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Cooperative Driving Based on Negotiation with Persuasion and Concession

Cheng Peng and Masayoshi Tomizuka

***Abstract*— Recently, along with emergence of autonomous driving vehicles, it is predicted that in the near future, human drivers need to share road and interact with self-driving cars in all the possible traffic scenarios. In this paper, an algorithm based on negotiation with both persuasion and concession is proposed to tackle the challenging task of cooperative driving involving both human and robot drivers. The decision making process is formulated as an optimization based negotiation problem. The persuasion of autonomous vehicle is achieved by making commitment to tipping towards cooperation in the form of convex constraint. The concession is accomplished by gradually tuning weights in the objective function. We propose an approach suitable for most common driving scenarios including ramp merging, lane keeping/changing and intersection crossing. The effectiveness of the proposed algorithm is demonstrated by simulation for several different driving scenarios.**

I. INTRODUCTION

With recent development of autonomous driving technology, it is becoming more and more convincing that a driving environment dominated by autonomous vehicles is coming in the future. However, current self-driving cars are not mature enough to totally replace human drivers. Several years or even decades of effort is needed to bring the conceptual fully connected autonomous driving into reality, which means that autonomous cars and human drivers will coexist for quite a long time. This predictable situation leads to the requirement that robot drivers not only need to communicate and interact with its robot siblings but also need to cooperate with human drivers safely and intelligently.

Recent work on cooperative driving mainly focus on cooperation among connected vehicles assuming that each vehicle can be controlled by the same strategy [1], [2]. With this assumption, the cooperative driving task can be formulated as a multi-agent system control problem. However, when it comes to human drivers who will follow his/her own driving logic or habits, the algorithms based on multi-agent system theory will fail as some of agents (human drivers) cannot be controlled and their behaviors may or may not comply with the multi-agent system's cooperation objective. In these scenarios, most algorithms simply require the autonomous vehicles to yield people or assume they are following certain simple predefined driving pattern. The disadvantages of these algorithms are obvious, the resulting autonomous vehicles will either be too conservative (bullied by human drivers in the extreme case) or drive into some dangerous situations due to incorrect assumption of human behavior.

Another approach dealing with human drivers is to model their behaviors as solutions of an optimal planner, the reward function of which can be learned through human driving data [3]. This method did produce some promising results illustrating autonomous cars' influence on human driver's action. However, this algorithm heavily depend on the accuracy of the learned reward functions. In addition, human drivers' behavior may be influenced by other road users so that reward function itself may not be reliable enough.

In this paper, in order to enable intelligent and cooperative interaction without dependency on learned reward function, we propose to use human driver's prediction informaition and make cooperative proposals accordingly by solving an optimization problem. Our algorithm models the decision making task as a negotiation process between human and robot (H-R) drivers similar to negotiation between human and human (H-H). Two key factors in H-H negotiation are concession and persuasion, which work together to help reach an offer acceptable to both sides [4], [5]. In the autonomous driving context, concession is formulated as sacrifice in self-objective and persuasion is fulfilled by showing preference among several available strategies. By their co-effect, the autonomous car can make its behavior more readable to human which results in more effective cooperation.

The paper is organized as follows. In Section II, the cooperative driving prolem is formulated as an optimization problem assuming all the traffic participants are autonomous vehicles. In Section III, the simplistic conservative control strategy is introduced. In Section IV, the human driver factors are taken into account which transform the optimization problem to a negotiation process. In Section V, simulation results in several driving scenarios are presented to illustrate the effectiveness of the proposed algorithm. Section VI concludes the paper.

II. COOPERATIVE DRIVING

In this section, the mathematical description of the vehicle dynamics is introduced and an optimization problem is formulated for cooperative driving in the framework of Model Predictive Control (MPC). The system is treated as a two-agent system consisting of two autonomous cars, both of which can be controlled.

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C. Peng and M. Tomizuka are with the Department of Mechanical Engineering, University of California, Berkeley, CA 94720 USA (e-mail: chengpeng2014@berkeley.edu; tomizuka@berkeley.edu).

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A. Vehicle Modeling

A popular model used for vehicle dynamics is the bicycle model [6]. We adopted the discretized version of the bicycle model described by the following difference equations:

$$x_{k+1} = x_k+T_s v_k \cos\left(\theta_k+\tan^{-1}(\frac{L_r}{L}\tan\delta_k)\right), \quad (1)$$

$$y_{k+1} = y_k+T_s v_k \sin\left(\theta_k+\tan^{-1}(\frac{L_r}{L}\tan\delta_k)\right), \quad (2)$$

$$\theta_{k+1} = \theta_k+T_s v_k \frac{\tan\delta_k}{L}\cos\left(\tan^{-1}(\frac{L_r}{L}\tan\delta_k)\right), \quad (3)$$

$$v_{k+1} = v_k+T_s a_k, \quad (4)$$

where k is the time index, T_s is the sampling time, the state vector $[x,y,\theta,v]^T \in \mathbb{R}^{4\times 1}$ includes mass center x,y positions, yaw angle and speed of the vehicle in the road aligned coordinate frame respectively. Control input vector of the system $[a,\delta]^T \in \mathbb{R}^{2\times 1}$ consists of the vehicle's acceleration a and steering angle δ. L_r, L_f and $L{=}L_r{+}L_f$ are the rear, front and full length of the car respectively.

