Game-based decision algorithm for socially compatible automated driving: a case study of unsignalized intersection driving

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Abstract

Smooth and harmonic interacting with 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). This is most likely due to the lack of understanding about the dynamic interaction process, especially about the human drivers. By investigating the causes of 4,300 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, especially for those involving trucks. Taking the interaction with a human-driven truck at an unsignalized intersection as an example scenario, a game-theoretic decision algorithm considering social compatibility is proposed. Starting from a probabilistic model for the visual field characteristics of truck drivers, social fitness and reciprocal altruism in decision are incorporated in the game payoff design. Results of human-in-the-loop experiments show that the proposed socially compatible algorithm can effectively improve both safety and time efficiency, and make AV decision more in line with the expectation of interacting human drivers. It can be viewed as a promising solution to handling the interactive issues between automated and human-driven vehicles.

Keywords: automated driving, social compatibility, game theory, interactive driving, unsignalized intersection
1. Introduction

In the foreseeable future, highly automated vehicles (AVs) are hopefully to share the open roads with human-driven vehicles (HVs). Considering the infinite variety of human driving behaviors, it is challenging for AVs to safely and efficiently interact with HVs in dynamic scenarios. Concerns over the harmonious coexistence of AVs and HVs have been raised by both academics and industries. Public safety reports indicate that current AVs are driving in unexpected ways from human drivers’ point of view, which leads to several traffic accidents (State of California Department of Motor Vehicle, 2021). A public road test report by Waymo also shows that human driver is the critical factor in the interactions between AVs and HVs, posing a significant threat to AVs’ safety (Schwall et al., 2020). However, available driving decision-making algorithms have not sufficiently considered the interactions between AVs and HVs. There is an urgent need of research on decision making of automated vehicles, especially in highly dynamic and interaction-intensive driving scenarios.

As defined by Ladegard(1997), 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. Previously, we collected a total of 4,300 video clips of traffic accidents 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 (Traffic accident video, 2020). To investigate into the causes of all accidents, we reviewed the scenarios, including the road/traffic conditions and the vehicle-driver behaviors. For the total 530 accidents involving vehicle-vehicle interaction, the main causes can be roughly divided into three categories, as shown in Fig.1a. 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.1b. Therefore, to realize excellent social compatibility in driving, especially when interacting with trucks, AVs should consider the influences of driver visual field characteristics in HVs.

As for AV decision algorithms, there have been some researches on socially compatible driving. A
common way is to directly imitate the cooperation and interaction behaviors of human drivers. For example, Beaucorps et al. (2017) 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. (2019) proposed a limitation learning framework to design the driving policy for complex urban scenarios. Theoretically, given sufficient interaction data of human driving, such models can provide 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 corner cases not covered.

Another common approach is to make interactive decisions and planning by predicting the interacting vehicle’s future behaviors. Sezer et al. (2015) handled the interaction problem through predicting the interacting driver’s intents with uncertainties, while the parameters of the driver behavior model were selected intuitively, and the human decision mechanism were not considered. Wang (2020) modelled 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 does not include the characteristics of human drivers, such as driving style, intent and other psychological factors. Menendez-Romero et al. (2018) proposed a cooperative driving strategy 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 a “courtesy” behavior. Similarly, Wang et al. (2020) 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 not only AV’s own rewards, but also its courtesy to others. To summarize, these prediction-based approaches can model how the AV should respond with social compatibility, if the interacting vehicle behaves as predicted. However, 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 may lead to a collision.

The existing literature 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, while there is no open report of AV decision algorithms that consider the visual limitation of interacting HV drivers. Comparing to imitation- and prediction-based approaches to the socially compatible decision, a framework based on the human-like decision mechanisms is needed. For this, many crucial questions need to be answered. For example, how can social compatibility be realized in AV decision? When interacting with HVs, will it improve the decision performance of AV, e.g. safety and human driver’s acceptance?

To address these needs, in this research we attempt to incorporate such social compatibility in the AV decision algorithm, with a specific focus on the visual limitation of interacting human drivers. 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. The contribution of this paper is two-fold. (1) A probabilistic model of the truck driver’s visual field is constructed, which can estimate the probability of AV being observed by the HV driver during the interaction process. (2) A game-theoretic framework is proposed to incorporate social compatibility into AV decision, for which the improvements on benchmark algorithms are proved via human-in-the-loop experiments.

