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Game-Theoretic Decision-Making and Payoff Design for UAV Collision Avoidance in a Three-Dimensional Airspace

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Safety and efficiency are primary goals of air traffic management. With the integration of unmanned aerial vehicles (UAVs) into the airspace, UAV traffic management (UTM) has attracted significant interest in the research community to maintain the capacity of three-dimensional (3D) airspace, provide information, and avoid collisions. We propose a new decision-making architecture for UAVs to avoid collision by formulating the problem into a multi-agent game in a 3D airspace. In the proposed game-theoretic approach, the Ego UAV plays a repeated two-player normal-form game, and the payoff functions are designed to capture both the safety and efficiency of feasible actions. An optimal decision in the form of Nash equilibrium (NE) is obtained. Simulation studies are conducted to demonstrate the performance of the proposed game-theoretic collision avoidance approach in several representative multi-UAV scenarios.

Keywords: UAV traffic management; collision avoidance; game theory.

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1. Introduction

Unmanned aerial vehicles (UAVs) are envisioned to be an important component of future smart cities, providing flexible on-demand services such as cargo transport, last-mile delivery, aerial taxi, and infrastructure surveillance. With the forthcoming demands of commercial UAVs in diverse applications, the airspace is anticipated to be crowded with UAV operations, and requires UAV traffic management (UTM) solutions to be developed to maintain the safety and efficiency of the airspace. In UTM, the centralized traffic control scheme does not work well because the possible high volume of UAVs in dense airspace can easily overload traffic controllers. Instead, decentralized approaches, including collision avoidance, are anticipated to play a more significant role.

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Existing methods for UAV collision avoidance can be roughly classified into the following categories, including geometric guidance, potential field, path planning, model predictive control (MPC), and conflict resolution [1–3]. In the geometry guidance method [4, 5], the geometric attributes of agents are analyzed such that the minimum distances among agents are guaranteed to be larger than a predefined threshold. The potential field methods [6, 7] leverage the concept of repulsive and attractive force fields originating from physics and allow agents to avoid collision with the repulsive forces among agents. These two methods can incur extensive requirements on robust onboard sensing/communication equipment to obtain geometric information from other agents and the environment. In the path planning method [8–10], collision-free paths are selected by methods such as the rapidly exploring random tree (RRT) algorithm and its variants, and graph-based algorithms. The long-term safety of the agents can be guaranteed by such methods, but usually require global information to be known in advance and error-free

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maneuver executions by agents. MPC for collision avoidance [11, 12] has its advantage in considering various constraints and costs in optimization. However, the solutions obtained by MPC can be local optimal [13], and solving nonlinear MPC (because of nonlinear UAV dynamics) can be computationally expensive. Conflict resolution methods [14–17] include deterministic and stochastic optimal control, rule-based approaches, and protocol-based approaches. The computational load of optimal control can be inevitably heavy considering multi-agent interactions and even heavier when uncertainties are involved. In addition, the rule-based and protocol-based approaches are less capable of dealing with unexpected events or flexible conflict cases and can lead to high risks for UAVs.

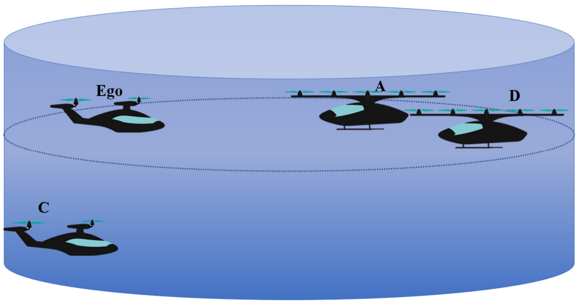
Of our interest, game-theoretic methods have been attractive in providing a systematic framework to capture multi-agent interactions and to solve for optimal payoffs in cooperative and noncooperative environments. Game-theoretic methods have been utilized for collision avoidance of unmanned ground vehicles (UGVs) [18–20]. Unlike the ground traffic environments with road geometry constraints in a two-dimensional (2D) plane, the three-dimensional (3D) airspace is more challenging, considering the more complicated states of interactive agents as well as the dynamic environment. In particular, more feasible actions are possible to avoid aerial collisions, and limited resources onboard, e.g. computing and power, can add constraints to the games. The pursuit–evasion game has been used in the literature for UAV collision avoidance, by assigning roles of "pursuer" and "evader" to interactive agents [21, 22]. The differential game is often integrated with the pursuit–evasion game to provide solutions [23, 24]. Reference [25] also uses the simultaneous game with the minmax strategy in game-tree search to solve the pursuit–evasion game. The mean-field game [21, 26], leader–follower Stackelberg game [27], and satisficing game [28, 29] are implemented for cooperative collision avoidance of teams of multi-UAVs. We notice that decisions in most of the above game formulations are determined by solving complicated constrained optimization problems, leading to a high computational burden in safety-critical real-time decision-making. Furthermore, the pursuit–evasion relationship can limit the feasible maneuvers of UAVs to achieve collision avoidance. Although simple to implement, the game-tree approach in [25] applied identical costs associated with the terminal leafs for both UAVs. However, the costs (or payoffs) corresponding to the same action combination for two UAVs can be different due to, e.g. different objectives, heterogeneous types, and changing environments.

In this paper, a novel game-theoretic approach is proposed for the collision avoidance of multiple UAVs in a 3D airspace (see Figs. 1(a) and 1(b) for an illustration). We formulate the problem into a repeated normal-form game and integrate rule-based cognitive information to determine the optimal decisions. High-level control actions, i.e. keeping the current direction, changing to the right within the horizontal plane, and descending to a lower altitude are available maneuvers for game players. A set of rules that describe general appropriate behaviors in the airspace are proposed for the payoff design. Compared with the aforementioned game-theoretic methods, the proposed game formulation is more efficient because the solution can be readily identified by looking up the payoff matrices (see Fig. 2). In addition, the comprehensive payoff design realizes safety and efficiency by considering the different effects of action combinations for game players.