Compactly, (1)-(4) can be written as

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k), \quad (5)$$

where $\mathbf{x}_k{=}[x_k, y_k, \theta_k, v_k]^T$ and $\mathbf{u}_k{=}[a_k, \delta_k]^T$ are the state and control input vector respectively.

B. Optimization formulation

In this subsection, the two-agent cooperative driving problem is formulated as an optimization by applying the bicycle model.

Aiming at achieving driving efficiency and satisfying comfort demand, the following cost function is defined:

$$J_k = \sum_{i=1}^{2}\frac{1}{Z_i}\sum_{t=0}^{N-1}\left(\|\mathbf{x}_{i,k+t|k}-\mathbf{x}_{des}\|_Q^2+\|\Delta\mathbf{u}_{i,k+t|k}\|_R^2\right), \quad (6)$$

where k is the current time instant, i is the vehicle index, N is the receding horizon length, Z_i are predefined normalizing factors and $\mathbf{x}_{des}$ is the desired state. $\mathbf{x}_{i,k+t|k}$ and $\mathbf{u}_{i,k+t|k}$ denote state and control input signal at $k+t$ predicted at the current time step k. $\Delta\mathbf{u}_{i,k+t|k}{=}\mathbf{u}_{i,k+t|k}{-}\mathbf{u}_{i,k+t-1|k}$ defines the control change, representing the comfort level, Q and R are penalty matrices for deviation from desired state and control change respectively.

With regard to the constraints, the most critical one is associated with safety. To guarantee collision avoidance with both moving obstacles i.e. other vehicles sharing the road and static ones such as lane boundaries and parked vehicles, the following safety constraints are defined:

$$\begin{aligned} & y_{min,k+t} \le y^j_{i,k+t|k} \le y_{max,k+t}, && (7)\\ & (x_{1,k+t}, y_{1,k+t}) \in \mathbb{S}(x_{2,k+t}, y_{2,k+t}), && (8)\\ & i\in\{1,2\}, \quad j\in\{1,2,3,4\}, \quad t=0,1,\cdots,N-1, \end{aligned}$$

where (7) describes constraints formulated by static obstacles and (8) accounts for safety constraint between two agents. y^j's denote the lateral positions of the vehicle's four corners and W is the width of the vehicle. y_{min} and y_{max} denote lower and upper bounds of lateral position defined by the lane and parked cars and $\mathbb{S}(x,y)$ represents the safety set formulated by position (x,y). There exist quite a few approaches to define safety set $\mathbb{S}(x,y)$ in literatures. One simple case exemplifying $\mathbb{S}(x,y)$ is the halfplane defined by the line passing through (x,y) with slope equal to $\tan\theta$. Another example is the region outside a circle centered at (x,y) with radius of pre-assigned safety distance.

In addition to the safety constraints, other demands imposing on the vehicle consist of the initial state consistency, control saturation, kinematics and dynamics feasibility which are formulated as:

$$\begin{aligned} & \mathbf{u}_{i,k+t|k} \in \mathbb{U}_i, && (9)\\ & \mathbf{x}_{i,k+t+1|k} = f(\mathbf{x}_{i,k+t|k}, \mathbf{u}_{i,k+t|k}), && (10)\\ & \mathbf{x}_{i,k|k} = \mathbf{x}_i(k), && (11)\\ & i\in\{1,2\} \quad t=0,1,\cdots,N-1, \end{aligned}$$

where $\mathbb{U}_i$ is the feasible set of vehicle i's control input $\mathbf{u}_i$ and $\mathbf{x}_i(k)$ is vehicle i's current state.

Combining cost function (6) and constraints (7)-(11), the agent-based cooperative driving optimization problem can be stated as:

$$\begin{aligned} \min_{\mathbf{u}_{i,k+t|k}, i=1,2, t=0,1,\cdots,N-1} \quad & J_k && (12)\\ s.t. \quad & \text{constraints}(7)-(11) \end{aligned}$$

Note that in this optimization, both the agents can be controlled so that the Pareto optimal solution can be achieved in which no vehicle can obtain better performace without hurting the other one. This Pareto optimal solution is defined to be the cooperative driving strategy.