The rest of the paper is organized as follows. Section 2 models the driver behavior and introduces the
socially compatible decision algorithm. Section 3 describes the driving simulator experiment design. The results and discussions are summarized in Section 4. Finally, Section 5 concludes the paper and discusses some potential future work.

2. Method

2.1 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. The SC in driving interactions is embodied in two aspects. 1) Based on the sensing data about the interacting HV, 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) The decision game of AV and HV considers safety, efficiency and also social compatibility, which finally outputs a decision of acceleration or deceleration for the lower level controller.

![Fig. 2 The overall framework of socially compatible decision algorithm](image)

2.2 Probabilistic model of AV visibility

As shown 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. rear-view 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, we can define the blind zone with 3 parameters, i.e. $L_{left}$, $L_{right}$, $L_{front}$, as shown in Fig. 4. $L_{left}$ and $L_{right}$ represent the horizontal width of the blind zone on the left/right side of the driver cabin, while $L_{front}$ stands for the longitudinal length of the blind zone in front of the cockpit. The parameters can be calculated as follows.
\[
\begin{aligned}
L_{\text{left}} &= h_{\text{sm}} \times \frac{w_e}{(h_e - h_{\text{sm}})} \\
L_{\text{right}} &= h_{\text{sm}} \times \frac{(w - w_e)}{(h_e - h_{\text{sm}})} \\
L_{\text{front}} &= h_{\text{fm}} \times \frac{l_e}{(h_e - h_{\text{fm}})},
\end{aligned}
\]

where \( h_{\text{sm}} \) indicates the vertical distance from the bottom edge of the side window to the ground. \( h_{\text{fm}} \) represents the height of the bottom edge of the windshield/center stack, which blocks the driver’s front line of sight. \( h_e \) means the vertical distance from the driver’s eye point to the ground.

For the intersection scenario, we only calculate the AV visibility for areas 1 and 3 in Fig. 3. 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), we further divide it into (A1) the left peripheral, (A2) the central and (A3) the right peripheral sub-fields.

Here we assume 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.

\[
F(\theta) = \sum_{i=1}^{3} \omega_i f_i(\theta),
\]

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, as shown in Fig. 6. 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.

$$f_i(\theta) = \begin{cases} \xi, & \theta \in A_c \\ \xi P(\theta), & \theta \in A_{max} - A_c \end{cases}$$  \hspace{1cm} (3)

where $A_{max}$ 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 $P(\theta)$ is estimated with the following exponential function.

$$P(\theta) = p_{min} \frac{4(\theta - \mu_c - 0.5\alpha)^2}{(A_{max} - A_c)^2}$$  \hspace{1cm} (4)

where $\mu_c$ is the angle between the angular bisector and the front sight line. $p_{min}$ is a minimum visibility probability of AV when it is at the boundary of HV driver’s peripheral sub-field. Assuming the HV driver’s head turns to the left or right by 45 degrees, $p_{min}=0.3$, then the HV driver visual field and the observation probability function $f_i(\theta)$ of AV are schemed in Fig. 6.
2.3 Game design considering social compatibility

The intersection decision game is formulated as a static game, which contains the following elements: 1) players \{AV, HV\}, 2) strategy set \{Yield, Not Yield\}, and 3) utility set \((U_{AV}, U_{HV})\). The utility matrix is shown in Table 1, in which \((u_{AV,mn}, u_{HV,mn})\) is the utility set under corresponding strategies when AV takes strategy \(m\) and HV takes strategy \(n\).

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

|          | HV          |           |
|----------|-------------|-----------|
|          | Yield(1)    | Not Yield(0) |
| AV       |              |            |
| Yield(1) | \((u_{AV,11}, u_{HV,11})\) | \((u_{AV,10}, u_{HV,10})\) |
| Not Yield(0) | \((u_{AV,01}, u_{HV,01})\) | \((u_{AV,00}, u_{HV,00})\) |

(a) AV utility

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

\[
U_{AV} = (1 - \lambda)[\alpha u_{s,AV} + \beta u_{t,AV} + \gamma u_{sf,AV}(\theta)] + \lambda U_{HV},
\]

where \(u_{s,AV}\) and \(u_{t,AV}\) are the safety and traffic efficiency utilities of AV, respectively. Social compatibility is represented by both the social fitness utility function \(u_{sf,AV}\) and the reciprocal utility, i.e. the HV utility \(U_{HV}\). \(\alpha, \beta, \gamma, \lambda\) are the corresponding weights to trade-off between utilities. The AV position variable \(\theta\) helps to consider the AV visibility.