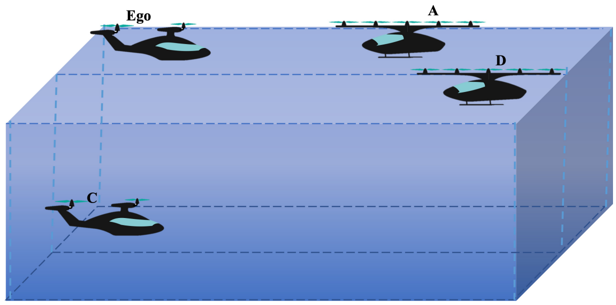
The rest of this paper is organized as follows. An overview of the game theory is presented in Sec. 2. The game-theoretic collision avoidance of UAVs is then developed in Sec. 3. Simulation studies are illustrated in Sec. 4, and Sec. 5 concludes this paper.

2. A Brief Overview on Game Theory

Game theory is a strategical mathematical model definition for decision-making among cooperative/noncooperative systems. Depending on the combination of actions executed, a



(a)



(b)

Fig. 1. An air traffic scenario with four UAVs in two different reviews. (a) UAVs fly at two different altitudes shown in a cylinder. (b) UAVs fly within virtual lanes (indicated by blue dash lines) shown in a cuboid.

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		UAV A	
		KVS	CVR
Ego	KVS	a_{11}, b_{11}	a_{12}, b_{12}
	CVR	a_{21}, b_{21}	a_{22}, b_{22}
	DLA	a_{31}, b_{31}	a_{32}, b_{32}

Fig. 2. A two-player normal-form game for UAV collision avoidance in the air traffic scenario shown in Fig. 1. Ego has three possible actions and UAV A has two possible actions. a_{ij} and b_{ij} with $i \in \{1,2,3\}$ and $j \in \{1,2\}$ denote the payoffs of Ego and UAV A for the corresponding action combination.

payoff is assigned to each player. Formally, a game in normal form is defined as $(\mathcal{N}, \mathcal{A}, J)$, where $\mathcal{N} = \{1, 2, \ldots, N\}$ is the set of N players. $\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_N$ denotes the players' actions where $\mathcal{A}_i = \{a_i^1, a_i^2, \ldots, a_i^{|\mathcal{A}_i|}\}, i \in \mathcal{N}$ is the set of $|\mathcal{A}_i|$ available actions for player i. $J = \{J_1, J_2, \ldots, J_N\}$, where $J_i : \mathcal{A} \to \mathbb{R}$ is the action-dependent payoff function for player i [30].

Each player $i \in \mathcal{N}$ in the game aims to select the action to maximize its payoff function given the other players' actions. Let $J_i = J_i(a_i, a_{-i})$ represent the payoff received by player i in the game where a_{-i} denotes the actions of all players except i. The best response of player i is the action $a_i^* \in \mathcal{A}_i$ that satisfies $J_i(a_i^*, a_{-i}) \geq J_i(a_i, a_{-i})$ for $\forall a_i \in \mathcal{A}_i$ given a_{-i}. Nash equilibrium (NE) is a critical concept for optimal solutions in game theory. An action profile $a^* = \{a_i^*, a_{-i}^*\}$ is referred to as an NE if each player in the game adopts its best response action, i.e. $J_i(a_i^*, a_{-i}^*) \geq J_i(a_i, a_{-i}^*)$ holds for $\forall a_i \in \mathcal{A}_i$ and $\forall i \in \mathcal{N}$. NE can provide a stable game solution because no player can achieve a higher payoff by changing its decision unilaterally [18]. Note that a game can have more than one NE [31].

3. Game-Theoretic Collision Avoidance for UAVs

In this section, we develop a game-theoretic collision avoidance approach for UAVs in a 3D airspace. First, the UAV collision avoidance problem is formulated into a repeated two-player normal-form game. Then, to integrate the rule-based cognitive information, the payoff function is designed based on output-oriented decision rules using critical-time-related decision variables.

3.1. *Game formulation for UAV collision avoidance*

Consider a representative scenario with four UAVs (Ego, A, C, and D) in Fig. 1(a) to illustrate the game design. UAVs Ego (E), A, and D fly at the same altitude and UAV C is at a lower altitude. To better show the relative positions of UAVs, it is assumed that there are virtual parallel lanes within both horizontal and vertical planes, as shown by blue dash lines in Fig. 1(b). Ego and UAV A fly in the same virtual lane in opposite directions, UAV D flies in the adjacent horizontal virtual lane and UAV C flies in the parallel virtual lane underneath.

The state variables are defined as UAV i's 3D coordinates (x_i, y_i, z_i) and velocity v_i in the local NED coordinate system for $i \in \{E, A, C, D\}$. Each UAV aims to achieve a safe and efficient flight, i.e. to avoid collision with the other UAVs at less cost of energy consumption while maintaining the desired velocity direction to its destination. To achieve these goals, Ego must take into account the other UAVs' possible actions given the same objective. The game-theoretic formulation of UAV collision avoidance facilitates Ego's safe and efficient decision-making in such a way that the other game players' optimal actions are also considered.

Figure 1 shows that UAV A poses the most significant danger for Ego because its trajectories coincide completely with opposite velocity directions. Therefore, for this particular scenario, there are two players in the game of collision avoidance, i.e. Ego and UAV A. Ego can take three actions including *keep the velocity direction the same* (KVS), *change velocity direction to right* (CVR), and *descend to a lower altitude* (DLA), i.e. $\mathcal{A}_E = \{\text{KVS}, \text{CVR}, \text{DLA}\}$. These are common actions used for collision avoidance [32, 33]. We consider that UAV A and all other non-Ego agents have two available actions, KVS and CVR, i.e. $\mathcal{A}_A = \{\text{KVS}, \text{CVR}\}$ for simplicity. Future studies will contain more possible actions with more scenarios as well as more players, and the reduction of players and action spaces to reduce computation will be considered.

Note that, because all UAVs aim to maintain a desired velocity direction considering their destinations, the UAVs will perform a lane changing to the virtual lane on their right side for action CVR. Similar execution is for action DLA except that Ego will change to the parallel virtual lane right below, i.e. the virtual lane within which UAV C flies. The aforementioned game formulation for UAV collision avoidance is summarized in Fig. 2, where a_{ij} and b_{ij} with $i \in \{1,2,3\}$, $j \in \{1,2\}$ are the payoffs received by Ego and UAV A, respectively, corresponding to the specific action combination. Detailed designs of a_{ij} and b_{ij} are given in the next section.