III. Conservative Driving Strategy

The most intuitive approach to handle human factors in driving is to assign human drivers with the highest priority. As a consequence, autonomous vehicles are required to always yield human drivers who can take any trajectory they please. Mathematically, this is equal to setting human drivers' behavior as hard constraints, which adjusts the original optimization problem (12) to the following:

$$\begin{aligned} \min_{\mathbf{u}_{1,k+t|k}} \quad & \sum_{t=0}^{N-1}\left(\|\mathbf{x}_{1,k+t|k}-\mathbf{x}_{des}\|_Q^2+\|\Delta\mathbf{u}_{1,k+t|k}\|_R^2\right) \quad (13)\\ s.t. \quad & y_{min,k+t} \le y^j_{1,k+t|k} \le y_{max,k+t},\\ & (x_{1,k+t|k}, y_{1,k+t|k}) \in \mathbb{S}(x^p_2(k+t), y^p_2(k+t)),\\ & \mathbf{u}_{1,k+t|k} \in \mathbb{U}_1,\\ & \mathbf{x}_{1,k+t+1|k} = f(\mathbf{x}_{1,k+t|k}, \mathbf{u}_{1,k+t|k}),\\ & \mathbf{x}_{1,k|k} = \mathbf{x}_1(k),\\ & j\in\{1,2,3,4\}, \quad t=0,1,\cdots,N-1, \end{aligned}$$

where the autonomous car and human driven car are assigned to be vehicle 1 and 2 respectively without loss of generality. $(x^p_2(k+t), y^p_2(k+t))$ is the prediction of human driver's future trajectcotry, which is assumed to be accessible either by an extra prediction module or Vehicle-to-Vehicle (V2V) communication. Compared to the optimization (12), decision variables in the altered optimiztion (13) only involve the autonomous car.

Note that as the autonomous vehicle always treats human driver's behavior as hard constraints, the human driver thus has no incentive to change his planned trajectory. Resultantly, the solution to (12) is a conservative instead of a cooperative one for human driver's behavior cannot be influenced. Hence there is no interaction between vehicles. The outcome of this conservativity can be easily foreseen. An examplar situation is that an autonomous vehicle and a vehicle driven by human meet at an intersection. In this scenario, the autonomous car will always let the human driver pass first regardless of whether this decision is reasonable or not. In the extreme case where traffic is heavy on the other lane and all human drivers happen to be selfish implying that they will not yield the autonomous car spontaneously, the robot driver then has no choice but a ridiculously long wait.

IV. HUMAN ROBOT DRIVER NEGOTIATION

In order to avoid undesirable over-cautious behavior caused by the conservative algorithm in (13), we formulate the cooperative drving problem as a negotiation process with concession and persuasion reflecting human's natural behavior in negotiation. The concession is fulfilled by introducing a tunable cost function and the persuasion is achieved by integrating a persuasion constraint into the original optimization (13).

Negotiation has been an effective tool in almost every aspect of the society. People are involved in different forms of negotiation purposely or unconciously. In the traffic system, human drivers are negotiating with others for right of the road in whatever driving scenarios. A general definition of negotiation is the necessary dialogues between agents in order to arrive at a globally acceptable offer when two or more of them have conflicting preferences over a set of issues or a fixed amount of resource. In addition, agents are most likely to be only aware of its own preference without enough knowledge about the other participants in most such negotiations. This feature requires the players to make tentative proposals and check for the others' reactions. In the specific driving problem, this proposal-based behavior can be observed in all common scenarios:

1) Lane Changing: Suppose that a rational human driver intend to change to the neighboring lane, he/she will first turn on the indicator, then slightly move towards boundary of the target lane in order to make the behavior more evident and eventually finish lane changing when a safe space is existent. This safe gap can be found by either patient waiting or persuading the car behind on the target lane to decelerate for driving efficiency purpose. The indicator and possible persuasion process both constitute the proposals in lane changing case.

2) Lane Keeping: Now we switch the point of view from drivers making lane changing proposals to drivers already on the target lane but passively influenced by the lane changing cars. To obviously show his/her preference for yielding (not yielding), the lane keeping cars are predicted to decelerate (accelerate or keep current speed). These possible actions formulate the lane keeping cars' proposals representing their responses to lane changing cars.

3) Intersection Crossing: Suppose two cars reach an intersection without stop signs around the same time, then they need to negotiate about who should pass first. Another interesting situation is the two-way stop (cross traffic does not stop), the question facing the drivers stopping at the stop sign is how to find or make a safe space for passing. In these examples, drivers again have two choice, which are passing as soon as possible and waiting patiently. The corresponding proposals are then moving forward to show preference for passing and staying still or even backing up to express patience.

In the following subsection, the negotiation based cooperative driving problem is formulated as an optimization.

A. Negotiation Formulation

In order to enable negotiation between robot driver and human driver, the control input of both human driver vehicle and autonomous vehicle should be treated as decision variables. Meanwhile, the prediction of human driving behavior should be taken into account. Hence, the negotiation objective function is adjusted as

$$\begin{aligned} J_k^n &= \frac{1}{Z_1}\sum_{t=0}^{N-1}\left(\|\mathbf{x}_{1,k+t|k}-\mathbf{x}_{1,des}\|_Q^2+\|\Delta\mathbf{u}_{i,k+t|k}\|_R^2\right) \\ &\quad +\frac{1}{Z_2}\sum_{t=T_n}^{N-1}\|\mathbf{x}_{2,k+t|k}-\mathbf{x}_2^p(k+t)\|_2, \end{aligned} \tag{14}$$

where $\mathbf{x}_2^p(k+t)$ is the human driver's state trajectory prediction and T_n is the pre-defined near future horizon during which human driver is assumed to follow the prediction exactly. The first term in (14) is the same as conservative objective function in (13) and the second term is included to reflect human driver's intention. Given that autonomous vehilce presumably has no access to accurate prior knowledge about human driver's objective function, it is assumed that the prediction trajectory minimizes (maximizes) human driver's hidden cost (reward) function. Thus, via minimizing the difference between planned human driver trajectory and predicted trajecotry in the 2-norm sense, the autonomous vehicle is enabled to consider its possible intervention to the human driver in its planning step.