(b) HV utility

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

\[
U_{HV} = \alpha u_{s,HV}(\theta) + \beta u_{t,HV} + \lambda_{HV} u_{atr,HV}(\theta),
\]

where \(u_{s,HV}\) and \(u_{t,HV}\) are the safety and traffic efficiency utilities of HV, respectively. \(u_{atr,HV}\) is the...
reciprocal utility of its altruistic behavior, which is weighted by $\lambda_{HV}$. When HV driver yields to AV, the value of $\lambda_{HV}$ is equal to $\lambda$. If the driver does not give way to AV, $\lambda_{HV}$ is 0. The utility functions of AV and HV are explained in Appendix A. For the detailed calibration of parameters, e.g. weighting factors and thresholds, is achieved via simulation (Chen, 2021).

To summarize, the flowchart of our socially compatible decision algorithm is briefed in Fig. 7. Firstly, the relative position between vehicles are obtained, and are used to calculate the visibility probability of AV. Then, the game utilities are calculated and used to find the Nash Equilibrium (NE) solution. Finally, the specific acceleration/deceleration value of AV is determined by the yield decision and the safety utility of AV.

![Flowchart of the socially compatible decision algorithm](image)

Fig. 7 Flowchart of the socially compatible decision algorithm

### 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, detailed in Definition 17 (Shalev-Shwartz et al., 2017). The adopted RSS model parameters are listed in Table 2.
parameter $a_{\text{brake},\text{min}}^{\text{HV}}$ is selected according to the results of natural driving study in China (Li et al., 2015).

| Parameters | Definition | Values |
|------------|------------|--------|
| $\rho_{\text{AV}}$ | Response time for AV | 0.5s |
| $\rho_{\text{HV}}$ | Response time for HV | 2s |
| $a_{\text{accel},\text{max}}^{\text{AV}}$ | Maximum acceleration for AV | 3.5m/s$^2$ |
| $a_{\text{accel},\text{max}}^{\text{HV}}$ | Maximum acceleration for HV | 3m/s$^2$ |
| $a_{\text{brake},\text{min}}^{\text{AV}}$ | Minimum deceleration for AV | -3m/s$^2$ |
| $a_{\text{brake},\text{min}}^{\text{HV}}$ | Minimum deceleration for HV | -4.43m/s$^2$ |
| $a_{\text{brake},\text{max}}^{\text{AV}}$ | Maximum deceleration for AV | -5m/s$^2$ |
| $a_{\text{brake},\text{max}}^{\text{HV}}$ | Maximum deceleration for HV | -8m/s$^2$ |

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 interacts with the truck. The EEG data at Fz and Cz positions are recorded using BioPac MP160.

3.3 Participants and experiment design

We recruited 24 subjects of 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, 3) SC algorithm. Three different speed limits were specified, i.e. 20 km/h (Lowspd), 45 km/h (Midspd), 70 km/h (Highspd), respectively. Subjects were asked to drive under specific speed limits in the rightmost lane and to complete 9 HV-AV interactions. When the truck was 120 meters away from the conflict area, the AV started with the same speed of the truck. Once the truck was
100 meters away from the conflict area, the decision algorithm was triggered ON. After the interaction, the subjective questionnaire for driving tasks (Appendix B) was filled in the parking area. Fig. 9 presents an example of interaction scenario in the experiments.

Fig. 9 HV-AV interaction in intersection scenes

Considering that the physiological data may have a large fluctuation during the interaction and need time to return to a stable state (Lin, 2019), the subjects used 3-5 minutes for free driving before next interaction. An experiment for each subject took about 90 minutes. The experimental procedure is shown as follow.

1) Subject fills in the driver self-ability (Lajunen and Summala, 1995) and driving style assessment questionnaires (Liu, 2017; Sun, 2017).
2) Subject wears the physiological acquisition devices and confirm the signal recordings.
3) Subject gets familiar with the simulator driving without interaction with AVs.
4) The formal experiment begins, subject conducts the Lowspd experiment. After each interaction, a subjective questionnaire of driving task 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 15km/h over limit). For detailed analysis, we further divide the interactive cases into 4 speed intervals according to the initial speed triggered by the algorithm, i.e. Low (10-30km/h), LowMid (30-40km/h), Mid (40-50km/h) and High (50-70km/h).

