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Social-aware Planning and Control for Automated Vehicles Based on Driving Risk Field and Model Predictive Contouring Control: Driving through Roundabouts as a Case Study

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***Abstract*—The gradual deployment of automated vehicles (AVs) results in mixed traffic where AVs will interact with human-driven vehicles (HDVs). Thus, social-aware motion planning and control while considering interactions with HDVs on the road is critical for AVs' deployment and safe driving under various maneuvers. Previous research mostly focuses on the trajectory planning of AVs using Model Predictive Control or other relevant methods, while seldom considering the integrated planning and control of AVs altogether to simplify the whole pipeline architecture. Furthermore, there are very limited studies on social-aware driving that makes AVs understandable and expected by human drivers, and none when it comes to the challenging maneuver of driving through roundabouts. To fill these research gaps, this paper develops an integrated social-aware planning and control algorithm for AVs' driving through roundabouts based on Driving Risk Field (DRF), Social Value Orientation (SVO), and Model Predictive Contouring Control (MPCC), i.e., DRF-SVO-MPCC. The proposed method is tested and verified with simulation on the open-sourced *highway-env* platform. Compared with the baseline method using purely Nonlinear Model Predictive Control, the DRF-SVO-MPCC can achieve better performance under various maneuvers of driving through roundabouts with and without surrounding HDVs.**

Keywords—Automated vehicles, Planning and control, Social-aware driving, Roundabouts, Driving Risk Field, Model Predictive Contouring Control

I. Introduction

Purely fully autonomous vehicles on roads are demonstrated to be beneficial to road safety and efficiency [1]. However, the gradual development and deployment of automated vehicles (AVs) and advanced driver assistance systems (ADAS) at various levels results in mixed traffic conditions where AVs need to interact with human driven vehicles (HDVs). Thus, making AVs' behavior understandable, expected, and accepted by human drivers through so-called social-aware driving models is critical for road safety and efficiency under various maneuvers, especially challenging ones, e.g., driving on weaving sections, highly curved roads, and driving through roundabouts.

There are some preliminary studies regarding social-aware driving [2]. These studies are usually focusing on social cooperation for AVs' path planning, whose methods can be mainly divided into two categories, i.e., learning-based, and model-based methods. Reinforcement learning methods, such as Deep Q-networks (DQN), Actor-Critic (A2C), and Proximal Policy Optimization (PPO), integrating Partially Observable Stochastic Games (POSG) can factor surrounding HDVs' influence into the AVs' path planning and then connect to proportional–integral–derivative (PID) as a low-level controller for path tracking [3], [4]. Since the reward for social compliance is difficult to quantify, many researchers employed inverse reinforcement learning (IRL) to learn and mimic how human drivers act in the real world using empirical driving data [5]-[8]. In addition to reinforcement learning-based approaches, some studies adopted deep learning, e.g., Social Long Short Term Memory (LSTM) [9] and Social Generative Adversarial Network (GAN) [10], incorporating social factors for trajectory prediction of the surrounding HDVs, and then designed socially aware path-planning for AVs correspondingly. These are all learning-based methods. Regarding model-based methods, in [11] and [12], a game-theoretic-based decision-making approach is combined with Model Predictive Control (MPC) under the dynamic bicycle model [13] to build a complete architecture tackling scenarios such as lane changing, overtaking, etc. This approach requires the estimation of the model parameters for different environments and is not robust to different scenarios. Another model-based approach is to build a field model to estimate the dangers around AVs [14]-[16]. In [15], 3D risk fields are created and combined with MPC for path planning and tracking to ensure a collision-free path of AV. In

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[16], the authors developed a driving risk field (DRF) model to quantify the risks perceived by drivers. And by coupling DRF to a controller that can maintain the perceived risk below a threshold, they generated human-like driving behavior. The required model parameters of the human driver were obtained through simulation. In addition, the model does not require real-time parameter estimation, improving the robustness regarding different environments. Although field-based planning and control can reduce the occurrence of hazards and is highly robust to different scenarios, little consideration is given to social cooperation and the impact of different driving styles on social compliance to surrounding HDVs.

On the other hand, MPC's capability to handle multiple-input multiple-output (MIMO) systems with various constraints makes it particularly suitable for real-world autonomous vehicle planning and control. Thus it is also necessary to review relevant research in this domain. MPC can be traced back to the 1980s when engineers in the process industry first started deploying it in real practice [17]. MPC methods assume a finite look-ahead horizon for which control signals are calculated to optimize an objective function. MPC allows direct planning and control of the vehicle, whether driving on the highway or parking in low-speed scenarios with different predicted models [18]-[20]. In [21], [22], the HDV was simply seen as an obstacle and the optimization goal of the MPC is to move away from the obstacle on the highway. This can lead to unexpected scenarios where vehicles are seen as dangerous objects even if they are driving in the same direction with no conflicts and it is hard to tackle uncertain environments such as an intersection. For this, in [23] the authors additionally employed the partially observable Markov decision process (POMDP) for decision-making before MPC allowing it to handle more uncertain scenarios. At the same time, to encourage vehicles to collaborate, MPCs that can control multiple AVs within a scenario were developed in [24], [25]. The problem is that it only enables cooperation between AVs and it is difficult to consider other users on the road, needless to say, delivering social-aware driving.