We notice that playing the game once is not sufficient to guarantee Ego's safety, because the states of all UAVs change with time leading to the change of game settings. For example, consider the scenario in Fig. 1. UAV D will become the most dangerous opponent for Ego after Ego changes to the right virtual lane to avoid collision with UAV A. Thus, we propose in this paper a repeated two-player normal-form game with mutative payoffs, i.e. the game is played every time period τ_p. A smaller τ_p allows Ego to

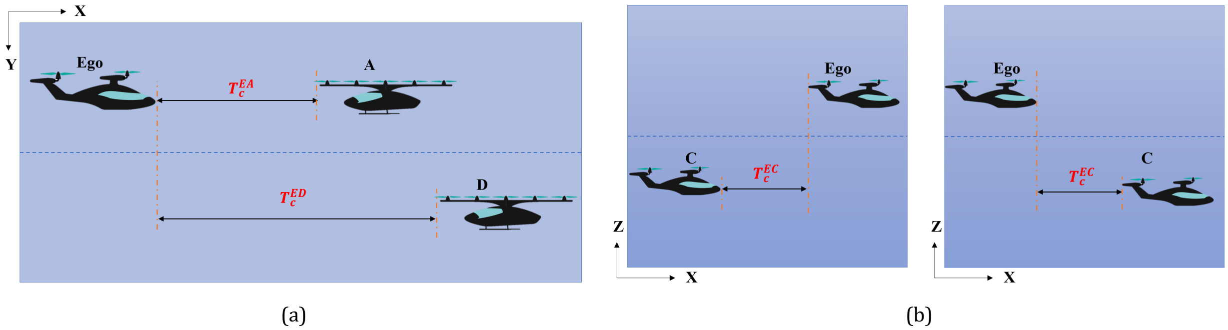

Fig. 3. Definition of TTC (a) top view, (b) front view.

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quickly re-evaluate the risk of collisions according to the most recently acquired information and to make timely decisions for collision avoidance.

3.2. *Payoff design*

In this section, we illustrate the payoff design for the UAV collision avoidance game such that the optimal behavior can be generated for Ego while the rule-based cognitive information can be integrated. In the following, the critical-time-related decision variables are first defined, based on which the output-oriented decision rules are described and then reflected in a_{ij} and b_{ij}.

3.2.1. *Critical-time-related decision variables*

Time-to-collision (TTC) is an important metric to quantify the risk of a UAV collision occurrence. For the air traffic scenario in this paper, we define the TTC between two UAVs using their state information as if they are flying within the same virtual lane, as shown in Fig. 3. More specifically, TTCs between Ego and UAVs A, D, and C denoted by T_c^{EA}, T_c^{ED}, and T_c^{EC} are given as follows:

$$T_c^{EA} = \frac{x_A - x_E}{v_E - v_A}, \tag{1}$$

$$T_c^{ED} = \frac{x_D - x_E}{v_E - v_D}, \tag{2}$$

$$T_c^{EC} = \frac{x_C - x_E}{v_E - v_C}, \tag{3}$$

where the superscript denotes the two involved UAVs. Note that v_i is the velocity vector with the direction component. A negative TTC is assigned an infinite positive value to indicate no potential collision.

The time used by Ego to finish its selected action is another critical factor for Ego's decision-making. This is to decide whether there is enough time to complete a specific maneuver. Thus, we define two additional variables T_r^E and T_l^E to indicate the time it takes for Ego to finish CVR and DLA, respectively. Note that these two variables can be determined by the specific dynamics of Ego given geographic information.

Last but not the least, we define the acceptable safety time T_s^E and T_s^A for Ego and UAV A, respectively, to indicate the threshold beyond which it is not necessary for UAVs to take actions for collision avoidance. Note that the two game players can have different acceptable safety times. We here apply an identical T_s for Ego and UAV A in the simulation studies for simplicity.

3.2.2. *Output-oriented decision rules*

A set of simple output-oriented rules is defined here to capture the preferred behavior of two game players given the decision variables derived from state information. Specifically, Ego considers the following rules to determine the action for collision avoidance with UAV A.

(1) If $T_c^{EA} > \gamma_1 T_s^E$, keep the current velocity direction (KVS);
(2) If $T_c^{EA} < \gamma_1 T_s^E$, $\gamma_2 T_r^E < T_c^{ED}$, and $\gamma_3 T_l^E > T_c^{EC}$, change to the right virtual lane (CVR);
(3) If $T_c^{EA} < \gamma_1 T_s^E$, $\gamma_2 T_r^E > T_c^{ED}$, and $\gamma_3 T_l^E < T_c^{EC}$, descend to the lower virtual lane (DLA);
(4) If $T_c^{EA} < \gamma_1 T_s^E$, $\gamma_2 T_r^E < T_c^{ED}$, and $\gamma_3 T_l^E < T_c^{EC}$, descend to the lower virtual lane (DLA),

where γ_i with $i \in \{1, \ldots, 3\}$ denotes the positive constant parameters to provide appropriate decisions for game players. These parameters are to be determined under different scenarios and can be obtained using neural networks [18]. In this study, we set all γ_i to be 1 for simplicity.

Rule (1) indicates that Ego is encouraged to take actions only when its TTC with UAV A gets smaller than its acceptable safety time; otherwise, it will maintain its originally planned routes. $\gamma_2 T_r^E < T_c^{ED}$ says that, Ego can complete the CVR maneuver before it collides with UAV D; otherwise, there is not enough time for Ego to finish CVR. Similarly, $\gamma_3 T_l^E < T_c^{EC}$ says that, Ego can complete the DLA maneuver before it collides with UAV C; otherwise, it cannot. These two conditions indicate whether CVR and DLA

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are feasible actions under the safety requirement. Therefore, Rules (2) and (3) describe the conditions when only one of two actions CVR and DLA is feasible for Ego. If both actions are feasible, Ego is encouraged to choose DLA considering the energy efficiency of DLA compared with CVR [34, 35], as reflected in Rule (4).

Note that, we have considered a comprehensive situation where both UAVs surrounding Ego, i.e. UAVs D and C, have impacts on Ego's decision. The rules can be readily applied if only one UAV exists or both are absent, by assigning infinite TTCs. For instance, when both UAVs are absent, Ego can always choose DLA for collision avoidance considering the saving of energy consumption.