4.1 Safety analysis

In this study, the inter-vehicle interaction is assumed to end 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 $TTA = \frac{L}{v}$. If TTA is large, it means when the leading vehicle arrives at the intersection, the lagging vehicle is still far away, so the safety can be guaranteed. 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) (Li et al., 2015). Such danger-imminent case is defined as an ‘AEB’ case.

Statistics of all interaction cases are summarized in Table 3. In the low speed scenarios, there are 6 AEB cases with the noSC algorithm, and no AEB case with RSS or SC algorithms. In medium and high speed scenarios, the numbers of AEB cases with noSC, RSS and SC algorithms are 9, 11 and 6, respectively. This shows that the SC algorithm can provide the best safety performance for AV-HV interactions. The RSS algorithm seems conservative by showing the most courtesy behaviors, i.e. 16 full-stop cases. However, it still causes 11 AEB cases, which means that RSS is not the safest algorithm for the studied intersection driving scenarios.

| Scenarios of cases | AV decision algorithm |
|--------------------|-----------------------|
| Speed range        | noSC  | RSS  | SC   |
| Low (10-30km/h)    | 22    | 20   | 17   |
| LowMid (30-40km/h) | 15    | 12   | 15   |
| Mid (40-50km/h)    | 26    | 27   | 25   |
| High (50-70km/h)   | 8     | 9    | 6    |
| Effective case number | 207   |
| Failed case number | 9     |

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. 10a and Fig. 10b, respectively. The results of TTA and ending velocity in Fig. 10a show that when interacting with the RSS-based AV, the HV is very conservative and safe, but its traffic efficiency is low (its TTA average larger than 10s). When interacting with the noSC-based AV, the efficiency of HV is improved, but there are 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. The lowest TTA value of SC-based AVs is larger than that with two other algorithms, showing its best safety performance. From the cases when HV arrives first, it can be found that RSS is conservative and safe, but its traffic efficiency is low. For the noSC and SC algorithms, the traffic efficiency is higher, while the SC algorithm shows the best safety performance.
Furthermore, to explain the benefits of social compatibility, we select three interaction cases with similar initial speeds, i.e. 52.0km/h (noSC), 54.3km/h (RSS) and 50.1km/h (SC). For the HV in all three cases, the driver’s throttle input fluctuates between 30%-45%, the vehicle acceleration fluctuates between 0.1-0.15m/s², and the speed increment is between 3-4km/h.

Fig. 11 presents the two vehicles’ states, the AV inputs, as well as the AV visibility probability estimated using Eq. 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 0.79s, which is less than the specified threshold of 0.83 and triggers the AEB braking. 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 rules of the RSS, which finally leads an almost inevitable collision (TTA= 0.02s). 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 contrast, since the SC algorithm can directly consider the HV driver’s visual limitations, the SC-based AV decelerates at t=7.5s 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. In the end of the interaction, TTA is 0.95s, meaning a safe and efficient interaction with HV.
4.2 Subjective evaluation

Fig. 12 presents the mean and significance values of subjective evaluation on interactions, with all significance levels (p<0.05) indicated for corresponding question items. 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. In 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, we find 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. In 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.
4.3 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 120m away from the conflict area to the end of interaction. The After data correspond to the stage of 6s after the interaction. For the EEG signal features, the mean power values of Alpha (8-13Hz), Beta (13-30Hz) and Theta (4-8Hz) waves are extracted to judge the subjects’ emotion fluctuation. For each from 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 overspeed driving or lost EEG signals.

In a previous research, it is found that the power of Alpha and Theta waves increases with the increase of users’ pleasure degree, and the power of Beta wave rises with the enhancing of positive emotions (Cao, 2019). 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.

The 61 effective groups of EEG data, the variation percentage of EEG mean power in each interaction is defined as \( GR = \frac{P_{\text{base}} - P_{\text{int}}}{P_{\text{base}}} \times 100\% \), 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 the Fig. 14 below. It can be observed 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 lowest. In contrast, by considering social compatibility, the SC algorithm can provide an equivalent level of satisfaction as the conservative RSS algorithm.