From the previous reviews, it is identified that the disadvantage of MPC is that it is difficult to take into account the risks faced by other vehicles on the road, while purely using the aforementioned social cooperation-based path planning method alone can result in a less flexible and less reliable path. Furthermore, few studies implemented integrated planning and control together, and seldom did they cover the challenging maneuver of driving through roundabouts. To fill these research gaps, this paper studies the suitability of utilizing MPC incorporating the DRF method to generate a social-aware driving algorithm that can safely control the motion of a vehicle driving through a roundabout while being able to handle potential conflicts with surrounding HDVs and considering different levels of interests of other road users. There are several challenges. The first one is to ensure the safety and comfort of all users on the road. It is important to understand the intention of human drivers correctly and try to work with the HDVs correspondingly. Machines and humans do not understand the danger/risk in the same way. Thus, what AVs need is to "think" more like humans and anticipate possible dangers to interact with other HDVs safely. Furthermore, for social-aware driving, it is necessary to modify the AV's original objective by balancing its own benefits versus the benefits of other surrounding HDVs considering the different driving styles and characteristics of human drivers, thus making the AV accepted by HDVs. Different human drivers possess different priorities concerning safety, efficiency, and attitudes toward other vehicles, reflecting their different driving styles, e.g., aggressive, and defensive [2]. Also, the driving style of AVs determined by the needs of the passengers may vary from time to time, and case by case. For example, for daily commuters and those in a hurry, the efficiency of their journey should be assigned with a higher priority. While, if there is an elderly or sick person in the vehicle, he/she probably will place more weight on comfort level and be more willing to give precedence to others to ensure safety. Finally, it is challenging for the model to maintain robustness in tackling different scenarios and handling different driving styles.

To tackle these challenges, this paper develops an integrated social-aware planning and control algorithm incorporating Driving Risk Field (DRF), Social Value Orientation (SVO) [26], and Model Predictive Contouring Control (MPCC). DRF is adopted to model the surrounding drivers' perceived risk when interacting with the AV. The SVO, a social psychology-derived approach, is utilized to measure how individuals make the trade-off between personal benefits and the benefits to others [26]. Then, the model-based DRF-SVO is packaged into the MPC framework connecting to the specific MPCC algorithm to implement the integration of both planning and control. The integration avoids approaching the motion planning and feedback control hierarchically, and therefore brings more stability to the system. With the proposed DRF-SVO-MPCC algorithm, this study implements two types of driving styles, i.e., egoistic and prosocial, where an egoistic vehicle will not tolerate any increase in its own cost, a prosocial vehicle will prefer a minor increase in its own cost or the surrender of part of its benefits to reduce the danger of other vehicles. Lastly, the proposed model is verified on complex maneuvers, i.e., driving through roundabouts with large curvature, which is one of the most accident-prone scenarios. Both single-lane and two-lane roundabouts which are common in most countries are tested to verify the robustness and generalization ability of the proposed method.

In short, the main contributions of this paper are:

- A social-aware MPC is developed by combining MPC and DRF using SVO as the bridge to consider both the accuracy of controls and the perceived danger of other vehicles. While integration with SVO also makes it possible to balance the benefits of ego AV versus those of surrounding HDVs.
- Different driving styles are generated under the proposed DRF-SVO-MPCC method, especially with the help of SVO. SVO can also determine the desired driving style of the AV under different situations.
- The proposed DRF-SVO-MPCC integrates motion planning and feedback control simultaneously improving the stability of the vehicle control system.
- The performance of the proposed DRF-SVO-MPCC is validated on challenging maneuvers, i.e., driving through both single-lane and two-lane roundabouts with two different driving styles implemented.

II. BASIC THEORY

A. Model Predictive Control

In this study, the MPC aims to minimize the cost function for the system based on the non-linear prediction model on the vehicle and system constraints. The general formulation of the non-linear MPC can be written as follows:

$$min \ \sum_{k=0}^{N_P-1} J_k\left(X_k, U_k, X_k^{ref}\right) \tag{1a}$$

s.t.: $$X_{k+1} = f(X_k, U_k), k = 0, \ldots, N_P - 1 \tag{1b}$$

$$G(X_k, U_k) \leq g_b, k = 0, \ldots, N_P - 1 \tag{1c}$$

$$X_0 = X_{init} \tag{1d}$$

In (1), U_k and X_k are the input and state of the system, respectively. The function J_k is the cost function that determines the cost of the whole system, and the function G comprises all constraints with g_b being the bound value. These constraints ensure the system state and inputs are within a set boundary. Currently, the constraints are only defined as box constraints, however, they are flexible to be expanded. N_P is the prediction horizon for the MPC. The predicted mode $X_{k+1} = f(X_k, U_k)$ is based on the kinematic bicycle model [13] which is written as:

$$\dot{x} = vcos(\psi + \beta) \tag{2a}$$

$$\dot{y} = vsin(\psi + \beta) \tag{2b}$$

$$\dot{\psi} = \frac{v}{l_r}\sin(\beta) \tag{2c}$$

$$\dot{v} = a \tag{2d}$$

$$\beta = \tan^{-1}\left(\frac{l_r}{l_r + l_f}\tan(\delta)\right) \tag{2e}$$

As in Fig. 1, the x and y are the longitudinal and lateral positions of the vehicle, respectively. ψ is the heading angle of the vehicle, and v is the velocity of the vehicle. $[x, y, \psi, v]$ are the state variables of the kinematic bicycle model. The distance from the center of gravity to the front and rear wheels are l_f and l_r, respectively. β is the angle of the current velocity of the center of mass with respect to the longitudinal axis of the vehicle. The control input parameters are the front steering angle and the acceleration, which are $[\delta, a]$. This model is a non-linear model, which means that this study concentrated on Nonlinear Model Predictive Control (NMPC).

The continuous space model is discretized to $X_{k+1} = f(X_k, U_k) = X_k + \Delta_t f^c(X_k, U_k)$ with a discretization time Δ_t.

Several steps should be followed when using the MPC formulation described above. Firstly, the measured or estimated current state should be obtained as the initial state. The second step is to solve the optimal control formula. Then the optimal control input sequence (N_P elements) will be obtained. Finally, only the first element in the sequence will be applied to the system and then move to the next MPC round.

B. Driving risk field

The Driving Risk Field (DRF) [16] represents the driver's belief about the probability of the risk occurring. The value of a DRF can change with the vehicle's different velocities and steering angles. Since the kinematic bicycle model is used as the prediction model in MPC, to maintain consistency, it is also adopted to calculate the vehicle's path in DRF:

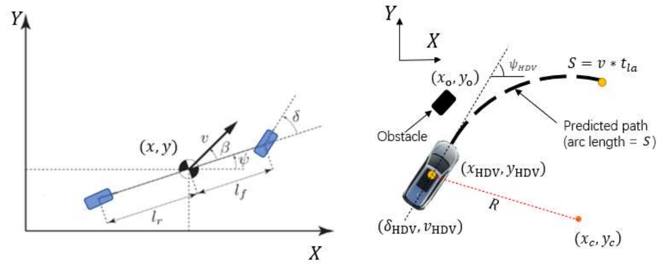


Fig. 1. Illustration of (a) kinematic bicycle model and (b) the predicted path in the DRF model

$$R = \frac{l_r + l_f}{\tan(\delta)} \tag{3}$$

As shown in Fig. 1(b), in (3), the radius of the arc (R) of the vehicle's preceding trajectory and the center of the turning circle (x_c, y_c) can be determined by the HDV's position (x_{HDV}, y_{HDV}), HDV's heading ψ_{HDV} and HDV's steering angle δ_{HDV}. The DRF of a vehicle is modeled as a torus with a Gaussian cross-section which can be written as:

$$DRF(x_o, y_o) = a \exp\left(\frac{-\left(\sqrt{(x_o - x_c)^2 + (y_o - y_c)^2} - R\right)^2}{2\sigma^2}\right) \tag{4}$$

The coordinate of a risk obstacle to the HDV is (x_o, y_o). The height (a) of the Gaussian is modeled as a parabola and the width (σ) of the Gaussian is modeled as a linear function which is a simplification of the parabolic function:

$$a(s) = p(s - vt_{la})^2 \tag{5}$$

$$\sigma = (m + k_i|\delta|)s + c \quad i = 1\ (inner\ \sigma), or\ 2\ (outter\ \sigma) \tag{6}$$

The t_{la} is a fixed look-ahead time. Based on it, the look-ahead distance increases linearly with the velocity of the vehicle. And p is a parameter that defines the parabola's steepness. The width of DRF at the location of the vehicle (c) is related to the car width and m defines the slope of widening of the DRF when driving straight. Then, k_1 and k_2 which represent the parameters of the inner and outer edges of the DRF, respectively, can affect the width of the DRF, and they can help to generate asymmetric DRFs. With this modeling method, the risk grows linearly with the increasing steering angle. It is similar to a human when the driver controls the steering of the vehicle, which simulates the driver paying more attention to the environment in the direction turned, resulting in a higher risk presented in the other direction. The increase in DRF is proportional to δ, leading to higher risk when driving through sharp curves with cumulatively smaller radii.

So, all the hyper-parameters in DRF are related to the driver's status instead of the environment. In this work, the DRF is utilized to obtain the possible risk of the HDVs interacting with AVs. Therefore, the coordinates in (4) are from the HDV's perspective, while all other parameters represent those of the driver in the HDV. The human driver parameters are identified through a simulation and referring to [16], in this paper, the parameters are from a 25-year-old male volunteer driver, shown in Table III. This will allow AVs to put themselves in the shoes of other drivers to be informed of what they perceive as the probability of danger, which will also better reflect the consideration for social-aware driving.