Similarly, the rules considered by UAV A are defined as follows.

(5) If $T_c^{EA} > \gamma_4 T_s^A$, keep the current velocity direction (KVS);
(6) If $T_c^{EA} < \gamma_4 T_s^A$, and $\gamma_2 T_r^E < T_c^{ED}$ or $\gamma_3 T_l^E < T_c^{EC}$, keep the current velocity direction (KVS);
(7) If $T_c^{EA} < \gamma_4 T_s^A$, $\gamma_2 T_r^E > T_c^{ED}$, and $\gamma_3 T_l^E > T_c^{EC}$, change to the right virtual lane (CVR),

where γ_4 is also a positive constant parameter for the same purpose as the other γs.

Rules (5) and (6) indicate the conditions where UAV A can maintain its current velocity direction when either it is not necessary as reflected in $T_c^{EA} > \gamma_4 T_s^A$, or Ego will yield to avoid a potential collision. Note that, it's not favorable that both game players change their current velocity directions at the same time to avoid a collision, which is safe but not efficient. Rule (7) says that UAV A is forced to change its velocity direction to the right if both CVR and DLA are not feasible actions for Ego such that the safety of both UAVs is guaranteed.

From these rules, we can derive the game payoffs a_{ij} and b_{ij} for both Ego and UAV A, as illustrated in the following section.

3.2.3. *Payoffs for UAV collision avoidance games*

This section presents the payoff designs to avoid collisions according to the decision rules. The payoffs are defined for Ego first, followed by UAV A. θ_i with $i \in \{1, \ldots, 12\}$ denotes weights to account for preference in different scenarios. In this paper, we assume all θ_i to be 1 for simplicity.

Ego should keep its current velocity direction if $T_c^{EA} > \gamma_1 T_s^E$. Therefore, we define

$$a_{11} = \theta_1(T_c^{EA} - \gamma_1 T_s^E). \tag{4}$$

Ego is encouraged to change to the right virtual lane if inequalities $T_c^{EA} < \gamma_1 T_s^E$, $\gamma_2 T_r^E < T_c^{ED}$, and $\gamma_3 T_l^E > T_c^{EC}$ hold. Thus, the payoff is given by

$$\begin{aligned} a_{21} = \theta_2(\gamma_1 T_s^E - T_c^{EA}) + \theta_3(T_c^{ED} - \gamma_2 T_r^E) \\ + \theta_4(\gamma_3 T_l^E - T_c^{EC}), \end{aligned} \tag{5}$$

which implies a high payoff if Ego chooses the action CVR in this case.

The third and fourth rules describe two situations where Ego selects the action DLA to achieve a higher payoff, i.e. DLA is the only feasible action or both CVR and DLA are feasible actions. In both cases, when $\gamma_2 T_r^E > T_c^{ED}$ and $\gamma_2 T_r^E < T_c^{ED}$, Ego decides DLA. Therefore, we do not consider this condition and define a_{31} as follows:

$$a_{31} = \theta_5(\gamma_1 T_s^E - T_c^{EA}) + \theta_6(T_c^{EC} - \gamma_3 T_l^E). \tag{6}$$

The payoffs for UAV A are also defined similarly. In the seventh rule, $T_c^{EA} < T_s^A$, $T_r^E > T_c^{ED}$, and $T_l^E > T_c^{EC}$ lead to the expression

$$\begin{aligned} b_{12} = \theta_7(\gamma_4 T_s^A - T_c^{EA}) + \theta_8(\gamma_2 T_r^E - T_c^{ED}) \\ + \theta_9(\gamma_3 T_l^E - T_c^{EC}). \end{aligned} \tag{7}$$

For the fifth and sixth rules which favor the action KVS for UAV A, the payoffs are defined as

$$\begin{aligned} b_{11} = b_{21} = b_{31} = \theta_{10}(T_c^{EA} - \gamma_4 T_s^A) + \theta_{11}(T_c^{ED} - \gamma_2 T_r^E) \\ + \theta_{12}(T_c^{EC} - \gamma_3 T_l^E). \end{aligned} \tag{8}$$

Note that although the inequalities $T_c^{EA} > \gamma_4 T_s^A$ in the fifth rule and $T_c^{EA} < \gamma_4 T_s^A$ in the sixth rule have conflict, UAV A can still get a higher payoff for the action KVS when $T_c^{EA} < \gamma_4 T_s^A$ strongly holds due to the existence of rest part in the defined payoffs b_{11}, b_{21} and b_{31}, as in (8).

As mentioned when defining the decision rules for UAV A, the action combination where both UAVs change their velocity directions is not efficient. In this case, we introduce a positive constant ϵ in the payoffs such that action combinations "CVR/CVR" and "DLA/CVR" will never be selected by both players. For example, we define

$$b_{22} = b_{21} - \epsilon, \tag{9}$$

which makes the inequality $b_{22} \leq b_{21}$ always hold, indicating a lower payoff received by UAV A if it selects action CVR given Ego's action as CVR. Similar definitions for the rest of the payoffs are given as follows:

$$a_{22} = a_{32} = a_{12} - \epsilon, \tag{10}$$

$$b_{32} = b_{31} - \epsilon. \tag{11}$$

We choose $\epsilon = 10$ in this paper.

The next theorem shows the existence of NE.

Theorem 1. *Consider a two-player game in Fig. 2 with three and two possible actions for two players, respectively. Let the game payoffs a_{ij} and b_{ij} with $i \in \{2, 3\}$ and $j = 2$ be as*

Conditions	PSNE
$a_{11} \geq a_{21}, a_{11} \geq a_{31}, b_{11} \geq b_{12}$	KVS/KVS
$a_{11} \geq a_{21}, a_{11} \geq a_{31}, b_{12} \geq b_{11}$	KVS/CVR
$a_{21} \geq a_{11}, a_{21} \geq a_{31}, b_{11} \geq b_{12}$	CVR/KVS
$a_{21} \geq a_{11}, a_{21} \geq a_{31}, b_{12} \geq b_{11}$	CVR/KVS and KVS/CVR
$a_{31} \geq a_{11}, a_{31} \geq a_{21}, b_{11} \geq b_{12}$	DLA/KVS
$a_{31} \geq a_{11}, a_{31} \geq a_{21}, b_{12} \geq b_{11}$	KVS/CVR and DLA/KVS

Fig. 4. PSNEs for all combinations of payoffs.

in (10) *and* (11). *Then, the game has at least one pure-strategy NE (PSNE).*

Proof. Note that, if (10) and (11) hold, we have $a_{12} \geq a_{22} = a_{32}$, $b_{21} \geq b_{22}$ and $b_{31} \geq b_{32}$. Considering all possible relationships of the rest of the payoffs, there exists at least one PSNE for each case, as shown in Fig. 4. □

4. Simulation Studies

The simulation studies are conducted to demonstrate the efficiency of the proposed game-theoretic collision avoidance approach for UAVs.