The constraints for the negotiation optimziation problem will be altered correspondingly as:

$$\begin{aligned} & y_{min,k+t} \le y_{i,k+t|k}^j \le y_{max,k+t}, \quad j\in\{1,2,3,4\} \\ & \mathbf{u}_{i,k+t|k}\in\mathbb{U}_i, \quad \mathbf{x}_{1,k|k}=\mathbf{x}_1(k), \\ & \mathbf{x}_{i,k+t+1|k}=f(\mathbf{x}_{i,k+t|k},\mathbf{u}_{i,k+t}), \\ & t=0,1,\cdots,N-1, \text{ if } i=1, \\ & t=T_n,T_n+1,\cdots,N-1, \text{ if } i=2, \\ & (x_{1,k+t|k},y_{1,k+t|k})\in\mathbb{S}(x_2^p(k+t),y_2^p(k+t)), \\ & t=0,1,\cdots,N-1, \\ & \mathbf{x}_{2,k+t|k}=\mathbf{x}_2^p(k+t), \quad t=0,\cdots,T_n-1 \end{aligned} \tag{15}$$

Summarily, the negotiation problem is formulated as:

$$\min_{\substack{\mathbf{u}_{1,k+t}, t=0,1,\cdots,N-1 \\ \mathbf{u}_{2,k+t}, t=T_n,\cdots,N-1}} J_k^n \tag{16}$$
$$s.t. \quad \text{set of constraints(15)}.$$

Remark 1: The solution to the optimzation problem (16) is not broadcasted to the human driver so that vehicle-to-vehicle (V2V) communication is not necessary in this approach. The autonomous vehicle will take the action given by the solution showing its intention. In this manner, the human-robot driver interaction can be fulfilled.

Remark 2: Despite treating human driver's control input as one of optimziation decision variables, it does not mean that human driver will follow the solution obtained. The planned trajectory merely serves as a proposal to the human driver which may be accepted or refused.

However, the interaction modeling still remains incomplete as human driver's response is not inclued yet. Thus, we propose the introduction of two more factors which are concession and persuasion strategies in the next subsections.

B. Concession Strategy

The most intuitive and natural strategy when negotiating with another party possessing a different utility function is to make concession, revising the originally proposed relatively more selfish offer to a more likely acceptable one for both sides [7]. A negotiation protocol is defined as a set of rules or sequential steps restricting negotiating agents' available moves into a certain range.

In order to fit the concession characteristic into the optimization based negotiation problem defined by (16), a time-varying tunable weight is introduced to the cost fucntion. The adjusted cost function is as following:

$$\begin{aligned} J_k^{n,c} &= \frac{w_k}{Z_1}\sum_{t=0}^{N-1}\left(\|\mathbf{x}_{1,k+t|k}-\mathbf{x}_{1,des}\|_Q^2+\|\Delta\mathbf{u}_{i,k+t|k}\|_R^2\right) \\ &\quad +\frac{1-w_k}{Z_2}\sum_{t=T_n}^{N-1}\|\mathbf{x}_{2,k+t|k}-\mathbf{x}_2(k+t)^p\|_2. \end{aligned} \tag{17}$$

The tunable weight w_k at time instant k is defined as

$$\begin{cases} w_0 = 0.5, \\ w_{k+1} = w_k\beta^{1-p_{a,k}}, \end{cases} \tag{18}$$

where $\beta<1$ is a predefined scalar and $p_{a,k}$ is the proposal acceptance probability at time instant k reflecting intention of the human driver involved in the negotiation. The initial value w_0 is set to 0.5 since at the first round of negotiation, it is assumed that autonomous vehicle and human driver vehicle share equal priority using the road.

As the negotiation proceeds, the priority of human and autonomous vehicle will be adjusted according to human driver's acceptance of proposal. Particularly, if human driver instantly accepts the proposed trajectory by exactly following it thereafter, then $p_{a,k}$ will be equal to 1 so that w_k remains at 0.5, assigning autonomous vehicle and human driver the same priority for the entire negotiation process. Another extreme case is that human driver totally refuses to consider the proposed driving plan, never willing to change his/her originally planned trajectory and act in ignorance of existence of the autonomous vehicle. In this scenario, $p_{a,k}$ will quickly decrease to nearly 0 and the autonomous vehicle's behavior will coincide with the conservative strategy as human driver purposely leaves no space for negotiation. In practice, these two extremes may be quite rare, most probably $p_{a,k}$ will be some number between 0 and 1 and keep changing during the negotiation process as human driver's behavior may not properly reflect his/her true intention or the human drivers simply changes his/her intention which is a fairly common phenomenon in everyday life.