C. Social Value Orientation

Social Value Orientation (SVO), a metric from social psychology [26], is a parameter that describes how much a person is willing to consider the benefits of other people versus his/her own. In psychology, each individual wants to maximize the reward and minimize the cost when considering only himself or herself. However, as social road users, some of our planning needs to take into account the welfare of others. The SVO term conducts us to model each individual's social preferences by expressing their cost function as a combination of two terms, the cost to self J_{self} and the cost to others J_{other}:

$$J_{total} = \cos\,\alpha\, J_{self} + \sin\alpha\ J_{othe} \tag{7}$$

where α, as an angle, indicates the value of SVO. It reflects the selfishness or altruism of each individual. Just like in Fig. 2, when this angle is 0^0, it means that the system is completely individualistic; while when the angle is 90^0, it means that the system is completely altruistic to other systems. In Fig. 2, it is noticed that most people's SVO are between 0^0 and 60^0 illustrated by the blue points. In this work, to motivate AVs to behave with different personality traits like human drivers, two different styles, i.e., prosocial and egoistic, are implemented. Furthermore, it should be ensured that the lower limit of SVO is set so as not to completely ignore the risk of colliding with other vehicles. As a result, regarding the two driving styles, α is set as 60^0 for prosocial driving and 15^0 for egoistic driving.

III. Social-aware DRF-SVO-MPC Implementation

A. Quantifying Perceived Risk

Referring to the previous study by Kolekar et al, the perceived risk is the product of the subjective probability of an event occurring and the consequences of that event [16]. In this paper, the DRF captures the probability of collision with the AV at the next timestep t as perceived by other drivers at the current position. According to [28], the consequence of the collision should be represented by the impulse as:

$$I = m_{total}\,(|v_1 - v_2|) \tag{8}$$

where m_{total} is the total weight of the two colliding vehicles, and v_1 and v_2 are the relative velocities of the two vehicles before and after the collision. This study simplifies the collision of the two vehicles as a rigid body collision so that the relative velocity after the collision is $0\ m/s$ ($v_2 = 0\ m/s$).

The risk perceived by other vehicles can be seen as a cost to them. Therefore, the cost to others in (7) is obtained as follows:

$$J_{othe}\ = I * DRF_{other} \tag{9}$$

With (3)-(6) and (8)-(9), this study calculates the DRF risk

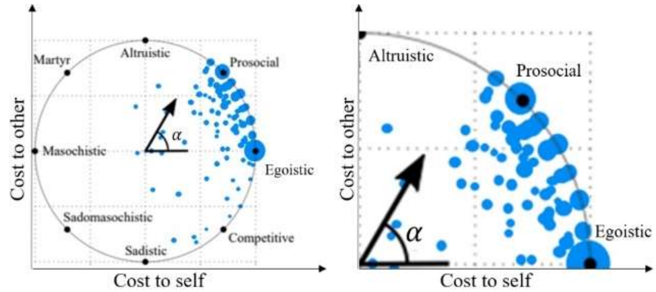


Fig. 2. Illustration of SVO and the distribution of SVO values in the population [27]

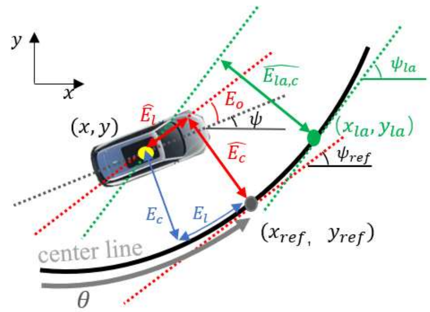


Fig. 3. Illustration of MPCC

perceived by HDVs. Connecting with the SVO, the calculated DRF will be embedded into the MPC cost function enabling AV to consider the benefits/costs of HDV in its planning and control.

B. Cost Function and Social-aware MPC Formulation

The basis of the cost function is provided by the model predictive contouring control (MPCC) formulation [29] which has been utilized in the AVs field for motion planning [24], [30], or path generation and tracking [31]. The main idea of this approach is to track the position of the vehicle regarding a reference point on the path and to introduce a new state quantity, i.e., progress, so that it is intuitively possible to balance the maximization of progress along the path with the minimization of lateral, longitudinal and angular offset from the path. Furthermore, this study introduces a "far point", which is used mainly as a second reference point to only minimize contouring error which is similar to lateral error from the reference path.

The progress variable θ can be seen as the distance that the vehicle had moved. Compared with MPC, the state vector in MPCC is updated to $x_{mpcc} = [x, y, \psi, v, \theta]^T$ and the input of the model is updated by the progress rate as: $u_{mpcc} = \left[a, \delta, \dot{\theta}\right]^T$. The goal of MPCC is to maximize the progress θ and track the reference trajectory.