UAVs' dynamics is captured using the kinematic model derived from [36–38]. It is given as follows:

$$\begin{aligned} \dot{x}_i &= v_i \cos(\phi_i + \beta_i)\cos(\phi_i), \\ \dot{y}_i &= v_i \cos(\phi_i + \beta_i)\sin(\phi_i), \\ \dot{z}_i &= v_i \sin(\phi_i + \beta_i), \\ \dot{\phi}_i &= \frac{v_i}{d_r}\sin(\beta_i), \\ \dot{v}_i &= a_i, \\ \beta_i &= \tan^{-1}\left(\frac{d_r}{d_r + d_f}\tan(\delta_i)\right), \end{aligned} \tag{12}$$

where $i = \{1, \ldots, N\}$ denotes the UAVs treated as mass points. x_i, y_i, and z_i are the longitudinal, lateral, and vertical positions of the mass center of UAV i along x-, y-, and z-axes, respectively. v_i and a_i are the velocity and acceleration, respectively. ϕ_i, β_i, and δ_i are the heading angle, slip angle, and steering angle, respectively. d_f and d_r are distances from the mass center of a UAV to its front and rear ends, respectively.

In the simulation, $d_f = d_r = 0.5$ m is applied for all UAVs. We consider three scenarios to illustrate the performance of the proposed repeated normal-form game for UAV collision avoidance.

4.1. *Case* 1

First, consider the air traffic scenario in Fig. 1 that Ego and UAV A fly toward each other at the same altitude while UAV D flies toward Ego at the same altitude but in the virtual right lane of Ego. In addition, UAV C flies in the lower horizontal virtual lane of Ego. To illustrate the decisions, Ego, UAV A, UAV D, and UAV C are initially located at the following $[x, y, z]$ coordinates: Ego $= [200, 0.15, 2]$, UAV A $= [1000, 0.15, 2]$, UAV D $= [1300, -0.15, 2]$, and UAV C $= [150, 0.15, 1]$. For clear demonstration, the values of the positions are chosen to be modest.

In this case, Ego first keeps the same velocity direction until it is unsafe. Then, Ego decides to DLA to avoid collision with UAV A. This action is chosen because its small distance from UAV D limits its action of changing direction to the right for collision avoidance and its distance to UAV C makes the descending action feasible, indicated by a higher payoff of action DLA for Ego. In the beginning of simulation, first Ego decides to keep velocity direction the same according to payoff calculation. Figure 4 shows conditions which are $a_{11} = 1956$, $a_{21} = -451.15$, $a_{31} = 294.4$, $b_{11} = 920.044$, and $b_{12} = -920.044$. As clearly seen that $a_{11} \geq a_{21}$, $a_{11} \geq a_{31}$, $b_{11} \geq b_{21}$ leads keep velocity direction the same.

Then, when Ego decides to descend the lower altitude according to payoffs, $a_{11} = 564$, $a_{21} = -590.35$, $a_{31} = 572.800$, $b_{11} = 780.84$, and $b_{12} = -780.84$. As clearly seen from Fig. 4, $a_{31} \geq a_{11}$, $a_{31} \geq a_{21}$, $b_{11} \geq b_{12}$ leads Ego to DLA.

In addition, the decisions are demonstrated in Fig. 5, where the UAVs' trajectories and UAVs' positions at four time instants are displayed. Figure 5(a) shows that Ego and UAV A fly toward each other because the payoff associated with KVS is higher and this means that there is no potential collision between Ego and UAV A at this moment. Then, Fig. 5(b) shows a risk for collision between Ego and UAV A. Therefore, Ego decides to DLA according to the higher payoffs of DLA. Figure 5(c) shows Ego reaches the lower altitude where UAV C is. Lastly, Fig. 5(d) shows that it completes the descending process and Ego and UAV C fly in the same lower altitude and same direction.

Finally, the demonstration of case 1 is shown in the following link [39].

4.2. *Case* 2

Now revisit the scenario in Fig. 1 with different initial positions of the four UAVs. In this scenario, Ego and UAV A fly toward each other at the same altitude and on the same virtual lane. UAV D is on the virtual right lane of Ego and flies opposite direction of Ego. In addition, there is UAV C on the lower virtual lane of Ego and fly the same direction as Ego. The initial positions of UAVs are given as follows: Ego $= [200, 0.15, 2]$, UAV A $= [1000, 0.15, 2]$, UAV D $= [2000, -0.15, 2]$, and UAV C $= [210, 0.15, 1]$.

