooperative driving strategy to consider AV’s safety and comfort expectations, and also the conflict vehicle’s efficiency in merging at highway ramps. An intention prediction algorithm is integrated to provide the system with a “courtesy” behavior. Wang [15] modeled the interaction at unsignalized intersections using utility functions of safety and efficiency. The algorithm predicts the other vehicle’s driving directions and calculates the optimal speed planning by analyzing the possible collision points. However, the utility settings do not include the characteristics, such as intent and other psychological factors. To summarize, these prediction-based approaches can model how the AV should respond with social compatibility, if the interacting vehicle behaves as predicted. However, as Wang et al. [20] suggest, human drivers do not always rely on accurate prediction when making an efficient interaction, and it is significant to find out other key aspects of socially compatible interactions. Moreover, in dynamic scenarios with intense two-way interactions, the interacting vehicle may be influenced by the AV maneuvers and deviate from the predicted motion, which should be further addressed. As pointed out by a recent review on vehicle motion prediction [21], to accommodate highly dynamic interactions between ego vehicle and other traffic participants, the coordination between motion prediction and ego-motion planning is one of the major challenges.

The existing literatures have clarified that a clear understanding of other traffic users is key to safe and efficient driving in interaction-intensive scenarios. However, there are only limited studies on socially compatible decision algorithms for AV. Among them, game theory has been often applied to the interactive decision-making involving multiple traffic participants [22–29]. These approaches formulate an AV decision problem in an integrated framework by considering all players simultaneously, with which the game payoff design can also be viewed as one special case of prediction-based methodology. For example, Li et al. [22] presented a Leader-Follower game-theoretic algorithm for various parametrized intersection scenarios. Wang et al. [27] proposed an integrated prediction and planning framework that allows the AVs to infer the characteristics of other road users. By learning the weights of selfish, altruistic and mediocre driving behaviors, the socially compatible reward is constructed, which optimizes AV’s own rewards, and its courtesy to others. In a previous work [28], Prospect Theory is incorporated for the payoff design in an unsignalized intersection game with two or four vehicles. In Ref. [29], a level-k game model is developed for the overtaking behaviors on two-lane two-way highways. In summary, game-theoretic decision algorithms have shown promising performances in modeling human-like decisions. However, there is an urgent need on how to develop a design method for decision payoff of drivers, especially in complex and interactive driving contexts.

Therefore, many crucial questions related to interactive driving need to be answered. For example, what are the key influencing factors of social compatibility that need to be considered in inter-vehicle interactions? How can social compatibility be realized in AV decision? When interacting with HVs, will social compatibility improve the decision performance of AV, e.g., safety and human driver’s acceptance?

To overcome these challenges, this research attempts to incorporate such social compatibility in the AV decision algorithm, with a specific focus on the visual limitation of interacting human drivers. The contribution of this study is twofold.
(1) A probabilistic model of the truck driver’s visual field is constructed and applied in AV decision design. The model can estimate the probability of AV being observed by the HV driver during the interaction process. To the best of our knowledge, this is the first attempt to consider the visual limitation of interacting HV drivers in an AV decision algorithm.

(2) A game-theoretic framework is proposed to incorporate social compatibility into AV decision, for which the safety and efficiency improvements over commonly used algorithms are validated via human-in-the-loop experiments.

The rest of the study is organized as follows: Section 2 briefs the research’s motivation, constructs the AV visibility model and introduces the socially compatible decision algorithm. Section 3 details the driving simulator experiment design, while the results and discussions are summarized in Sect. 4. Finally, Sect. 5 concludes the paper and discusses some potential future work.

2 Method

2.1 Motivation

As defined by Ladegård [30], social compatibility (SC) is the integration of social fitness and reciprocity, which represents an agent’s responsiveness in social interactions. Similar to daily interpersonal interactions, interactive driving in traffic, as a kind of interaction on wheels, also needs SC in decision-making. The realization of SC in driving decision should be based on perception and prediction of other road users. In other words, an inter-vehicle interaction starts from the perception of each other. Among other things, visual perception plays a key role in the human driver perception, since it provides most of information for further prediction and planning tasks in driving.

A total of 4300 video clips of traffic accidents were collected in various scenarios in China (including urban, suburbs, villages and highways), which happened in 4 consecutive months from March 22, 2020, to July 27, 2020 [31]. To investigate the causes of all accidents, the scenarios were reviewed, including the road/traffic conditions and the vehicle-driver behaviors. The total 530 accidents involving vehicle-vehicle interactions, as shown in Fig. 1, were labeled according to their main causes as: (1) dangerous driving behaviors (e.g., emergency braking, crossing multiple lanes in one movement and tailgating), (2) dangerous road sections (e.g., sharp turn, unsignalized intersection and merging ramp), and (3) visual blind zones (e.g., limited view via the rearview mirror, dynamic blind zone due to driver head rotation).