The contouring error E_c and the longitudinal error E_l are also linked to progress. To improve the efficiency, an approximation is adopted to calculate the two errors:

$$\widehat{E_c} = -\left(x - x_{ref}\right)\sin\left(\psi_{ref}\right) + \left(y - y_{ref}\right)\cos\left(\psi_{ref}\right) \tag{10a}$$

$$\widehat{E_l} = \quad \left(x - x_{ref}\right)\cos\left(\psi_{ref}\right) + \left(y - y_{ref}\right)\sin\left(\psi_{ref}\right) \tag{10b}$$

$[x_{ref}, y_{ref}, \psi_{ref}]$ means the reference point on the center line of the roundabout which is obtained by the perception module. In addition to these two types of error, an orientation error as a penalty term is added to ensure that not only is the car positioned in the middle of the road but also the prediction of the vehicle movement is close to the center line. The orientation error can be written as follows:

$$\widehat{E_o} = 1 - \left|\cos(\psi_{ref})\cos(\psi) + \sin(\psi_{ref})\sin(\psi)\right| \quad (11)$$

In parallel to the current reference point, the "near point" information is considered. The information from the "far point" (x_{la}, y_{la}), illustrated in green color in Fig. 3, also needs to be used as a reference to correct the contouring error of the vehicle and expand the vehicle's forward visibility. The upgraded formula can be established by referring to the previous formula for contouring error:

$$\widehat{E_{la,c}} = -(x - x_{la})\sin(\psi_{la}) + (y - y_{la})\cos(\psi_{la}) \quad (12)$$

In (12), the $[x_{la}, y_{la}, \psi_{la}]$ provides the far-point's information. This study finally combines all the errors with a linear progress maximization reward on $\dot{\theta}$ (which is the derivation of θ) in the MPCC cost function:

$$J_{mpcc} = \sum_{k=2}^{N_P+1}\left(q_c\hat{E}_{ck}^2 + q_l\hat{E}_{lk}^2 + q_o\hat{E}_{ok}^2 + q_{la,ck}\hat{E}_{la,ck}^2\right) - \sum_{k=1}^{N_P} q_v\dot{\theta}_k \quad (13)$$

This part of the cost function ensures that the vehicle can follow the reference path and maximize the progress as much as possible and $(q_c, q_l, q_o, q_{la,ck}, q_v)$ are weighting factors for every part. Minimizing this J_{mpcc} loss enables the ego vehicle to track the reference trajectory accurately.

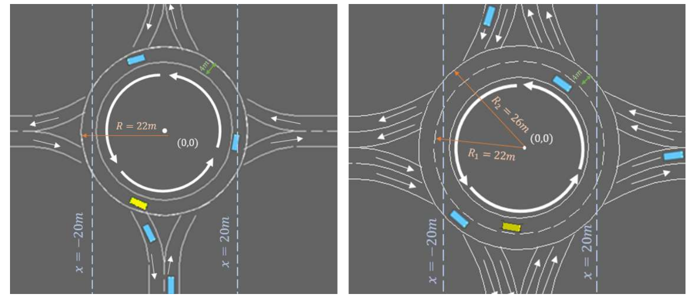
In addition, AVs also need to ensure the comfort of the passengers in the vehicle. The main cause of discomfort in the car is the steering wheel swinging back and forth from side to side, followed by sudden acceleration and deceleration of the AV. So, the variation in the system inputs is set to be as small as possible and the weight of δ should be bigger than the other parts. Thus the comfort cost J_{comf} is demonstrated as

$$J_{comf} = \sum_{k=1}^{N_P}\|u_k - u_{k-1}\|_S^2 \quad (14)$$

Combining the two cost functions, i.e., J_{mpcc} in (13) and J_{comf} in (14), the total cost to the self-AV is obtained, which considers safety, efficiency, and comfort, as a function of:

$$J_{self} = J_{mpcc} + J_{comf} \quad (15)$$

Thus, according to SVO, this study combines J_{self} and J_{other} using (7) to obtain the total cost function J_{total} and adopts it as the objective function for social-aware MPC as in (1a). The inequality constraints in MPC are mainly based on the mechanical limits of the vehicle and traffic regulations, for example, the speed limit on the road, the maximum acceleration that the engine can provide, and the maximum steering angle the steering gear can provide. This study adapts the driving style and social characteristics of AVs by adjusting the desired velocity, the weighting of the individual costs, and the SVO.