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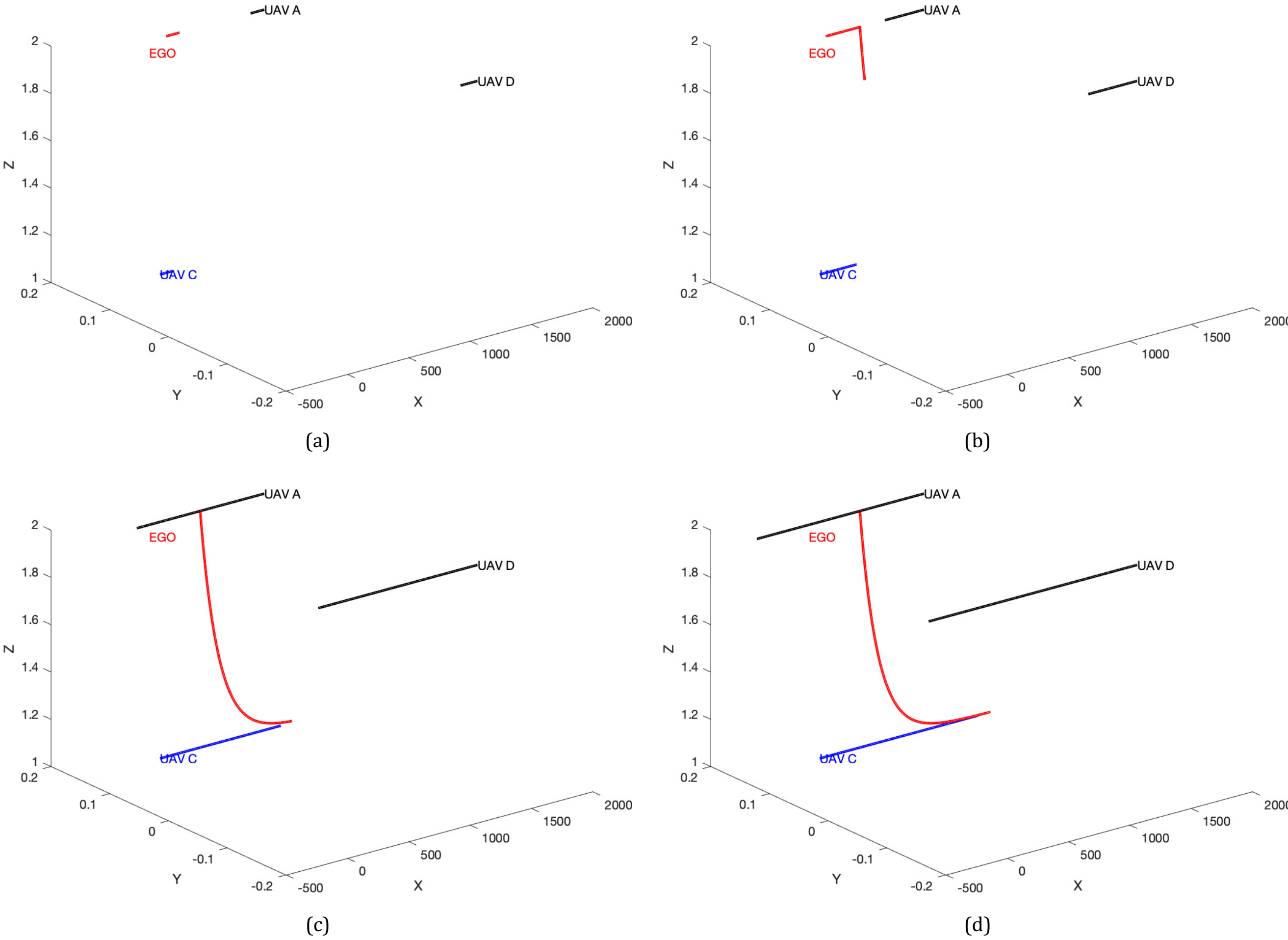

Fig. 5. Case 1 when Ego descends to a lower altitude. Each subfigure shows the UAVs' positions at different time instants during the descending process. (a) When Ego and UAV A fly toward each other at the same altitude. (b) When Ego descends to a lower altitude after some time. (c) When Ego reaches the lower altitude where UAV C is. (d) When Ego and UAV C fly in the same lower altitude and same direction.

Figure 6 shows the scenario where Ego first decides to CVR to avoid collision with UAV A, and then decides to DLA to avoid collision with UAV D. This is made possible with the repeated game setup. At first, Ego conducts CVR for collision avoidance with UAV A, considering that DLA may lead to a collision with UAV C, indicated by a smaller payoff. After being on the same virtual lane with UAV D, the new game informs Ego to choose DLA among the two feasible actions DLA and CVR, considering that a higher payoff can be achieved for DLA with less energy consumption.

To begin with, Ego keeps velocity direction the same with values of payoffs $a_{11} = 1560$, $a_{21} = 344$, $a_{31} = -301$, $b_{11} = 366$, and $b_{12} = -366$ that support the expressions from Fig. 4, i.e. $a_{11} \geq a_{21}$, $a_{11} \geq a_{31}$, $b_{11} \geq b_{12}$. Then, when it is not safe for UAVs, Ego has to decide the actions to choose next. In this case, Ego decides to change the velocity direction to the right. In order to support the decisions, the values of the payoffs at the decision instants are $a_{11} = 208$, $a_{21} = 208.8$, $a_{31} = -30.6$, $b_{11} = 230.8$, and $b_{12} = -230.8$. This maneuver selection of Ego in the simulation has validated the PSNE, i.e. the action combination CVR/KVS under the conditions $a_{21} \geq a_{11}$, $a_{21} \geq a_{31}$, $b_{11} \geq b_{12}$, as shown in Fig. 4. The last decision to DLA according to payoffs $a_{11} = 305.58$, $a_{21} = -887$, $a_{31} = 2602$, $b_{11} = 4439$, and $b_{12} = -4439$ supports the theoretical result in Fig. 4 with expression $a_{31} \geq a_{11}$, $a_{31} \geq a_{21}$, $b_{11} \geq b_{12}$.

Furthermore, when Ego chooses different maneuvers with the energy term, each subfigure of Fig. 6 shows the UAVs' positions at different time instants. Figure 6(a) presents Ego and UAV A flying toward each other at the same altitude. Figure 6(b) presents Ego to change the velocity direction to the right after playing the game with UAV A. Figure 6(c) presents the Ego's decision to DLA after playing the game with UAV D and considering the energy in the payoff. In Fig. 6(d), Ego completes the process of descending to the lower altitude.