From Fig. 1(a), it is found that dangerous driving behaviors account for more than 65% of accidents; however, visual blind zones also contribute to about 22% of accidents, half of which involve heavy trucks, as shown in the example cases of Fig. 1(b). It is understandable that for truck drivers, it is more difficult to achieve sufficient searching for visual information, as also pointed out by Larsen [32]. Considering the greater severity of truck-involved collisions, safe interaction with truck drivers must be guaranteed in AVs.

When it comes to unsignalized intersections, these visual limitations of human drivers make the interactive driving even more accident-prone. On the one hand, in such dynamic driving situations, it is challenging for drivers to get accurate perception of the right of way, either for the ego or interacting vehicles. On the other hand, the priority rules to guide vehicle interaction are not clearly predetermined by traffic regulations. In such situations, the aggravated complexities of intersection interactions are safety challenges that AVs have to overcome, especially in those countries and regions that do not strictly enforce the stop or yield sign regulation.

Based on these above analysis, it is believed that the influences of HV driver visual field characteristics should be considered to realize AV’s social compatibility in interactive driving.

2.2 Framework

To achieve social compatibility, including social fitness and reciprocity, the AV decision algorithm should (1) promote the HV driver’s understanding of the AV intention, (2) behave with consistency and cooperate tacitly with HV, (3) and consider HV’s interests while guaranteeing AV’s own interests.

For the unsignalized intersection scenario, a socially compatible decision framework based on game theory is proposed, as illustrated in Fig. 2.

(1) The inputs of the proposed algorithm consist of two parts, the sensing data of AV states (i.e., position and
(1) Based on the sensing data, a visibility probability model is adopted to estimate the truck driver’s visual characteristics, which outputs the probability of AV being observed by the HV driver.

(2) Then, with the designed HV/AV utilities, the decision game of AV and HV considers safety, efficiency and also social compatibility is solved, which finally outputs a decision of acceleration or deceleration.

(3) Finally, the output decision is executed by the lower level controller.

2.3 Probabilistic Model of AV Visibility

The two-vehicle interaction in an unsignalized intersection is taken as an example scenario, where the HV is a heavy truck and the ego AV is a passenger vehicle, as schemed in Fig. 3. The 360-degree vision of truck drivers can be divided into the blind zones, the direct and indirect fields of view. The direct field of view is the area that can be seen without the aid of any devices. The blind zone is an area around the vehicle that cannot be directly observed when the driver is in a normal sitting position. The indirect field of view can only be seen by using auxiliary devices, e.g., rearview mirrors. Considering the example intersection, only the blind zone and the direct field of view, i.e., areas 1 and 3, need to be modeled.

With simplification, the blind zone is defined with 3 parameters, as shown in Fig. 4. $L_{\text{left}}$ and $L_{\text{right}}$ represent the horizontal width of the blind zone on the left/right side of the driver cabin, while $L_{\text{front}}$ is its longitudinal length.

$$L_{\text{left}} = h_{\text{sm}} \times \frac{w_e}{(h_e - h_{\text{sm}})}$$

$$L_{\text{right}} = h_{\text{sm}} \times \frac{(w - w_e)}{(h_e - h_{\text{sm}})}$$

$$L_{\text{front}} = h_{\text{fm}} \times \frac{l_e}{(h_e - h_{\text{fm}})}$$

where $w$ is the overall width of the cockpit, $w_e$ is the distance between the eye point and the left side of the cockpit, and $l_e$
is the distance between the eye point and the front end of the cockpit. $h_{um}$ indicates the vertical distance from the bottom edge of the side window to the ground. $h_{rm}$ represents the height of the bottom edge of the windshield/center stack, which blocks the driver’s front line of sight. $h_c$ means the vertical distance from the driver’s eye point to the ground.

For the intersection scenario, it is assumed that both AV and HV travel straight, i.e., HV goes from left to right, and AV goes from bottom to top, and only the AV visibility for areas 1 and 3 in Fig. 3 are calculated. When AV is in the blind zone of HV driver, the probability of AV being observed by HV driver is assumed 0. For the front direct field of view (area 3), it is further divided into (A1) the left peripheral, (A2) the central and (A3) the right peripheral sub-fields, as shown in Fig. 5.

Assuming that there are normally three natural combinations of head-eye rotation of drivers. (1) If to pay attention to the left, head rotates naturally to the left and eyes rotate freely. (2) If to pay attention to the center, head keeps straight forward and eyes rotate freely. (3) If to pay attention to the right, head rotates naturally to the right and eyes rotate freely. Then, the AV’s visibility probability $F(\theta)$ is estimated as follows:

$$F(\theta) = \sum_{i=1}^{3} \omega_i f_i(\theta)$$

(2)

where $\theta$ is the viewing angle of AV from the perspective of HV driver. The first part, $\omega_i$, is the probability of HV driver paying attention to the left ($i = 1$), center ($i = 2$) or right ($i = 3$) directions. The probability $\omega_i$ is related to whether there is an object worthy of attention in the specific direction. For the intersection scenario shown in Fig. 3, 162 cases from the “DADA-2000” dataset [33] are extracted, and then, the probabilities $\omega_1$, $\omega_2$, $\omega_3$ are determined according to the statistical results, which are 0, 0.17 and 0.83, respectively. When HV driver pays attention to the $i$th direction, $f_i(\theta)$ is the observation probability function, representing the probability of AV being observed by the driver, as shown in Fig. 6.