Therefore, definition of the acceptance probability term $p_{a,k}$ is crucial to the algorithm. In order to model human drivers' reaction in the negotiation, we propose to define $p_{a,k}$ as

$$p_{a,k} = \frac{\|trj_k^p - trj_{k-1}^p\|_2^2}{\|trj_k^p - trj_{k-1}^p\|_2^2 + \|trj_k^p - trj_{k-1}^{h,c}\|_2^2}, \tag{19}$$

where

$$\begin{aligned} trj_k^p \;=\; & [x_{2,k|k}^p,\cdots,x_{2,k+t|k}^p,\cdots,x_{2,k+T-1|k}^p, \\ & y_{2,k|k}^p,\cdots,y_{2,k+t|k}^p,\cdots,y_{2,k+T-1|k}^p]^T \end{aligned}$$

represents the predicted (x,y) trajectory of the human driver vehicle at time instant k. Similarly,

$$\begin{aligned} trj_{k-1}^p \;=\; & [x_{2,k|k-1}^p,\cdots,x_{2,k+t|k-1}^p,\cdots,x_{2,k+T-1|k-1}^p, \\ & y_{2,k|k-1}^p,\cdots,y_{2,k+t|k-1}^p,\cdots,y_{2,k+T-1|k-1}^p]^T \end{aligned}$$

denotes the prediction at the last time instant which is human driver's original plan before the autonomous vehicle makes the move and

$$\begin{aligned} trj_{k-1}^{h,c} \;=\; & [x_{2,k|k-1},\cdots,x_{2,k+t|k-1},\cdots,x_{2,k+T-1|k-1}, \\ & y_{2,k|k-1},\cdots,y_{2,k+t|k-1},\cdots,y_{2,k+T-1|k-1}]^T \end{aligned}$$

is the solution trajectory for human to the negotiation optimization problem (16) at the last time step $k-1$, i.e., the previous cooperative driving proposal for human driver.

The definition (19) is based on the idea that the human driver is given two options at each decision making step. One is to follow his/her original plan and the other one is to cooperate with the autonomous car after recognizing its intention leading to a predicted trajectory relatively close to the cooperative proposal. Thus, the similarity of the new predicted trajectory with the initial planned one and the cooperative proposal provides us with a metric of acceptance probability. In this paper, the Euclidean distance (2-norm) is selected due to the same sampling rate of trajectories, intuitive physical meaning and its simplicity. Therefore, the acceptance probability (19) can be interpreted as normalized trajectory similarity between updated and original prediction, inferring that less similar the new prediction is with the original one, the larger p_a is and more likely human driver is to cooperate.

C. Persuasion

In order to distinguish the negotiating agents from ones with conservative strategies, in addition to concession, the autonomous vehicle also needs to express its intent to cooperate properly, claiming its own right of using the road. As concession strategy, persuasion is another useful technique in negotaition. Unlike concession focusing on making more acceptable offers, persuasion on the other hand is utilized to influence opponents' beliefs and behaviors so that the offer can be more beneficial to the self-agent. The persuasion used in business and other fields where interaction happens is mainly based on dialog. Dialogs enable agents holding different points of view or involved in a conflict of interest to exchange arguments and persuade each other [8]. However, in the context of driving, as all the agents are making moves simultaneously and the dialogs are in the form of driving behavior, it is necessary to reformulate the concrete implementation of persuasion.

In this paper, the persuasion is introduced as a constraint imposed on the negotiation process formulated as:

$$p_{coop,k} \geq \alpha_k p_{con,k}, \tag{20}$$

where α_k=$1+\gamma p_{a,k}$ is a scalar dependent on $p_{a,k}$ defined by (19) and a predefined parameter γ, $p_{coop,k}$ and $p_{con,k}$ denote the cooperating and conservative probability at time instant k respectively. Following the same idea of definition of $p_{a,k}$, $p_{coop,k}$ and $p_{con,k}$ are formulated as:

$$p_{coop,k} = \frac{\|trj_k^{coop} - trj_{k-1}^{con}\|_2^2}{\|trj_k^{coop} - trj_{k-1}^{con}\|_2^2 + \|trj_k^{coop} - trj_{k-1}^{coop}\|_2^2}, \tag{21}$$

$$p_{con,k} = \frac{\|trj_k^{coop} - trj_{k-1}^{t}rj_{k-1}^{coop}\|_2^2}{\|trj_k^{coop} - trj_{k-1}^{con}\|_2^2 + \|trj_k^{coop} - trj_{k-1}^{coop}\|_2^2}, \tag{22}$$

where

$$\begin{aligned} trj_k^{coop} \quad = \quad & [x_{1,k|k}, \cdots, x_{1,k+t|k}, \cdots, x_{1,k+T-1|k}, \\ & y_{1,k|k}, \cdots, y_{1,k+t|k}, \cdots, y_{1,k+T-1|k}]^T, \end{aligned}$$