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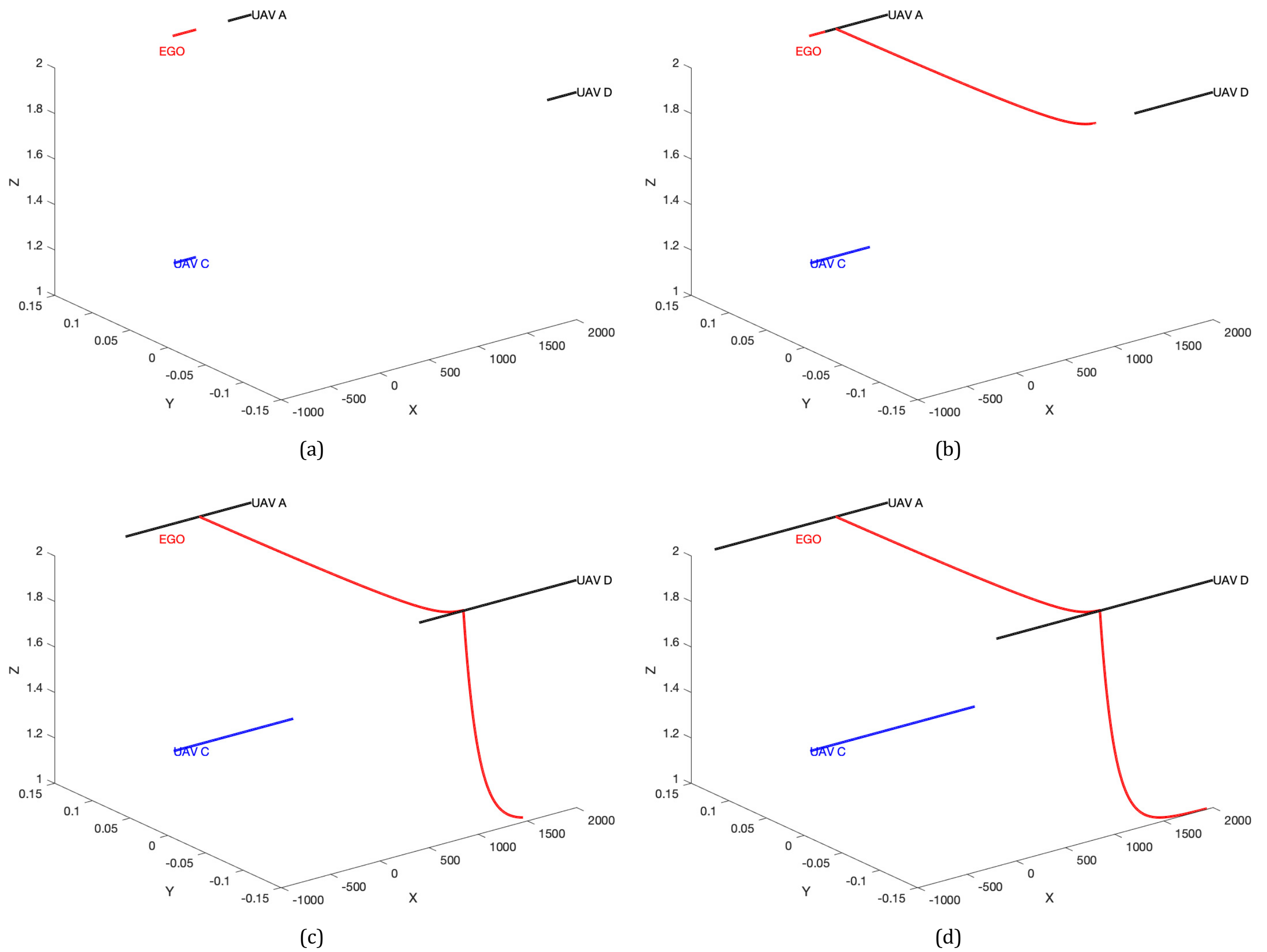

Fig. 6. Case 2 when Ego plays repeated games with UAV A and UAV D where different maneuvers were selected for Ego due to the consideration of energy in the game payoff. Each subfigure shows UAVs' positions at different time instants in the repeated games with UAV A and UAV D. (a) When Ego and UAV A fly toward each other at the same altitude. (b) When Ego changes its velocity direction to the right after playing the game with UAV A. (c) When Ego plays the game with UAV D and Ego decides to descend the lower altitude considering the energy in the payoff. (d) Ego completes the descending to the lower altitude.

To conclude with the simulation of case 2, the following link shows the demo of this case [40].

4.3. *Case* 3

Now consider a more complex air traffic scenario with an extra UAV Y flying at the same altitude as UAV C but within the virtual lane directly below and opposite direction of UAV D. This situation further verifies the effectiveness of our game design. Contrary to the scenario in Fig. 6 where there are no UAVs on the right-hand side of and below Ego, the existence of UAV Y can have an impact on Ego's decision. As shown in Fig. 7, Ego determines to change velocity direction to the right to avoid collision with UAV D considering the influence of UAV Y.

To illustrate the decisions, Ego, UAV A, UAV D, UAV C, and UAV Y are initially located at the following $[x, y, z]$ coordinates: Ego $= [200, 0.15, 2]$, UAV A $= [1000, 0.15, 2]$, UAV D $= [2000, -0.15, 2]$, UAV C $= [210, 0.15, 1]$, and UAV Y $= [40, -0.15, 1]$.

To begin with the simulation, Ego first keeps the velocity direction the same by using the payoff function with the expression $a_{11} \geq a_{21}$, $a_{11} \geq a_{31}$, $b_{11} \geq b_{12}$ in Fig. 4. The values $a_{11} = 1560$, $a_{21} = 344$, $a_{31} = -301$, $b_{11} = 366$, and $b_{12} = -366$ taken from simulation clarify the theoretical result. Second, Ego plays the game with UAV A and decides to change the velocity direction to the right while using the payoff function from Fig. 4 with the values $a_{11} = 208$, $a_{21} = 208.8$, $a_{31} = -30.6$, $b_{11} = 230.8$, and $b_{12} = -230.8$. Lastly, Ego plays the game with UAV D and decides to change velocity direction to the right again because UAV Y restricts Ego from descending to a lower altitude. The payoff values in the simulation are $a_{11} = 305.5835$, $a_{21} = 1303.8$, $a_{31} = 45.41$, $b_{11} = 1516.9$,