Human visual observation is affected by the dynamic characteristics of eyeballs. For instance, the macula is located in the optical central area of eye, and its central depression part is the most sensitive area of vision to capture dynamic objects. Therefore, the observation probability function $f_i(\theta)$ in Equation (2) is defined as follows:

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**Fig. 5** The HV driver’s direct field of view

**Fig. 6** The HV driver visual field and the observation probability function. a Head turned to the left by 45°. b Head fixed forward. c Head turned to the right by 45°
where \( A_{\text{max}} \) is the front direct field’s angular range scanned by driver head rotation, and \( A_{c} \) is the central sub-field’s angular range scanned by head rotation. \( \xi \) is a compensation coefficient to consider the environmental factors of the visual capturing ability, e.g., velocity, color and lighting. When AV is in the peripheral sub-fields of view, the AV observation probability of \( P(\theta) \) can be estimated as follows:

\[
f_{\theta}(\theta) = \begin{cases} \xi, & \theta \in A_{c} \\ \xi P(\theta), & \theta \in A_{\text{max}} - A_{c} \end{cases} \tag{3}
\]

where \( A_{\text{max}} \) is the front direct field’s angular range scanned by driver head rotation, and \( A_{c} \) is the central sub-field’s angular range scanned by head rotation. \( \xi \) is a compensation coefficient to consider the environmental factors of the visual capturing ability, e.g., velocity, color and lighting. When AV is in the peripheral sub-fields of view, the AV observation probability of \( P(\theta) \) can be estimated as follows:

\[
P(\theta) = \min\left(\frac{(\theta - \mu_{c} - A_{c})}{(A_{\text{max}} - A_{c})}\right) \tag{4}
\]

where \( \mu_{c} \) is the angle between the angular bisector and the front sight line. \( \mu_{\text{min}} \) is a minimum visibility probability of AV when it is at the boundary of driver’s peripheral sub-field. Referring to Fig. 6, as an object moves away from the sub-fields of the driver’s view, i.e., the value of \( \| \theta - \mu_{c} - A_{c}/2 \| \) increases, the probability of the object being observed decreases rapidly. To model such descending probability, the exponential form in base \( \mu_{\text{min}} \) is used, which is similar to the probability density function of Normal distribution. Here, \( A_{\text{max}} - A_{c} \) is used to normalize the scanning range of driver. If the driver’s head is naturally turned to the left or right, an angle of 45 degrees is supposed, then \( \mu_{\text{min}} = 0.3 \), and the HV driver visual field and the observation probability function \( f_{\theta}(\theta) \) of AV are schemed in Fig. 6.

### 2.4 Game Design Considering Social Compatibility

The intersection decision game is formulated as a static game, which contains the following elements: the players (AV, HV), the strategy set (Yield, Not Yield) and the utility set \((U_{\text{AV}}, U_{\text{HV}})\). The utility matrix is shown in Table 1, where \((U_{\text{AV},m}, U_{\text{HV},m})\) is the utility set if AV takes strategy \( m \) and HV takes strategy \( n \).

#### 2.4.1 AV Utility

To achieve safety, traffic efficiency, and also social compatibility, the AV utility \( U_{\text{AV}} \) is constructed as follows:

\[
U_{\text{AV}} = (1 - \lambda)[u_{s,\text{AV}} + \beta u_{t,\text{AV}} + \gamma u_{\text{sd},\text{AV}}(\theta)] + \lambda U_{\text{HV}} \tag{5}
\]

where \( u_{s,\text{AV}} \) and \( u_{t,\text{AV}} \) are the safety and traffic efficiency utilities of AV, respectively. Social compatibility is represented by both the social fitness utility function \( u_{\text{sd},\text{AV}} \) and the reciprocal utility, i.e., the HV utility \( U_{\text{HV}} \). \( \alpha, \beta, \gamma, \lambda \) are the corresponding weights to trade-off among utilities. The determination of corresponding weights is to compare the performance of safety and traffic efficiency under different initial conditions. And the collisions are avoided as much as possible. The AV position variable \( \theta \) is used to consider the AV visibility, as shown in Fig. 5.

#### 2.4.2 HV Utility

Considering safety, traffic efficiency and reciprocal behavior, the HV utility \( U_{\text{HV}} \) is designed as

\[
U_{\text{HV}} = \alpha u_{s,\text{HV}}(\theta) + \beta u_{t,\text{HV}} + \lambda_{\text{HV}} u_{\text{altr},\text{HV}}(\theta) \tag{6}
\]

where \( u_{s,\text{HV}} \) and \( u_{t,\text{HV}} \) are the safety and traffic efficiency utilities of HV, respectively. \( u_{\text{altr},\text{HV}} \) is the reciprocal utility of its altruistic behavior, which is weighted by \( \lambda_{\text{HV}} \). When HV driver yields to AV, the value of \( \lambda_{\text{HV}} \) is equal to \( \lambda \) in Eq. (5). If the driver does not give way to AV, \( \lambda_{\text{HV}} = 0 \). The utility functions of AV and HV are further explained in Appendix A.