(a) (b)

Fig. 4. Illustration of (a) single-lane roundabout and (b) two-lane roundabout

IV. Simulation Experiments And Results

In this study, the architecture of the social-aware DRF-SVO-MPCC is the same as NMPC but with the redefined cost function. Moreover, this study takes the benefits/costs of surrounding vehicles into consideration tackling the risks faced by HDVs. At the same time, the MPCC was used in defining the proposed own cost, and the "far point" was introduced to make the vehicle more stable over curves with large curvature. Since the proposed DRF-SVO-MPCC integrates and outputs both planning and control simultaneously, in the simulation experiments, two test cases are carried out. Firstly, this study compares the control accuracy of the developed social-aware DRF-SVO-MPC with regard to two baselines, i.e., the pure NMPC and the well-established tracking trajectory methods pure pursuit controller [32] combined with PID controller, which is simply referred to as the PP controller in this paper (since pure pursuit controller is the main part of this method). This is done by testing on the single-lane roundabout scenario with no HDVs. Secondly, this study also verifies whether the proposed method can consider other vehicles' benefits/costs and whether it can generate different driving styles under different SVOs and other parameter settings. This is done by testing on single-lane and two-lane roundabout scenarios with AVs interacting with HDVs in two different situations.

A. Controller and Simulation Setups

This study adopts *highway-env* [33] simulation (a platform widely used in relevant publications) with Python to test the proposed approach. The examined scenarios are presented in Fig. 4. In the simulation, the radius of the roundabout is $22m$, while the connection between the straight road and the roundabout is made with a curve fitted by a *sine* function which is shown in Fig. 4. In the simulation, the AV, indicated in the yellow color, travels from west to east (left to right), while the HDV, indicated in the blue color, travels from south to north (bottom to up) randomly at 3~7 m/s. The parameters of the vehicles that appear in all the scenarios are shown in Table I. Because of the road peculiarities of roundabouts, vehicles are generally not allowed to pass through them at very high speeds, so the maximum velocity limit in the simulation is 15 m/s. The initial speed of the vehicle v_0 is set randomly within 0~3 m/s.

In the simulations, two baseline controllers, i.e., PP and NMPC controllers, together with the proposed society-aware DRF-SVO-MPCC were tested. In the PP controller, there is only a look-ahead distance that needs to be sited and it is sited to $5m$. The parameters of NMPC and DRF-SVO-MPCC are set as

TABLE I. PARAMETERS OF THE VEHICLE

Parameter	l_r	l_f	$mass$	$width$
Value	$2.46m$	$2.49m$	$2020Kg$	$2.0m$

TABLE II. PARAMETERS OF MPC CONTROLLER

Parameter	$v_{road,max}$	a_{lim}	δ_{lim}	$\Delta\delta_{lim}$	N_p
Value	$15.0\ m/s$	$3.0\ m/s^2$	$30°$	$30°/s$	15

TABLE III. PARAMETERS OF DRF

Parameter	p	m	k_1	k_2	t_{la}	c
Value	0.0064	0.001	0	1.3	$3s$	$0.5m$

TABLE IV. PARAMETERS OF MPCC IN DIFFERENT STYLES

Driving Style	SVO	Desire Velocity
Prosocial	$\theta = 60°$	$v_{ref} = 5.0\ m/s$
Egoism	$\theta = 15°$	$v_{ref} = 6.8\ m/s$

TABLE V. QUANTITATIVE RESULTS OF THE EXPERIMENTS (AV ENTERS THE ROUNDABOUT FIRST)

Scenarios	Method	Driving styles	Max positional error	Average positional error	Collision
Single-lane roundabout with no HDV	PP Controller	---	$3.08m$	$1.37m$	---
	NMPC	---	$1.27m$	$0.65m$	---
	DRF-SVO-MPCC	---	$\mathbf{0.23m}$	$\mathbf{0.12m}$	---
Single-lane roundabout interacting with an HDV	NMPC	---	---	---	Yes
	DRF-SVO-MPCC	Prosocial	$\mathbf{0.19m}$	$\mathbf{0.09m}$	No
		Egoistic	$0.28m$	$0.16m$	No
Two-lane roundabout interacting with an HDV	NMPC	---	---	---	Yes
	DRF-SVO-MPCC	Prosocial	$\mathbf{0.26m}$	$\mathbf{0.17m}$	No
		Egoistic	$0.34m$	$0.22m$	No

TABLE VI. QUANTITATIVE RESULTS OF THE EXPERIMENTS (HDV ENTERS THE ROUNDABOUT FIRST)

Scenarios	Method	Driving styles	Start Braking Distance	Min. distance to HDV	Min. Velocity
Two-lane roundabout interacting with an HDV	DRF-SVO-MPCC	Prosocial	$18.22m$	$8.49m$	$1.47m/s$
		Egoistic	$13.87m$	$3.65m$	$3.17m/s$

shown in Table II. These two MPCs are solved by the optimization solver framework CasADi [34].

To test and verify the performance of the social-aware planning and control of the developed DRF-SVO-MPCC, three main scenarios are implemented. The first scenario focuses on only comparing the control performance of the three controllers with no other HDVs present in the roundabout and thus the developed DRF-SVO-MPCC will not consider social factors. In the second scenario, there will be HDV merging from other lanes of the roundabout. In the last scenario, the HDV travels from north to south (up to down) and enters the roundabout first. This study considers two different driving styles of ego AVs and compares their differences in motion planning. The common parameters of DRF are shown in Table III and the different parameters corresponding to the different driving styles are shown in Table IV. The bottom line in both driving styles is that no collisions can occur, so the AV driving model needs to at least consider HDV's safety cost, which means that the SVO cannot be set to 0°. Furthermore, maneuvers of driving through both single-lane and two-lane roundabouts are simulated (Fig. 4).