![Fig. 14 The statistical results of EEG features](image)

To summarize, the statistics of interaction process show that compared to the other benchmarks, the SC algorithm can better balance safety and traffic efficiency, making the interaction between AV and HV more harmonious and smoother. Through the interaction comparisons of three algorithms in similar scenarios, it is found that the consideration of human visual limitations and social compatibility can prevent the vehicle from entering the blind zones of the HV driver, which can better improve safety. The advantages of the proposed SC decision algorithm are further validated by the HV drivers’ evaluation on the AV-HV interactions.

5. Conclusion

The aim of this study is to propose an unsignalized intersection decision algorithm that can achieve better social compatibility during dynamic interactions with human-driven vehicles. For this, a probabilistic model of the interacting driver’s visual limitations is constructed, which can estimate the probability of AV being observed by the human driver during the interaction process. Based on this visibility model, the social compatibility is further realized using a game-theoretic framework. Human-in-the-loop experiment results show that in addition to the well-balanced safety and time efficiency, the proposed AV decision algorithm can significantly improve social compatibility and make AV decision more in line with the expectation of human drivers.

This study is one step further towards more advanced and human-like decision algorithms for automated
vehicles. However, here we focus on realizing social compatibility from the perspective of other driver’s 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 applied in other interacting driving scenarios.

**Nomenclatures**

| Notation | Variable | Notation | Variable |
|----------|----------|----------|----------|
| $\mathcal{A}_c$ | Central sub-field’s angular range scanned by head rotation | $u_{alt r, HV}$ | Reciprocal utility of HV |
| $A_{max}$ | Front direct field’s angular range scanned by driver head rotation | $u_{s, AV}$ | Safety utility of AV |
| AV | Automated vehicle | $u_{s, HV}$ | Safety utility of HV |
| $f_i(\theta)$ | Visibility probability function of eye zone when driver focus on $i^{th}$ direction | $u_{sf, AV}$ | Social fitness utility of AV |
| $F(\theta)$ | Visibility probability of AV | $u_{t, AV}$ | Traffic efficiency utility of AV |
| $h_e$ | Altitude distance from the driver’s eye point to the ground | $u_{t, HV}$ | Traffic efficiency utility of HV |
| $h_{fm}$ | Height from the ground to the upper edge of the front windshield/center stack | $U_{AV}$ | Utility of AV |
| $h_{sm}$ | Height from the bottom edge of the cabin’s side window to the ground | $U_{HV}$ | Utility of HV |
| HV | Human-driven vehicle | $w$ | Width of vehicle body |
| $l_e$ | Longitudinal distance from driver’s eye point to the front windshield/center stack | $w_e$ | Horizontal distance from driver’s eye point to left side of vehicle body |
| $L_{front}$ | Longitudinal length of the blind area directly in front of the cockpit | $\alpha$ | Weight of safety utility |
| $L_{left}$ | Horizontal width of blind area on the left side of the driver’s cabin | $\beta$ | Weight of traffic efficiency utility |
| $L_{right}$ | Horizontal width of blind area on the right side of the driver’s cabin | $\gamma$ | Weight of social fitness utility |
| noSC | Game-based decision algorithm without considering social compatibility | $\theta$ | Angle between center sight of HV’s driver and AV |
| NE | Nash equilibrium in a game | $\lambda$ | Weight of HV utility |
| $P_{min}$ | Visibility probability of AV when it’s at the boundary of driver’s peripheral view area | $\lambda_{HV}$ | Weight of reciprocal utility for HV |
| $P(\theta)$ | Observed probability of AV when it’s in the driver’s peripheral view area | $\mu_c$ | Bisecting line angle of the central field of view |
| RSS | Responsibility-Sensitive Safety | $\xi$ | Impact factor that affects the driver’s visual capture ability |
SC | Game-based decision algorithm considering social compatibility $\omega_i$ | Probability of $i^{th}$ sub-field that the driver pays attention to
TTA | Time to arrive at the conflict area of the lagging vehicle

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**Supplementary material**

A video abstract is provided, which includes a brief introduction of the proposed approach and a video of experiments.

**CRediT authorship contribution statement**

**Daofei Li:** Conceptualization, Funding acquisition, Supervision, Writing -original draft, Video abstract.  
**Ao Liu:** Software, Visualization, Writing - review & editing, Validation.  
**Hao Pan:** Software, Visualization, Writing - review & editing, Video abstract.  
**Wentao Chen:** Methodology, Data curation, Writing -original draft.

**Declaration of Competing interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**Appendix A: Detailed utility functions of AV and HV**

**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 $\Delta t$, we can describe the safety utility $u_s$ of a two-vehicle interaction process 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.