To calibrate the model parameters, e.g., weighting factors, totally 4590 cases are simulated, with 18 sets of weighting combinations and 255 sets of initial conditions (distances, speeds and accelerations), while the detailed setting-up can be found in Ref. [26]. Then, the optimal parameters are determined according to the overall performances of decision. The selected parameters for further evaluations are shown in Table 2.

To solve this formulated game of socially compatible decision, a flowchart is summarized in Fig. 7. Firstly, the relative position between vehicles is obtained and is used to calculate the visibility probability of AV. Then, the game utilities are calculated and used to find the Nash Equilibrium (NE) solution. As for the NE solution, there may be multiple solutions or no solution cases, except the ideal case where there is only one solution. As discussed in the previous work [28], if there is no NE solution, a potential measure is to increase safety weight and re-play the game until at least one solution is found, meaning to find a safer and more cautious strategy. Here, a rule-based solution is found as follows, if the AV safety utility \( u_{s,\text{AV}} \) in Eqs. (5)

### Table 1 The utility matrix of the proposed decision-making algorithm

| AV   | HV   |
|------|------|
| Yield (1) | \((U_{\text{AV},1}, U_{\text{HV},1})\) |
| Not yield (0) | \((U_{\text{AV},0}, U_{\text{HV},0})\) |

### Table 2 The optimal model parameters

| Parameters | \( \alpha \) | \( \beta \) | \( \gamma \) | \( \lambda \) |
|------------|--------------|--------------|--------------|--------------|
| Values     | 0.6          | 0.4          | 2.0          | 0.2          |
and (A1) is larger than 0, meaning there is safety margin, the Not Yield strategy is chosen; otherwise, a safety-oriented Yield strategy is chosen. For the cases with multiple NE solutions, either the same strategy as in the last subgame or the strategy with the largest total payoff of two players is preferred. Finally, the specific acceleration/deceleration of AV is decided by combining the yield decision and the safety utility of AV.

**3 Human-in-the-Loop Experiments**

**3.1 Benchmark Algorithms**

Two benchmark decision algorithms are selected to compare with the proposed socially compatible (SC) algorithm. One is the game-based algorithm that only considers safety and traffic efficiency (noSC algorithm), i.e., \( \gamma = \lambda = \lambda_{HV} = 0 \). The other benchmark algorithm is responsibility sensitive strategy (RSS) by Intel Mobileye, which defines a set of safety rules to guarantee “it won’t lead to accidents of the autonomous vehicle’s blame” [34]. RSS is also one of the most popular algorithms that are currently adopted in academia and industry. The adopted RSS model parameters are listed in Table 3. The parameter \( d_{HV, brake, min} \) is determined according to the results of natural driving study in China [35].

**3.2 Apparatus**

As shown in Fig. 8, a driving simulator with six degrees of freedom is used as the human-driven truck (HV). The simulator cabin is modified to better reproduce the driver visual limitations in the real truck cabin. The real-time simulation is based on MATLAB and TASS PreScan. The human drivers’ inputs in simulator cabin, i.e., steering, throttle and brake, are collected for the vehicle dynamic model in PreScan, while the AV algorithm in MATLAB outputs the interaction decisions. The data of subject Electroencephalogram (EEG) at Fz and Cz positions are recorded and analyzed with BioPac MP160.

**3.3 Participants and Experiment Design**

A total of 24 subjects were recruited with age between 21 and 28, including 22 males and 2 females. They were asked to drive as in daily driving and to interact with AVs deployed with 3 different decision-making algorithms,
namely (1) noSC algorithm, (2) RSS algorithm, and (3) SC algorithm. Three different speed limits were specified, i.e., 20 km/h (Lowspd), 45 km/h (Midspd), and 70 km/h (Highspd), respectively. For each algorithm, subjects were asked to drive under specific speed limits in the rightmost lane and to complete 9 HV-AV interactions. When the HV truck was 120 meters away from the conflict area, the AV started with the same speed of the truck, to simulate the intense levels of interaction conflict. Once the truck was 100 meters away from the conflict area, the decision algorithm was triggered ON. After each intersection, the HV stopped at the parking area and the subject filled the questionnaire to evaluate the last AV-HV interaction, as detailed in Appendix B. Figure 9 presents an example of intersection scenario in the experiments. In this example, HV travels from left to right with lane keeping tip and speed limit tip, while AV travels from bottom to top. The HV driver needs to pass through the interactive intersection area safely and stop in the parking area to finish the questionnaire.

Considering that the physiological data may have a large fluctuation during the interaction and need time to return to a stable state [36], the subjects used 3–5 min for free driving before the next interaction.