is the autonomous vehicle trjectory to be solved at current time instant,

$$\begin{aligned} trj_{k-1}^{coop} \quad = \quad & [x_{1,k|k-1}, \cdots, x_{1,k+t|k-1}, \cdots, x_{1,k+T-1|k-1}, \\ & y_{1,k|k-1}, \cdots, y_{1,k+t|k-1}, \cdots, y_{1,k+T-1|k-1}]^T, \end{aligned}$$

is the robot driver's solution to the negotiation problem at the last time step and trj_{k-1}^{con} is the conservative trajectory plan for the autonomous vehicle at previous time instant. There exist many candidates for the conservative plan trj_{k-1}^{con}, among which the most simple one is to decelerate until the interacting human vehicle pass through. A more reasonable and decent option is to use the solution from a conservative MPC like the one in (13). In this paper, we selected the latter method.

According to definition (21) and (22), it is shown that the persuasion constraint (20) pushes the solution trajectory to the cooperative direction harder when interacting with human drivers more likely to cooperate, i.e. higher acceptance probability.

The constraint (20) can be reformulated as:

$$\|trj_k^{coop} - trj_{k-1}^{con}\|_2^2 \geq \alpha \|trj_k^{coop} - trj_{k-1}^{t}rj_{k-1}^{coop}\|_2, \tag{23}$$

which is a convex quadratic constraint. Thus, it will not bring in much more computational load to the original problem.

The complete negotiation optimization with concession weight in the cost function and persuasion constraint is then written as:

$$\begin{aligned} \min_{\substack{\mathbf{u}_{1,k+t}, t=0,1,\cdots,N-1 \\ \mathbf{u}_{2,k+t}, t=T_n,\cdots,N-1}} \quad & J_k^{n,c} \\ s.t. \quad & \text{set of constraints}(15), \\ & \text{persuasion constraint (23).} \end{aligned} \tag{24}$$

V. Simulation Results

In this section, simulations are performed in several driving scenarios based on the proposed negotiation optimization approach. The exemplifying scenarios include lane changing, lane keeping and intersection crossing. One interacting vehicle is considered in the intersection and lane keeping case, while two are taken into account for lane changing. The MPC strategies with different weights on safety term are utilized to represent human drivers with different driving styles. Higher safety term is used for "nice" human drivers who is more willing to negotiate or cooperate and lower/zero weight on safety is used for selfish human drivers who are "iron nerved" and tough in negotiation. Thus, the simulation results are able to show the proposed algorithm's performance in different scenarios interacting with different kinds of human drivers.

A. Lane Changing

In this scenario, the autonomous vehicle and two human driver vehicles are interacting in the setting of two-lane highway driving. The autonomous vehicle attempt to make lane changing and human drivers will decide to yield or not based on their internal driving strategy.

The strategy we use to handle multi-vehicle scenario is as follows:

- Select the front vehicle in the neighbour lane as the interacting vehicle and solve the negotiation optimization problem (24) accordingly.
- Check the interacting vehicle's acceptance probability (19). If $p_{a,k+1} - p_{a,k} \leq \varepsilon$ (ε is a predefiend small scalar) holds for five sequential time steps, then switch the interacting vehicle to the rear vehicle in the neighbour lane.
- Treat the previous interacting vehicle's trajectory prediction as hard constraint using similar method in the conservative control strategy described in section III.

Figure 1 shows the case with "nice" human drivers (relatively high sfety weight), where the yellow car is the self autonomous vehicle, blue/green car is the front/rear vehicle in the neighbour lane and the red line represents the car trajectory. It is demonstrated in Fig. 1 that with persuasion constraint and concession cost function, the autonomous vehicle is able to cut in on the human driver when the cooperation proposal is accepted.

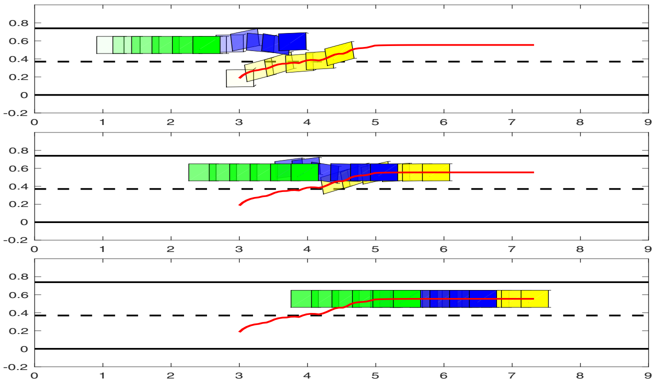

Fig. 1: Lane changing scenario with “nice” human driver

On the other hand, Fig. 2 shows the lane changing scenario interacting with a “tough” human driver (the front car) and a nice driver (the rear car). It is shown that the autonomous vehicle first attempt to cut in, however, the front tough human driver refuse to yield. The self vehicle then needs to wait and try again on the rear human driver. It turns out that the second driver is a nice one and willing to cooperate. Hence, the autonomous vehicle cut in on the rear human driver on the neighbour lane and finish lane changing.