B. Analysis and Results

In the first testing scenario, this study focuses on comparing the control accuracy and performance of the three controllers: PP controller, NMPC, and social-aware DRF-SVO-MPCC. Fig. 5 shows all the trajectories controlled by the three controllers. It is easy to identify that all three AVs can follow the reference path, the centerline, to pass the roundabout. However, the PP controller gets the worst tracking performance, with a large error from the reference path. The maximum positional error is about $3m$, which means that the bodywork of the AV is partly outside of the lane. As can be seen in Fig. 6, due to the large curvature of the roundabout, the PP controller gets difficulties in trajectory tracking resulting in large fluctuations in δ, especially when $x = \pm 20m$. Compared to the PP controller, the optimization-based method, NMPC, delivers a much better tracking of the reference trajectory, except for two instances of inappropriate steering around $x = \pm 20m$ due to the lack of proper judgments of the future path, as shown by Fig. 5(b). Unlike the PP controller, the NMPC is a lateral and longitudinal coupled control, and therefore a will experience waves during steering at $x = 20m$ and $x = -18m$ as shown in Fig. 6(a). The proposed social-aware DRF-SVO-MPCC demonstrates a good solution to the above problems. As the roads are stitched together using aggregate shapes, they are not completely smooth at the road joints, however, as shown in Fig. 5 (c), the proposed DRF-SVO-MPCC not only tracks the reference trajectory well but also comes out with a smoother curve than the reference trajectory. At the same time, Fig. 6 (a) shows that the social-aware DRF-SVO-MPCC can still maintain a smooth a during steering with high curvature at around $x = \pm 20m$.

Having demonstrated the control performance of the developed social-aware DRF-SVO-MPC outperforms the two baselines, this study further compares the effects of different driving styles on the planning of the AV. In the second scenario, an aggressive HDV is added which attempts to enter the roundabout even if the AV is already inside and running from its left. Two driving styles, i.e., prosocial and egoistic, are tested with Fig.7 showing the acceleration of the AV under the two driving styles. As shown in Fig. 7 (a), under the prosocial driving style, AV will first actively slow down with $a = -1.02\text{m/s}^2$ to avoid the HDV minimizing the risk to which the HDV is exposed, and then it will accelerate to v_{ref}. Conversely, an egoistic AV with a small SVO (e.g., 15^0), will be more biased to consider minimizing its own costs. Thus, as in Fig. 7 (b), the AV decides to accelerate with $a = 0.43\text{m/s}^2$ driving through the junction before the HDV to avoid collision and improve its efficiency through the roundabout. These statistics show that the proposed DRF-SVO-MPC can generate different driving styles while all maintaining safety. As shown in Fig. 4 (b), this study further sets up a two-lane roundabout to test the performance of

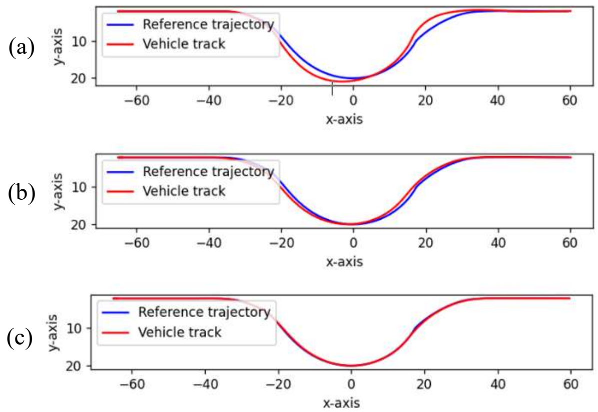


Fig. 5. The paths obtained by using (a) PP controller, (b) NMPC, and (c) social-aware DRF-SVO-MPCC in comparison to the reference trajectory

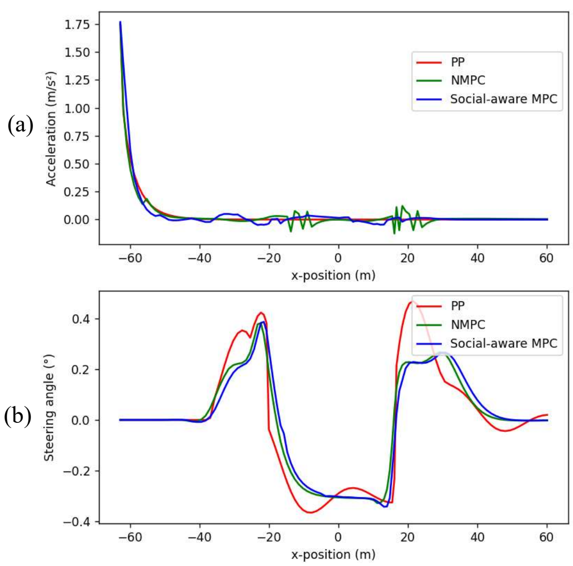
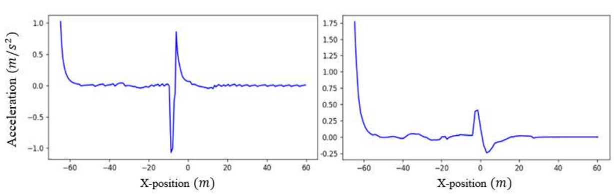
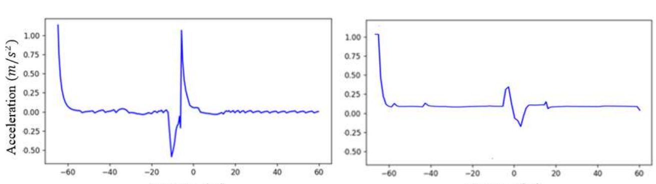


