Modern air combat environment software

In a one-on-one aerial combat game, the adversary manoeuvre strategy is usually not deterministic, having us consider different opponent strategies when designing our maneuvering strategy. This paper proposes an alternative game freezing framework based on deep reinforcement learning to create an air combat pursuit manoeuvring strategy. Manoeuvring strategy agents to guide aircraft from both sides are designed at flight level with fixed speed and one-on-one air combat scenario. Middleware connecting agents and air combat simulation software has been developed to provide a reinforcement learning environment for agent training. The reward design approach is used, which increases the speed of training, and improves the performance of the generated trajectory. Agents are trained in alternative freezing games with a deep amplification algorithm to address non-rationality. A league system is being adopted to avoid the red queen effect in a game where both sides are implementing adaptive strategies. The results of the simulation show that the proposed approach can be applied to air combat maneuvering, and typical angle combat tactics can be learned by deep-amplification learning agents. To train opponents with an adaptive strategy, the winning rate can reach more than 50%, and the rate of loss can be reduced to less than 15%. In competition with all opponents, the winning rate of the strategic agent chosen by the league system is more than 44%, and the probability that they will not lose is about 75%.1. IntroducingDespit improvements to long-range radar and missile technology, there is still a scenario that two fighter jets may not detect each other until they are within visual range. Therefore, modern fighters are designed for close combat, and military pilots are trained in the aerial combat of basic combat maneuvers (BFM). The chase is a kind of BFM, which aims to control the aircraft to reach the position of advantage when fighting another aircraft [1]. To reduce the workload of pilots and eliminate the need to provide them with complex spatial orientation information, many research studies focus on the decision on an autonomous aerial combat manoeuvre. Toubman et al. [2–5] used rules-based dynamic scripting in one-on-one, two-on-one and two-on-two air combat, which requires hard coding of air combat tactics into a maneuver selection algorithm. A bill was introduced to list combat maneuvers based on the virtual pursuit of an unmanned combat aerial vehicle (UCAV) and used in a nonlinear combat simulation based on the six-degree freedom X-Plane [6,7]. Eklund et al. [8,9] introduced a nonlinear, online predictive controller model for pursuit and avoidance of two autonomous fixed-wing aircraft, which rely on prior knowledge of maneuvers. Game-based approaches are widely used in automating air combat pursuit maneuvers. Austin et al. [10, 11] is access to the game matrix to generate intelligence intelligence decisions for one-on-one air combat. A limited method of searching through discrete manoeuvre choices has been adopted to increase scoring function, and the feasibility of an autonomous fight in real time is demonstrated in the simulation. Ma et al. [12] He formulated the problem of cooperative occupancy in air combat as a zero-sum matrix and designed a combined double oracle algorithm with neighborhood search to solve the model. In [13, 14], the aerial fighting game is considered Mark's game, and then the chase manoeuvring strategy is addressed counting his Nash balance. This approach addresses an issue that the game matrix cannot cope with continuous multiple states. However, it is suitable only for rational opponents. The optimal maneuver of the chase evasion hunter was formulated as a differential game and then solved by nonlinear programming, which is complex and requires a huge amount of calculation [15]. Other approaches to produce chase maneuver strategy include impact diagram, genetic algorithm and approximate dynamic programming. The impact diagram is used to model the decision on sequential manoeuvre in air combat, and the results of the high performance simulation [16-18] have been obtained. However, this approach is difficult to apply in practice because the impact diagram turns into a nonlinear programming problem, which can not meet the demand of rapid computing during aerial combat. In [19], a genetics-based machine learning algorithm is implemented to generate high-angle attack air combat maneuver tactics for an X-31 fighter jet in a one-on-one aerial combat scenario. Approximate Dynamic Programming (ADP) can be used to quickly and efficiently address the decision to manoeuvre air combat [20, 21]. Rolling speed control can provide a quick maneuvering response in a changing situation. Most previous studies have used different algorithms to solve chase maneuver problems and have some satisfactory results, while two problems still exist. One is that previous research has hypothesized that an opponent's maneuvering strategy is deterministic or generated by a fixed algorithm. However, in real situations, these approaches are difficult to cope with flexible strategies adopted by different opponents. Another is that traditional algorithms rely heavily on prior knowledge and have high computational complexity, which cannot be adapted