An experiment for each subject HV driver took about 90 min. The experimental procedure is as follows:

1. Subject fills in the driver self-ability [37] and driving style assessment questionnaires [38, 39].
2. Subject wears the physiological acquisition devices and confirms the signal recordings.
3. Subject gets familiar with the simulator driving without interaction with AVs.
4. The formal experiment begins, and subject conducts the Lowspd experiment. After each interaction, a subjective questionnaire of driving tasks is filled.
5. Subject completes Midspd and Highspd experiments as step 4.
6. Subject finishes the experiments and takes off the physiological acquisition devices.

4 Results and Discussion

Totally 216 interaction cases are obtained, including 207 effective interactions without collisions and 9 failed interactions due to HV’s severe overspeed behaviors (more than 15 km/h over limit). For detailed analysis, the interactive cases are further divided into 4 speed intervals according to the initial speed triggered by the algorithm, i.e., Low (10–30 km/h), LowMid (30–40 km/h), Mid (40–50 km/h), and High (50–70 km/h). Note that the extreme interaction cases with High initial speeds are rare but still possible in real traffic scenarios, which brings severe time pressure to both human drivers and AV algorithms.

4.1 Statistical Analysis of Safety and Efficiency

To focus on the intersection interactions, it is assumed that the inter-vehicle interaction ends when one of the vehicles reaches the conflict area, while the following-up behaviors are not further considered. Therefore, the time to arrive (TTA) is selected as the safety evaluation index. When the leading vehicle, either AV or HV, arrives at the conflict area at time $t$, and the lagging vehicle with a speed $v$ is still $L$ distance away from the conflict area, then $TTA = L/v$.

If TTA is large, it means when the leading vehicle arrives at the intersection, the lagging vehicle is still far away, so safety can be guaranteed. The definition of conflict is shown in Fig. 10. However, if TTA is too large, the traffic efficiency is compromised since the lagging vehicle is too conservative to make use of the cleared intersection space. Note that if the lagging vehicle fully stops to show its courtesy, a special value $TTA = -1$ is given rather than infinity, and such case is tagged as “full-stop”. On the other hand, a small TTA means that both vehicles cross the intersection at a very close moment. If TTA is less than a specified threshold, for safety the AV decision algorithm will be overridden by automated emergency braking (AEB) [35]. Such case is defined as a danger case. Considering the extreme inter-vehicle interactions with high initial speeds, the goal is to minimize the number of danger cases, if not possible to completely avoid all danger cases.

Statistics of all interaction cases are summarized in Table 4. In the Low and Low-Mid speed scenarios, there are 6 danger cases with the noSC algorithm, and no danger case with RSS or SC algorithms. In Mid and High speed scenarios, the numbers of danger cases with noSC, RSS and SC algorithms are 9, 11 and 6, respectively. The RSS algorithm seems conservative by showing the most courtesy behaviors, i.e., 16 full-stop cases. However, it still causes 11 danger cases. Therefore, although RSS is not responsible for any collisions, i.e., the interacting HVs...
bear the responsibility, it is not the safest algorithm for the studied intersection driving scenarios. By contrast, the SC algorithm can achieve the best safety performances in AV-HV interactions, with no danger case with initial speeds below 40 km/h and 6 danger cases with initial speeds between 40 and 70 km/h.

In 207 effective cases, the distance $L$, speed $v$ and TTA of the lagging vehicle at the end of the interactions are summarized in Fig. 10. The cases when the AV or the HV arrives at the conflict area first are given in Fig. 10(a), (b), respectively. As shown in Fig. 10(a), when interacting with the RSS-based AV, the HV has the lowest ending velocity and

**Fig. 10** Statistics of the lagging vehicle’s states at the end of interactions. a Statistics of HV, when AV arrives first at conflict area. b Statistics of AV, when HV arrives first at conflict area

|                | Low     | Low-Mid | Mid     | High    |
|----------------|---------|---------|---------|---------|
| **noSC**       |         |         |         |         |
| Total          | 22      | 15      | 26      | 8       |
| Danger         | 4       | 2       | 4       | 5       |
| Full stop      | 0       | 0       | 0       | 0       |
| **RSS**        |         |         |         |         |
| Total          | 20      | 12      | 27      | 9       |
| Danger         | 0       | 0       | 2       | 9       |
| Full stop      | 11      | 0       | 4       | 1       |
| **SC**         |         |         |         |         |
| Total          | 17      | 15      | 25      | 11      |
| Danger         | 0       | 0       | 4       | 2       |
| Full stop      | 1       | 0       | 2       | 0       |

**Table 4** Statistics of interaction cases (danger: AEB activated, full stop: yield)
its average TTA is larger than 10 s, meaning that HV is the most conservative with the lowest traffic efficiency. When interacting with the noSC-based AV, the efficiency of HV is improved, but there are some extremely conservative or radical cases, that is, its TTA is either too large or too small. When interacting with the SC-based AV, the average TTA of HV is the lowest, indicating the best traffic efficiency. Also, the SC-based AV facilitates the interacting HV to have its lower bound of TTA larger than that with the other two algorithms, showing its best safety performance of HV.