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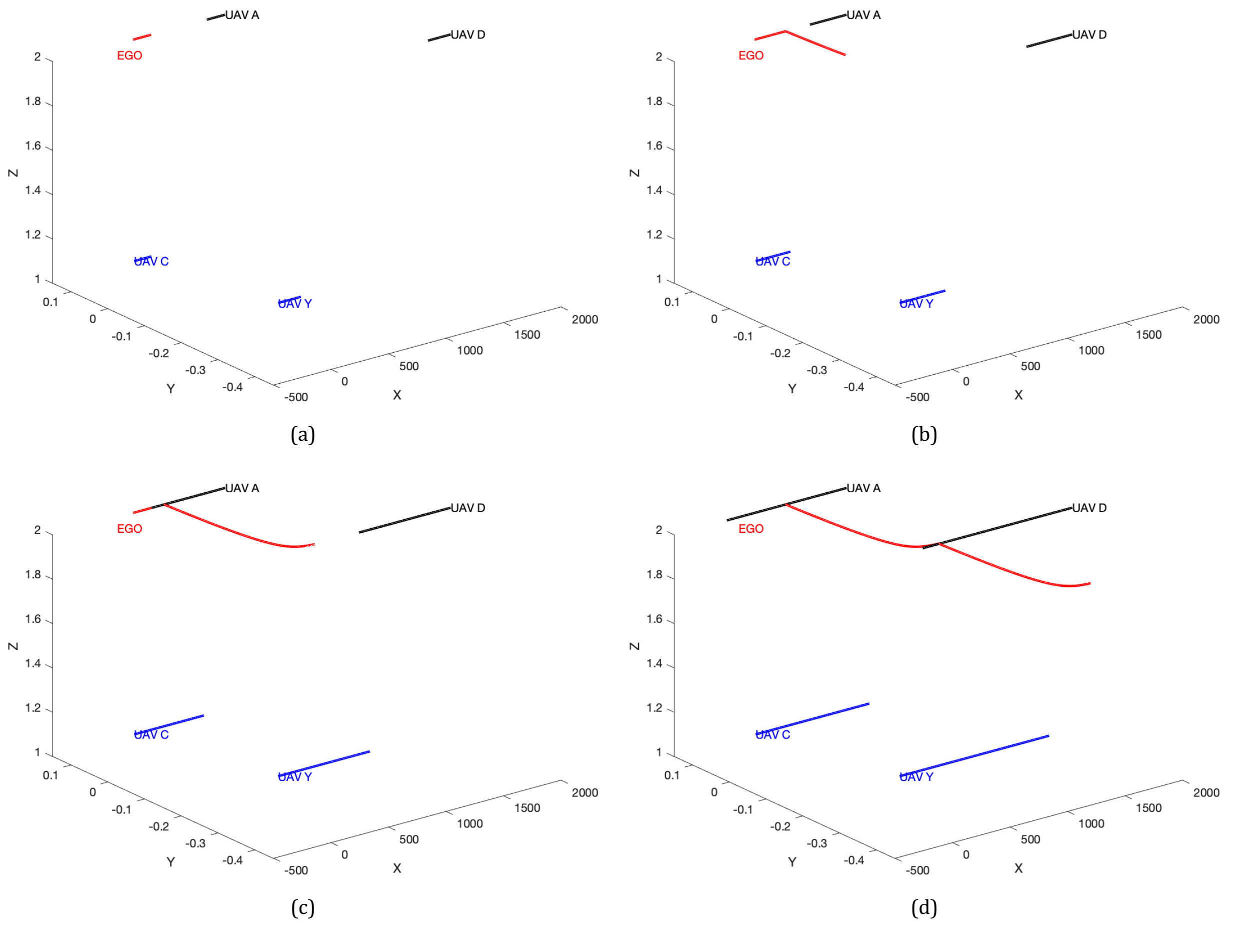

Fig. 7. Case 3 when Ego plays the repeated games with UAV A and UAV D where Ego chooses the change the velocity direction to right twice. Each subfigure shows UAVs' positions at different time instants in the repeated games with UAV A and UAV D. (a) When Ego and UAV A fly toward each other at the same altitude. (b) When Ego decides to change velocity direction to the right after playing the game with UAV A. (c) When Ego decides to change velocity direction to the right again after playing the game with UAV D. (d) Ego completes the changing of the velocity direction to the right.

and $b_{12} = -1516.9$, which numerically validates the theoretical result in Fig. 4 with the expression $a_{21} \geq a_{11}$, $a_{21} \geq a_{31}$, $b_{11} \geq b_{12}$.

Moreover, Fig. 7 displays UAVs' positions at four different time instants. From Fig. 7(a), note that Ego and UAV A fly toward each other until it is not safe anymore. Then, Fig. 7(b) demonstrates that Ego decides to change velocity direction to the right. Figure 7(c) demonstrates that the first Ego keeps the same velocity direction and then decides to change the velocity direction to the right. Lastly, Fig. 7(d) demonstrates completing the process to change the velocity direction to the right.

To conclude with case 3, the following link shows a visualization of the UAV's behavior in the repeated play [41].

5. Conclusions

By formulating the UAV collision avoidance problem into a multi-agent game in the 3D airspace, we developed in this paper a novel game-theoretic decision-making architecture for UAVs. This game-theoretic collision avoidance solution allows the safe and efficient operations of UAVs by equipping UAVs with the capability to make avoidance decisions in consideration of those of the neighboring UAVs. A repeated two-player normal-form game was proposed, and a few elements, such as game players, the possible course of actions, and the design of the payoff function, were described in detail. More specifically, payoff functions are designed to quantify the safety and efficiency of a certain set of practicable activities for both Ego and its adversary. Ego is allowed to quickly reconsider a taken decision according to the most updated states by playing a repeated game, which can guarantee its safety. Also, the decision is efficient in the sense that the urgency of collision avoidance actions is considered and that all game players taking collision avoidance actions simultaneously is avoided. In addition, energy efficiency takes effect when multiple actions are available for game players to avoid a potential collision. NE in Theorem 1 was proved using the payoffs in the game solution. Compared with existing optimization-based collision avoidance approaches, looking up the payoff table to achieve a game solution is more computationally efficient. The three simulation case studies validate the safety and efficiency of the game-theoretic collision avoidance method. Future research can involve extending our results to consider more complicated scenarios with more UAVs as well as with more possible actions. Having more players in the game may increase the chances of collision and challenging computational issues need to be addressed. To reduce computation, the reduction of players and action spaces will be considered. In addition, the weights used in the payoff functions can be tuned using reinforcement learning or other data-driven approaches, which require further investigation.

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