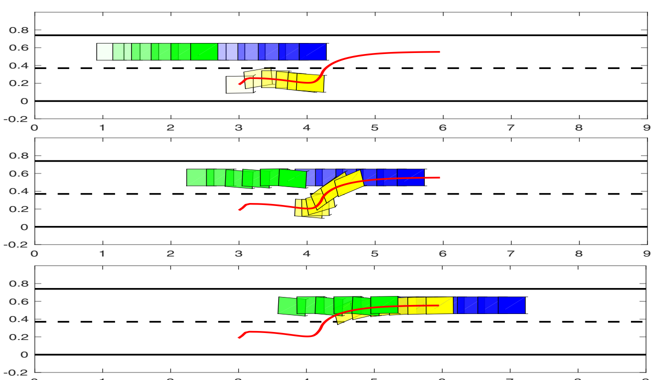

Fig. 2: Lane changing scenario with “tough” human driver

B. Lane Keeping

In this scenario, the autonomous vehicle becomes the one trying to keep lane and get to decide whether to yield the human driver who wants to make lane change. The simulation results are shown in Fig. 3 and Fig. 4 for interacting with nice and tough driver respectively, where the yellow/blue rectangle represents autonomous/human vehicle and the red solid line is the car trajectory. When interacting with a nice (tough) driver as shown in Fig. 3 (Fig. 4), the self vehicle express its intention of not yielding (yielding) by accelerating (decelerating). This effect can be seen more clearly in the speed profile plot as shown in Fig. 5 and Fig. 6.

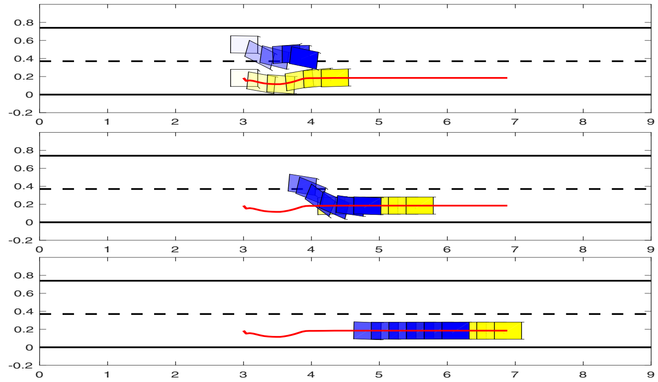

Fig. 3: Lane keeping scenario with “nice” human driver

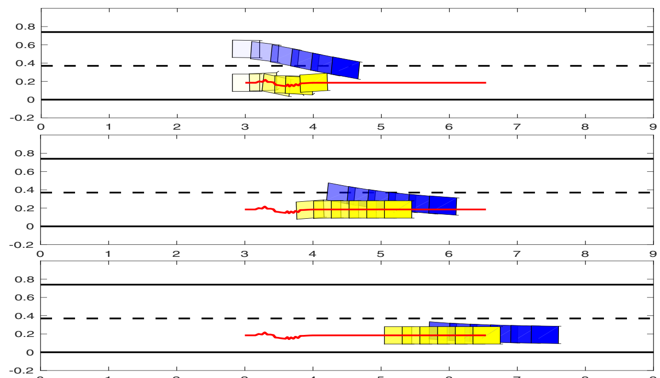

Fig. 4: Lane keeping scenario with “tough” human driver

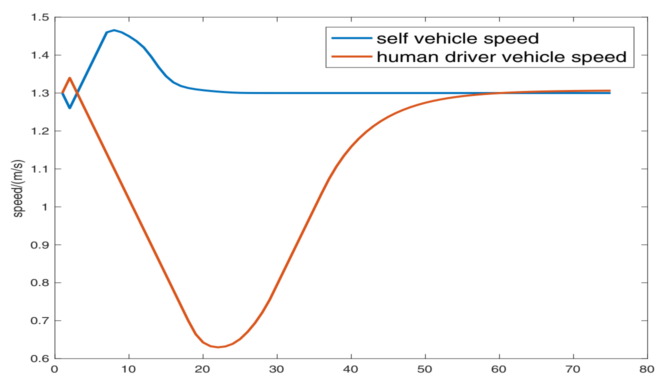

Fig. 5: Lane keeping speed profile (“nice” human driver case)

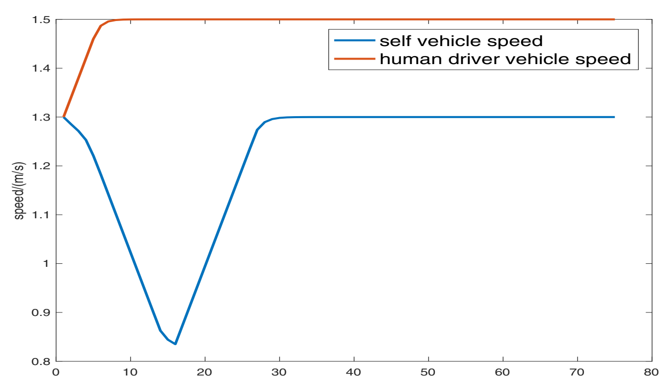

Fig. 6: Lane keeping speed profile (“tough” human driver case)