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

(7)

where the parameters $\Delta t_{rsk}$ and $\Delta t_{saf}$ are the risky and safe thresholds of time difference $\Delta t$, respectively. As shown in Fig. 15, 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 $\{\Delta t_{rsk}, \Delta t_{saf}\}$ are determined as follow. If when HV arrives at conflict area (location
已离开冲突区域（位置 $P_{AV1}$），此时时间差被定义为 $\Delta t_{\text{risk}}$。另一方面，如果AV已离开交叉口（位置 $P_{AV2}$），此时时间差被定义为 $\Delta t_{\text{saf}}$，如方程（10）所示。同样地，如果HV将在时间 $t_0$ 到达冲突区域，我们也可以计算相应的安全效用。

$$
\begin{align*}
\Delta t &= L_{HV}/v_{HV} \\
\Delta t_{\text{risk}} &= L_{\text{risk}}/v_{HV} \\
\Delta t_{\text{saf}} &= L_{\text{saf}}/v_{HV}
\end{align*}
$$

方程（8）

图15 交叉口驾驶描述

假设AV距离冲突区域的时间是 $L_{AV}$，速度是 $v_{AV}$，则 $t_{AV} = L_{AV}/v_{AV}$。如果设置的最大允许速度是 $v_{max}$，效率时间定义为 $t_{eff,AV} = L_{AV}/v_{max}$。然后交通效率效用 $u_{t,AV}$ 为

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

方程（9）

社会适合度效用 $u_{s,f,AV}$ 代表AV的决策有多符合HV的决策，它在方程（10）中以AV的可见性概率 $F(\theta)$ 和默示程度 $f_{\text{tacit}}(i,j)$ 来表示。如果 $F(\theta)$ 小，HV可以轻易地注意到AV，没有合作驾驶行为。默示程度度在表4中说明，其中 $(i,j)$ 表示AV和HV，分别。

当HV采用Yield策略，如果AV也退让，那么默示程度 $f_{\text{tacit}} = 0$，如果AV不退让，我们设置 $f_{\text{tacit}} = 1$。

$$
u_{s,f,AV} = F(\theta)f_{\text{tacit}}
$$

方程（10）

表4 $f_{\text{tacit}}$ AV在不同条件下的

| $f_{\text{tacit}}$ | HV       | Yield | Not Yield |
|-------------------|----------|-------|-----------|
| AV                | Yield 0  | 1     |           |
|                  | Not Yield | 1     | 0         |

HV详细效用

安全效用 $u_{s,HV}$ 设计为...
\[ u_{s,HV} = \begin{cases} \left( u_s \right)^{F(\theta)}, & u_s \geq 0 \\ \left( -u_s \right)^{F(\theta)} + 2F(\theta)u_s, & u_s < 0 \end{cases} \]  \quad (11)

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. (11), the traffic efficiency utility of HV is as follows.

\[ u_{t,HV} = \begin{cases} \frac{1 - (t_{HV} - t_{eff,HV})}{t_{efl,HV}}, & t_{HV} \leq t_{efl,HV} \\ 1, & t_{HV} > t_{efl,HV} \end{cases} \]  \quad (12)

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.

\[ u_{alt,AV}(\theta) = F(\theta)u_{t,AV}. \]  \quad (13)

**Appendix B: Driving Task Questionnaire**

Please give the scores based on your feelings during the interaction with the other vehicle.

| Questionnaire item                              | Score (0-10) |
|------------------------------------------------|--------------|
| 1. I feel safe in interaction                  | 0 1 2 3 4 5 6 7 8 9 10 |
| 2. I feel comfortable in interaction           | 0 1 2 3 4 5 6 7 8 9 10 |
| 3. I worry about collision with the other vehicle | 0 1 2 3 4 5 6 7 8 9 10 |
| 4. I feel satisfied with the interaction       | 0 1 2 3 4 5 6 7 8 9 10 |
| 5. I feel relaxed in interaction               | 0 1 2 3 4 5 6 7 8 9 10 |
| 6. I am confused by the behavior of the other vehicle | 0 1 2 3 4 5 6 7 8 9 10 |
| 7. I feel calm in interaction                  | 0 1 2 3 4 5 6 7 8 9 10 |
| 8. I feel happy in interaction                 | 0 1 2 3 4 5 6 7 8 9 10 |