to the rapidly changing situation in air combat. As drones have gained growing interest around the world, and the aircraft's flight control system is rapidly evolving towards intellectualization [22], an intelligent strategy of maneuvering in drones and manned aircraft combat needs to be explored. This paper proposes deep reinforcement learning (DRL-) [23] based on an alternative approach to the freezing game to train guidance agents that can provide instructions for air combat manoeuvring. Using alternative freezing games, in training period, one agent learns while is frozen. DRL is a type of artificial intelligence, combining reinforcement learning (RL) [24] and deep learning (DL) [25]. RL allows an agent to learn directly from the environment through trial and error without perfect knowledge of the environment in advance. A well-trained DRL agent can automatically determine adequate behavior within a given context by trying to maximize their performance using several computer times. Drl theory is very convenient for solving sequential decision-making problems such as air combat manoeuvring. DRL has been used in many decision-making areas, such as video games [26, 27], board games [28, 29] and robot control [30] and great achievements of human level or superhuman performance have been obtained. To investigate aircraft guidance, Waldock et al. [31] He proposed a DQN method for generating a trajectory to perform an emergency landing on the ground. Alejandro and Sur. [32] they proposed a DRL strategy for autonomous landing of a drone on a moving platform. Lou and Guo [33] presented a unique adaptive control framework using quadrotor rule search algorithms. The RL agent was developed to run a powered UAV from one thermal location to another by controlling the bank's angle [34]. To investigate air combat, You et al. [35] Developed an innovative framework for cognitive electronic warfare tasks using a DRL algorithm with no prior information. Luo et al. [36] He proposed an algorithm for a Q-based aerial goal task that avoids reliance on previous knowledge and works well. Reward formatting is a method of incorporating domain knowledge into RL so algorithms are driven faster toward promising solutions [37]. Award design is widely adopted in the RL community and is also used in aircraft planning and control. In [4], a reward function is proposed to correct false rewards and penalties for firing aerial combat missiles, which allows computer-generated forces (CGF) to generate more intelligent behavior. Tumer and Agogino [38] have proposed functions to reward differences in the multiagent air traffic system and shown that agents can manage efficient route selection and significantly reduce congestion. In [39], two types of reward functions are being developed to address ground keeping and air keeping, which help air traffic controllers maintain a high standard of safety and fairness between airlines. Previous studies have shown the benefits of using DRL to solve the problem of stating an aerial manoeuvre. However, there are still two problems in applying drl to air combat. One is that previous research did not have a specific air combat environment, whether they were developing an environment based on universal [32] or using the discrete world of the network, which do not have the function of simuling air combat. Another problem is that classic DRL algorithms are almost all one-sided optimization algorithms, which can only guide aircraft to location or regular movement. Movement. However, the opponent in the aerial fight has strategies for maneuvering diversity and variability, which are non-stationary, and classic DRL algorithms cannot cope with them. Hernandez-Leal et al. Reviewed how non-talent is modeled and solved by the most basic multi-person learning algorithms [40]. Some researchers combine MDP with game theory to study reinforcement learning in stochist games to solve the problem of non-stationary [41-43], while there are still two limitations. It is one to assume that the strategy of the opponents is rational. At each step of training, the opponent chooses the optimal action. A trained agent can only deal with a rational opponent, but he can not fight non-meals. The second is the use of linear programming or four-winged programming to calculate Nash's balance, which leads to a huge amount of calculations. A Minimax-DQN [44] algorithm combining DQN and Minimax-Q learning [41] for Mark's zero-sum game for two players was proposed in a recent paper. Although it can be applied to complex games, it can still only deal with rational opponents and should use linear programming to calculate Q values. The main contributions of this work can be summarized as follows:(i)Middleware is designed and developed, which makes specific software for air combat simulation used as an RL environment. The agent can be trained in this environment and then used to direct the aircraft to achieve a position of advantage in one-on-one air combat. (ii) The indications of air combat chase maneuver agents on both sides are designed. The reward design method shall be adopted to improve the speed of convergence of training and the performance of manoeuvre guidance strategies. The agent is trained in an environment where his opponent is also an adaptive so that a well-trained agent has the ability to fight opponents