Fig. 6. Comparison of the control inputs, i.e., (a) acceleration and (b) steering angle, in different controllers when passing the roundabout



(a) (b)

Fig. 7. Illustration of the acceleration in different driving styles when passing the single-lane roundabout: (a) prosocial driving (b) egoistic driving



(a) (b)

Fig. 8. Illustration of the acceleration in different driving styles when passing the two-lane roundabout (a) prosocial driving (b) egoistic driving

the proposed DRF-SVO-MPC when the two vehicles are in different lanes. An extra lane is added with AV driving in the inner lane and HDV driving in the outer lane. Fig. 8 (a) shows that the prosocial AV will still give precedence to the HDV by braking with $a = -0.52\mathrm{m/s^2}$, waiting to maintain a safe distance from the HDV before accelerating back to the v_{ref} to pass the roundabout safely. The choice of braking behind the HDV was made because it was calculated that there would be a greater risk to the HDV if the v_{ref} was maintained. Comparing Fig. 8 (a) and Fig. 7 (a), it can be seen that, compared to HDV running in the near lane, the AV will brake more sharply when the HDV wants to merge into the same lane. This is caused by the HDV blocking the AV's trajectory when in the same lane which potentially poses a greater risk to both HDV and AV. The simulation demonstrates the proposed DRF-SVO-MPCC's capability to handle interacting with HDVs in different lanes separately. Similar to the single-lane roundabout case, when the driving style is egoistic, the AV will accelerate aggressively, try to change to the right lane just before the HDV, and then exit the two-lane roundabout without any deceleration throughout the whole process. This helps the AV maintain a low cost and high benefits while sacrificing the benefits of the HDV. Furthermore, it will be dangerous if the HDV is more egoistic and more aggressive which will cause a collision.

In the last scenario, HDVs enter the roundabout first and the AV plan to merge into the roundabout afterward. Because of safety and traffic rules, AVs in both driving styles will brake to avoid collision with HDVs and this study is to compare the planning of the different driving styles. As shown in Table VI, The egoistic AV will slow down as late as possible keeping only a minimum of 3.65 m from the HDV for safety and maintaining a higher velocity compared to the prosocial driving style. While the prosocial AV starts slowing down earlier at 18.22 m from the HDV and keeps a longer distance with the HDV of 8.49 m. The results show that the prosocial AV focuses more on minimizing the risk, and it places more weight on the benefit of HDVs. On the contrary, the egoistic AV aims for minimizing its own costs while ensuring the safety of both vehicles.

All the quantitative results are wrapped up and shown in Table V and Table VI. And all the testing scenarios are better demonstrated in the supplementary video with a description document, which can be viewed at https://shorturl.at/lBHM9.

V. Conclusion

This study develops an integrated social-aware planning and control algorithm, i.e., DRF-SVO-MPCC, which incorporates Driving Risk Field (DRF), Social Value Orientation (SVO), and Model Predictive Contouring Control (MPCC) to enable AVs to consider HDVs' risk and balance their own benefits with regards to the benefits of HDVs. The DRF is used to model the perceived risk and SVO is adopted to measure how AVs make the trade-off between their own benefits and the benefits of other HDVs. Using the SVO-based DRF and MPCC costs, together with the desired velocity, this study implements two types of driving styles, i.e., prosocial and egoistic. The model-based DRF-SVO is packaged into the cost function established by MPCC to deliver integrated planning and control. The proposed DRF-SVO-MPCC model is tested and verified on various simulation experiments comparing with two baselines which demonstrates its good planning and control performance driving through both single-lane and two-lane roundabouts with or without interacting with HDVs. Future research directions could focus on the estimation of model parameters using learning-based methods. For example, the driving style of HDVs can be estimated using a reinforcement learning approach, leading to different DRF-SVO-MPCC models to better perceive risks under the proposed framework. Furthermore, it is suggested to validate the model on other challenging driving maneuvers (e.g., on-ramp merging, high-way lane changing, or overtaking) and scenarios involving interactions with more surrounding vehicles to verify the model's robustness.

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