C. Intersection Crossing

At the intersection, if the autonomous vehicle and the human driver vehicle arrive at the same time, the self car needs to make decision on passing first or second. The algorithm's performance shown in Fig. 7 and Fig. 8 demonstrate that when the other driver is nice (tough), the self vehicle will decide to cross intersection first (second). In the figures, the yellow (blue) rectangle represent self (human driver) vehicle and the red line is the car trajectory. It is shown that the algorithm leads to reasonable results consistent with human driving behavior: passing first when meeting a "nice" driver and waiting when meeting a "tough" driver. The vehicles' speed profiles are shown in Fig. 9 and Fig. 10. These two figures illustrate that autonomous vehicle choose to accelerate and pass first when interacting with negotiable "nice" driver and keep speed low when dealing with selfish "tough" driver.

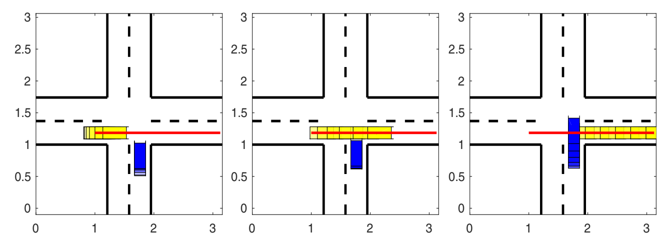

Fig. 7: Intersection scenario with "nice" human driver

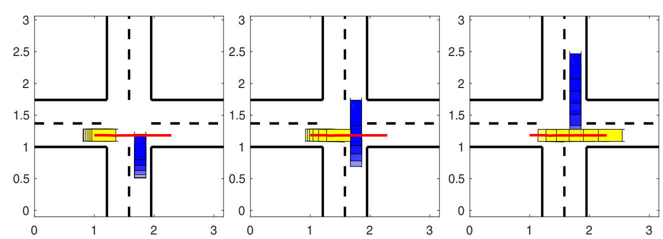

Fig. 8: Intersection scenario with "tough" human driver

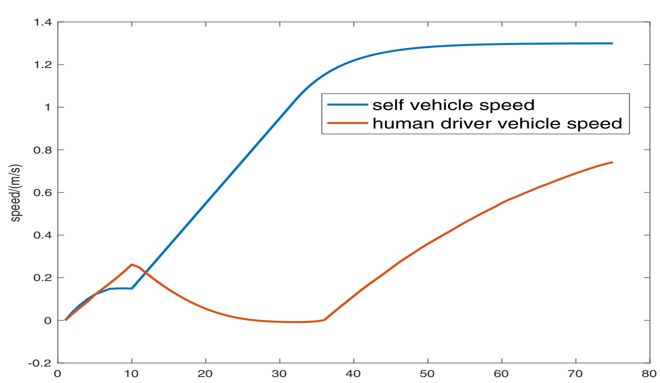

Fig. 9: Intersection crossing speed profile ("nice" human driver case)

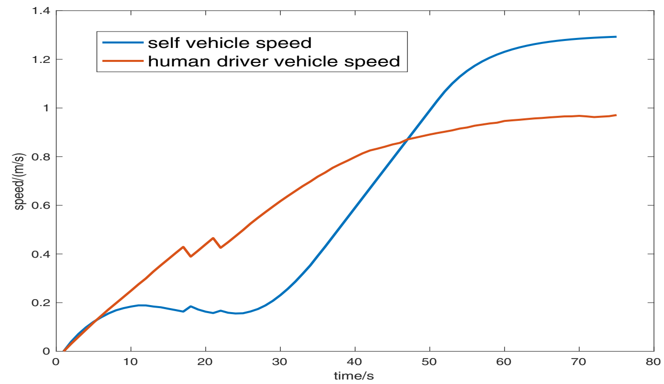

Fig. 10: Intersection crossing speed profile ("tough" human driver case)

VI. Conclusion

In this paper, the cooperative driving problem was formulated as an optimization based negotiation process. For more intelligent and effective interacting among human drivers and autonomous vehicles, a concession weight cost function and a convex persuasion constraint were introduced to the model predictive control (MPC) optimization framework. With the concession weight cost function, the autonomous vehciel could adjust its own priority in the driving negotiation process according to human driver's reaction (defined as acceptance probability of the cooperative proposal). The introduction of persuasion constraint enabled the autonomous vehicle to express its own intention and actively ask for right of the road. The proposed algorithm's performance was demonstrated by simulation results in several driving scenarios including lane changing, lane keeping and intersection crossing.

In our future work, the prediction uncertainty will be handled and the cost function form will be learned using machine learning approach.

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