with intelligent strategy. – iii.) An alternative game freeze framework is proposed to address nonstationarity, which can be used to address changing opponent strategies in the RL. The league system was adopted to select the highest performing agent to avoid the red queen effect [45]. This work is organized as follows. Section 2 introduces the problem of a strategy to list manoeuvres in a one-on-one manoeuvre manoeuvre that is being considered and a DRL-based model, as well as training environments to address this. Training optimization includes reward design and alternative freezing games that are presented in section 3. The simulation and results of the proposed approach shall be provided in Section 4. The final section concludes the work.2. The formulation problem In this section introduces the problem of maneuvering in air combat. The training environment was designed, and a DRL-based model was set up to solve it.2.1. Problem statement Problem solved in this paper is the problem of air combat avoidance manoeuvre one One. The red flag is considered our side, and the blue one is the enemy. Goal Target The agent is to learn the maneuvering strategy (policy) to lead the aircraft from its current position to the position of advantage and maintain the advantage. At the same time, it should guide the aircraft not to get into the position of the advantage of its opponent. The dynamics of the aircraft are described by the point-mass model [17], and are given by the following differential equations: where are the three-dimensional coordinates of the aircraft. The terms , which are the speed, angle of flight path and angle of direction of the aircraft. The mass of the aircraft and the acceleration due to gravity signify and , respectively. The three forces are the force of lifting, the force of retreat and the force of the descent. The remaining two variables are the angle of attack and the angle of the bank , as shown in figure 1.In this paper , it is assumed that the aircraft flies at a fixed speed in a horizontal plane, and the assumption can be written as follows: The equations of movement for the aircraft are simplified as follows: where , and are the speed, speed, rolling speed , bank angle, angle of turn and angle of direction of the aircraft at the same time . The term is an action generated by guidance, and the control actions available to the aircraft are roll-left, maintain-bank-angle, roll-right. The time step of the simulation is marked . In the design of the aircraft manoeuvring strategy, manoeuvres in a fixed plane are usually used to measure its performance. Figure 2 shows a one-on-one air combat scenario [20], in which each aircraft flies at a fixed speed in an X-Y plane under a maneuvering strategy at the time . The position of advantage is that one aircraft gets a chance to shoot at its opponent. It is defined as somewhere where superscripts are and refers to red and blue. The concept is the distance between the aircraft and the target at the time , is the angle of deviation defined as the angular difference between the vector line of sight and the direction of our aircraft, which is the angle of the aspect that is between the longitudinal simetric wasp (to the tail direction) of the target plane and the connecting line from the tail of the target plane to the attack on the nose of the plane. The terms , which are thresholds, where the subscripts are and represent the upper and lower limit of the corresponding variables, that is, which are determined by the combat mission and the performance of the aircraft. The term makes sure the adversary is within range of the aircraft's air weapons attack. The term refers to an area where it is difficult for a blue craft to escape with sensor locking. The term defines an area where the probability of killing is high when attacking from the back of a blue aircraft.2.2. The DRL-based Model RL Agent communicates with the environment over time and aims to maximize the long-term reward [24]. At all training times , the agent gets the state in the state space and generates action from the action space following the policy . Then, the agent receives a scalar award and until the next state according to environmental dynamics, as shown in Figure 3A, the value function is defined for the assessment of the air combat advantages of each state, which is the expectation of discounted cumulated rewards on all countries next time :where is the discount factor and the policy is mapping from the state premises to the action space. The agent guides the aircraft to the manoeuvre by changing the bank angle using rolling speed . The DRL action space is {−1, 0, 1}, and can take a value of three options at a time , meaning roll-left, maintain-bank-angle, or roll-right. The position of the aircraft shall be updated according to (3). The action value function can be used, which is defined as the value of taking action in the state according to politics :Bellman's equation of optimality is Now it is a policy that is greedy given the optimal function of evaluating the optimal policy. In fact, it can be obtained through iterations using time difference learning, and its updated formula is defined as where the action value function and learning rate is assessed. In aerial combat manoeuvres, the prize is rare, and only at the end of the game (terminal