For the cases when HV arrives at the conflict area first, shown in Fig. 10(b), it can be found that RSS-based AV is the most conservative, having the lowest traffic efficiency among all algorithms. The widely distributed TTA values indicate that RSS performs not stably or consistently in interacting with human drivers. Part of the reason is that RSS decides with a strict sense of right of the way (RoW), which may not always be precisely followed by human drivers. In highly dynamic interactions, human drivers are not sensitive enough of their RoW. Such problem is getting worse if a human driver has visual limitations in sensing other interacting vehicles approaching the intersection, as the truck drivers in the experiments. This unclear sense of RoW may lead to the ineffective communication between HV and AV, causing the RSS-based AV to switch frequently between “To Go” and “Not to Go” decisions. Based on the results of TTA and ending velocity distribution of AVs in Figure 10(b), the SC algorithm can provide the AV with the best trade-off between safety and efficiency.

4.2 Interaction Case Studies

To explain the benefits of social compatibility, three interaction cases with similar initial speeds are selected, i.e., 52.0 km/h (noSC), 54.3 km/h (RSS), and 50.1 km/h (SC). For the HV in all three cases, the driver’s throttle input fluctuates between 30–45%, the vehicle acceleration fluctuates between 0.1–0.15 m/s$^2$, and the speed increment is between 3–4 km/h.

Figure 11 presents the two vehicles’ states, the AV inputs, as well as the AV visibility probability estimated using Equation (2). Since the noSC algorithm cannot consider the influence of HV visual limitations, the AV enters the blind zone of HV driver at the end of the interaction, with its visibility probability dropping to 0. The resulting TTA is 0.79 s, which is less than the specified threshold of 0.8 and triggers the AEB braking [35].

As for the RSS case, the AV maintains the no-braking strategy according to the principle of right of way priority, but the HV does not slow down and yield according to the

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Fig. 11 Comparisons of AV-HV interaction processes with three algorithms. a noSC algorithm. b RSS algorithm. c The proposed SC algorithm

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rules of the RSS, which finally leads to an almost inevitable collision (TTA = 0.02 s). When the RSS-based AV is close to the intersection, it enters the blind zone of the HV driver, and its visibility probability drops to 0. Therefore, if HV follows the rule of right of way priority, the RSS algorithm can achieve a safe interaction, otherwise a collision accident may happen. In the latter case, the RSS algorithm still do not lead to any accidents of AV’s blame, but the accident still happens, showing that RSS is pursuing an egoism strategy and needs improvements for interaction-intensive driving.

By contrast, since the SC algorithm can directly consider the HV driver’s visual limitations, the SC-based AV decelerates at \( t = 7.5 \) s to keep away from the blind zone of HV driver. At the end of the interaction, its visual probability is 0.85, which is still a high probability of AV being observed by the HV driver. At the end of the interaction, TTA is 0.95 s, meaning a safe and efficient interaction with HV.

Together with the statistical results in Sect. 4.1, it is validated that by considering the social compatibility from the perspective of HV driver’s visual limitation, the proposed decision algorithm can achieve both safety and efficiency.

### 4.3 Subjective Evaluation

The HV drivers’ evaluations on AV are obtained via questionnaires in Table B1. Figure 12 presents the mean and significance values of subjective evaluation on interactions, with all significance levels \( p < 0.05 \) indicated for corresponding question items. It shows that, in all speed scenarios, the SC algorithm has better evaluation scores than the noSC algorithm in all items but item 2 “comfort” and item 7 “calmness”. In High speed scenarios, the SC algorithm performs better in all items than the noSC and RSS algorithms, with two items with significant improvements. By contrast, in Low speed scenarios, the SC algorithm shows the most significant improvements in 6 evaluation items. One possible reason is that if given a specified decision step size, there are more frequent interactions in a lower-speed interaction case. This makes the subjects easier to tell the differences among the three decision algorithms, so the advantages of the SC algorithm are more obvious.

When examining those subjects who gave significantly unsatisfactory evaluations than average, it is found that they have one or more of the following characteristics in driver self-ability assessment, i.e., poor driving ability, aggressive driving style, being prone to anger, or careless driving. A total of 12 subjects with the above characteristics are named Group A (sensitive), and the rest are classified into Group B (normal). The mean values and significance results of Groups A and B are shown in Fig. 13. With the SC algorithm, the evaluation items 5 “relaxed”, 6 “confused” and 8 “happy” are significantly improved for the sensitive subjects. By contrast, such improvements are not statistically significant for the normal subjects. It may be because Group A subjects are more sensitive to the process of dynamic interaction, and their mood fluctuations are more susceptible to the driving behaviors of interacting vehicle.

### 4.4 HV driver EEG

The EEG data at Fz and Cz are tagged with three stages. The Baseline data correspond to the stage before the AV decision algorithm is activated ON, which are considered as the EEG data before the interaction. The Interaction data correspond to the stage of interaction, i.e., when the HV drives from 120 m away from the conflict area to the

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**Fig. 12** HV drivers’ subjective evaluation on AV-HV interactions at different speeds. For each of 8 items of evaluation, the mean scores and significance values are given.
end of interaction. The After data correspond to the stage of 6 s after the interaction. For the EEG signal features, the mean power values of Alpha (8–13 Hz), Beta (13–30 Hz) and Theta (4–8 Hz) waves are extracted to judge the subjects’ emotion fluctuation. For each of the total 24 subjects, the EEG results during interactions for one speed limit are taken as a data group. Finally, 61 effective data groups are obtained by eliminating the failed group, including those with over speed driving or lost EEG signals.

Cao [40] pointed out that the power of Alpha and Theta waves increases when user feels more pleasure, and the power of Beta wave rises with the enhancing of positive emotions. Here, for the 61 effective data groups, with the power analysis of Alpha, Theta, and Beta waves, it is found that in 44 data groups, i.e., 72%, the EEG evidences can confirm the driver emotion changes represented by the corresponding subjective evaluation (items 2, 4, 5 and 8). In the rest of 17 data groups, the EEG results are not consistent with the subjective evaluation.

For the 61 effective groups of EEG data, the variation percentage of EEG mean power in each interaction is defined as $GR = (P_{\text{base}} - P_{\text{int}})/P_{\text{base}} \times 100\%$, where $P_{\text{base}}$ represents the mean power in the Baseline stage, $P_{\text{int}}$ represents the mean power in the Interaction stage. The statistical results are shown in Fig. 14. It is found that when subjects interact with the AVs with the RSS and SC algorithms, the mean power values of all EEG features are higher than those with the noSC algorithm. This confirms the subjective evaluation results that when interacting with the noSC algorithm, the satisfaction level of the subjects is the lowest. By contrast, by considering social compatibility, the SC algorithm can provide an equivalent level of satisfaction as the conservative RSS algorithm.

The findings of human-in-the-loop experiments of AV-HV interactions can be summarized as follows:

1. Compared with the other benchmarks, the proposed SC algorithm can better balance safety and traffic efficiency, and achieve smoother interactions between AV and HV.
2. From the microscopic case studies, the consideration of human visual limitations and social compatibility can help avoid less effective interactions due to blind zones, which can better improve safety.
3. When the AV with the proposed SC algorithm interacts with human drivers, in addition to objective performances of safety and efficiency, it improves its own predictability and makes the HV drivers feel safer and clearer about the inter-vehicle interactions. This is a significant improvement over the commonly used algorithms in current AVs. This further confirms that to be a real safe and trust-worthy traffic participant, AV should not only make decisions primly according to safety rules and the right of way, but also behave empathetically by considering other human drivers’ limits of driving capabilities.
5 Conclusions

The aim of this study is to propose an unsignalized intersection decision approach that can achieve safety, efficiency and social compatibility during dynamic interactions with human-driven vehicles.

(1) A probabilistic model of the interacting driver’s visual limitations was constructed, which can estimate the probability of AV being observed by the human driver during the interaction process.

(2) Based on this visibility model, social compatibility was further realized using a game-theoretic framework.

(3) Human-in-the-loop experiments were carried out for the validation of the proposed approach. Results show that in addition to the well-balanced safety and time efficiency, the proposed AV decision approach can significantly improve social compatibility and make AV decision more in line with the expectation of human drivers.

This study is one step further toward more advanced and human-like decision approaches for automated vehicles. However, this study focuses on realizing social compatibility from the perspective of other drivers’ visual perception, while in future work the AV visibility model can be improved by considering the interaction uncertainties.

Additionally, the main idea of incorporating social compatibility in AV decisions may be further applied in other interacting driving scenarios, e.g., ramp merging. As for computation efficiency, here only two-vehicle interaction game is considered, and the approach can run real-time in a personal computer with Intel i7-4720HQ CPU and 8GB of memory. In the previous work with a similar game formulation [28], a four-vehicle interaction algorithm for unsignalized intersection can also guarantee real-time computing, taking about 1-2 ms for each decision. By comparing with Ref. [28], the game design in this work further considers human driver visual probability in utilities and adds only limited extra computation cost, so the current algorithm can hopefully run in real-time, too. However, the computation time for applications in more complex interactions might grow longer and needs to be considered in future work.

6 Supplementary information

A video abstract is provided, which includes a brief introduction of the proposed approach and a video of experiments. Please visit http://b23.tv/xAOo2ib.