condition), according to the results of the win, loss or draw, is the prize value given. This makes learning algorithms for using delayed feedback to determine the long-term consequences of their actions in all non-terminal states, which is time consuming. Ng et al. [46] Proposes to shape rewards to bring additional rewards to the learning process, which will guide the algorithm towards faster learning of good policy. The formatting reward function takes shape where the real value function is over countries. It can be demonstrated that the final policy after using the design of the prizes is equivalent to the final policy without it [46]. in previous equations can be replaced . Taking the red agent as an example, the state space of one means of guidance can be described by a vector: The condition received by the agent in one step of training includes the position, angle of direction and angle of the bank itself and the position, angle of direction and angle of the opponent's bank, which is a 7-dimensional infinite vector. Therefore, the approximate method function should be used to combine the features of the condition and the weights learned. DRL is the solution to solving this problem. Great achievements were made using advanced DRL algorithms, such as DQN [26], DDPG [47], A3C [48] and PPO [49]. Since the action of listing aircraft is discreet, a DQN algorithm can be used. The function of the action value can be estimated with the approximation of functions such as, where the weights of the neural network. The DQN algorithm is executed according to the training time step. However, there is not only a time step of training, but also a simulation time step. Due to inconsistencies, the DQN algorithm needs to be improved to train a guidance agent. The DQN's pseudo-code for air combat aircraft maneuver guidance training is shown in Algorithm 1. On each step, the agent receives information about the aircraft and its opponent, and then generates action and sends it to the environment. After receiving the action, the aircraft in the environment manoeuvres according to this action in each simulation step. (1) Set the parameters of the controlled aircraft and opponent(2)Set the training time step size and time simulation step size (3)Initialize the maximum number of training episodes and maximum simulation time in each episode(4)Initialize replay memory to capacity (5)Initialize action value function and target random weight action value function(6)for episode = 0, to(7) Initialize status (8) for t = 0= , do(9) With probability select random action (10) Otherwise select (11) for i = 0, do(12) Perform the action in air combat simulation software (13) Get aircraft and target positions(14) if the episode ends then(15) pause(16) ends if(17) ends in(18) Observe reward and status (15) 19) Switch in store to (20) if the episode ends then(21) pause(22) end if(23) Sample random minibatch transitions from (24) if the episode ends on step then(25) set (26) other (27) set (28) finish if(29) Perform gradient descent step on with respect to network parameters (30) Each step reset (31) end for(32)end for2.3. Middleware DesignAn RL agent improves its capability through continuous interaction with the environment. However, there is no environment for directing air combat manoeuvres, and some combat simulation software can only execute agents rather than train them. In this paper, middleware was designed and developed based on commercial software to simulate air combat [50] encoded in C++. Middleware functions include an interface between software and RL agents, simulation time step coordination and RL training time step, and reward calculation. Using it, an RL training environment is performed to manoeuvre aircraft in aerial combat. The indication of agents of both aircraft has the same structure. Figure 4 shows the structure and training process of the red side. In a real or simulated aerial combat, the aircraft perceives the situation through multisensor. Analyzing the situation after the fusion of information, decisions on manoeuvres were made by the pilot or the auxiliary decision-making system. In this system, the perception of the situation and decision-making are the same as in real air combat. It is assumed that a sensor is used with the full ability to perceive the situation, through which the aircraft can obtain the position and angle of direction of its opponent. Air combat manoeuvring using RL is an episodic task, and there is the notion of episodes of some length, where the goal is to take an agent from the initial state to a target state [51]. First, the level of flight with fixed speed and the one-on-one combat scenario is the setup in simulation software. Then, information on the situation of both aircraft is randomly initialed, including their positions, heading angles, bank corners and rolling the initial status of each agent. The objective stated is achieved when one aircraft reaches the position of advantage and maintains it, one aircraft flies out of the sector, or the simulation time is out. Middleware can be used in stages of training and application of agents. The training phase is the process of making an agent from scratch to have the ability to specify manoeuvres, which includes training episodes and testing episodes. In the training episode, the agent is trained by the DRL