Appendix A: Utility Function

A.1 AV Utility

For a given interaction process, $\Delta t$ is defined as the time difference between the AV and HV’s arriving time at the conflict area. By normalizing the time difference $\Delta t$, the safety utility $u_s$ of a two-vehicle interaction process can be described as follows, which is a value between $-1$ and $1$. The safety utility of AV is $u_{s,AV} = u_s$, while the safety utility of HV depends on how well the AV can be observed by the HV driver.

\[
\begin{align*}
    u_s &= \begin{cases} 
    \frac{\Delta t}{\Delta t_{\text{rsk}}} - 1, & \Delta t \in [0, \Delta t_{\text{rsk}}] \\
    \frac{\Delta t_{\text{saf}} - \Delta t_{\text{rsk}}}{\Delta t_{\text{saf}}}, & \Delta t \in (\Delta t_{\text{rsk}}, \Delta t_{\text{saf}}) \\
    1, & \Delta t \in [\Delta t_{\text{saf}}, +\infty) 
    \end{cases}
\end{align*}
\]

where the parameters $\Delta t_{\text{rsk}}$ and $\Delta t_{\text{saf}}$ are the risky and safe thresholds of time difference $\Delta t$, respectively. As shown in Fig. A1, the overlapped path of interactive vehicles is defined as the conflict area. At time $t_0$, if AV arrives at the conflict area first, given HV’s location $P_{HV0}$, velocity $v_{HV}$, the distance to conflict area $L_{HV}$, the thresholds $\Delta t_{\text{rsk}}, \Delta t_{\text{saf}}$ are determined as follow. If when HV arrives at conflict area (location $P_{HV1}$), AV has just left conflict area meanwhile (location $P_{AV1}$), this time difference is defined as $\Delta t_{\text{rsk}}$. On the other hand, if AV has left the intersection (location $P_{AV2}$), this time difference is defined as $\Delta t_{\text{saf}}$, as shown in Eq. (A2). Similarly, if HV will arrive at the conflict area at time $t_0$, the corresponding safety utility can be calculated.

\[
\begin{align*}
    \Delta t &= L_{HV}/v_{HV} \\
    \Delta t_{\text{rsk}} &= L_{\text{rsk}}/v_{HV} \\
    \Delta t_{\text{saf}} &= L_{\text{saf}}/v_{HV}
\end{align*}
\]

Fig. A1 Intersection driving description
Assuming the AV distance from the conflict area at time $t$ is $L_{AV}$, and the velocity is $v_{AV}$, then $t_{AV} = L_{AV}/v_{AV}$. If setting the maximum allowable velocity is $v_{max}$, an efficiency time is defined as $t_{eff,AV} = L_{AV}/v_{max}$. Then, the traffic efficiency utility of AV, $u_{t,AV}$ is

$$
u_{t,AV} = \begin{cases} 1 - \frac{t_{AV} - t_{eff,AV}}{t_{eff,AV}}, & t_{AV} \leq t_{eff,AV} \\ 1, & t_{AV} > t_{eff,AV} \end{cases} \tag{A3}$$

The social fitness utility of AV $u_{s,AV}$ represents how much the AV decision fits to the HV decision, which is modeled in Eq. (A4) with the AV visibility probability $F(\theta)$ and the tacitness degree $f_{tacit}(i, j)$. If $F(\theta)$ is small, the HV driver can hardly notice AV, so there is no cooperative driving behavior between them. The degree of tacit cooperation is explained in Table A1, in which $(i, j)$ stand for AV and HV, respectively. When HV adopts the Yield strategy, if AV yields as well, the tacitness degree is $f_{tacit} = 0$, if AV does not yield, $f_{tacit} = 1$ is set.

$$u_{s,AV} = F(\theta)f_{tacit} \tag{A4}$$

### A.2 HV Utility

The safety utility of HV, $u_{s,HV}$ is designed as

$$u_{s,HV} = \begin{cases} (u_{s})F(\theta), & u_{s} \geq 0 \\ -u_{s}F(\theta), & u_{s} < 0 \end{cases} \tag{A5}$$

where the AV visibility probability $F(\theta)$ is introduced to correct the safety utility $u_{s}$. For example, when AV is in the blind zones or is almost invisible from the perspective of HV driver, it is assumed that there is no vehicle interacting with HV, and the maximum safety utility is achieved, $u_{s,HV} = 1$.

Similar to Eq. (A5), the traffic efficiency utility of HV is as follows:

$$u_{t,HV} = \begin{cases} 1 - \frac{t_{HV} - t_{eff,HV}}{t_{eff,HV}}, & t_{HV} \leq t_{eff,HV} \\ 1, & t_{HV} > t_{eff,HV} \end{cases} \tag{A6}$$

The reciprocal utility from the HV’s altruistic behavior is quantified with the traffic efficiency of AV and the AV visibility probability $F(\theta)$, i.e.,

$$u_{alt,HV}(\theta) = F(\theta)u_{t,AV} \tag{A7}$$

### Appendix B: Questionnaire

The questionnaire for the HV drivers’ evaluation on the AV-HV interaction is shown in Table B1. And the instruction for subject drivers are “Please score the items in Table B1 based on your feelings about your last interaction with the other vehicle.”

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### Author Contributions

Daofei Li contributed in conceptualization, methodology, algorithm, data curation and writing the original draft. Hao Pan contributed in algorithm, visualization, writing—review and editing, and video abstract. Wentao Chen was a major contributor in methodology, algorithm, data curation and writing the original draft.

### Declarations

Conflict of interest The authors declare that they have no competing interests.

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