algorithm, and his guidance strategy is continuously improving. After numerous episodes of training, some episodes of testing are performed to check the ability of the agent at the current stage, in which the strategy does not change. The application phase is the process of using a well-trained means for maneuvering guidance in the simulation of air combat. The training episode consists of training steps. At each step of the training, first, the information identified by the sensor in the air is sent via middleware guidance as a midware state pull coded in Python, see steps 1, 2 and 3 at number 4. Next, the agent generates action using his neural networks according to the research strategy, as shown in steps 4 and 5. Simulation software receives instructions for guidance transformed by middleware and sends the following information about the situation in middleware, see Steps 6 and 7. Then Middleware converts the situation information into government information and calculates the reward and sends it to the agent, as shown in steps 2, 3, and 8. Since agent training is an iterative process, all steps except step 1 are performed multiple times in the episode. Lastly, a tuple of the current state, actions, rewards, and the next state at every turn is stored in memory to train the guidance agent, see steps 9 and 10. In each simulation step, the aircraft manoeuvres according to the instructions and recognizes the situation according to its sensor configuration.3. Training optimization3.1. Reward ShapingTwo problems should be solved using the DRL method to train the means to specify the manoeuvre in air combat. One is that the only criterion for evaluating guidelines is a successful arrival at the position of advantage, which is a rare reward problem, leading to slow convergence of training. Secondly, in real situations, one should take into account the time of arrival at the position of advantage and quality of trajectory. In this paper, a method of shaping rewards is proposed to improve the speed of training and the success of the strategy of directing the manoeuvre. Rewards design [46] is usually used to modify the reward function to facilitate learning while maintaining an optimal policy, which is a manual endeavor. In this study there are four rules to follow in shaping the rewards:(i)Limited by combat area and maximum number of control times, the aircraft is guided to a position of advantage(ii)The aircraft should be guided closer and closer to its target zone(iii)Aircraft to be guided away from the target zone of your opponent(iv)The aircraft should lead to its target zone in a short time as possibleAccording to the above rules, the reward function is defined as somewhere where the original sladry prize is and is a function of the design award. elsewhere is a function of the termination award. The term is coefficient, and the penalty is for spending time, which is a constant. There are four types of countries of disruption: the aircraft arrives at the position of advantage; the opponent comes to his position of advantage; the aircraft moved out of the combat area; and the maximum number of control times has been reached, and each aircraft is still in the combat area and has not reached its advantage situation. The termination award is a reward received when the next state is dissolved, which is often used in standard RL training. It is defined asUsually, is a positive value; negative value; and they're non-positive. The formatting reward function has the shape as described in (9). The function of actual value is a function of the advantage of the state. The higher the value of this function, the more favorable the current situation. This function can provide additional information so that the agent can select the action, which is better than just using the termination reward. It is defined as where the prize function is at a distance and is a function of the orientation prize, which is defined as where it has units of meters/degrees and is used to adjust the relative effect of range and angle, and the effective value is 10.3.2. Alternative freeze game DQN to maneuver leadership agent TrainingUnlike board and RTS games, data of human players in aerial combat games are very rare, so pretraining methods using supervised learning algorithms cannot be used. We can only assume the strategy used by the opponent and then propose a strategy to defeat it. Then we think about what strategies the opponent will use to confront our strategy and then optimize our strategy. In this paper, an alternative learning freeze is used for games to solve the problem of non-rationality. Both aircraft in a one-on-one aerial combat scenario use DRL-based assets to adjust their maneuvering strategies. In each training session, one agent learns from scratch, while his opponent's strategy, obtained from the previous training period, is frozen. Through games, the maneuver stating the performance of each side grows interchangeably, and different agents with a high level of maneuvering decision-making abilities generate. The pseudo-code of the alternative freezing game DQN is shown in Algorithm 2. (1) Set the parameters of both aircraft (2)Set simulation parameters (3)Set the number of training periods and the condition for completing each training period (4)Set DRL parameters (5)Set an opponent's initialization policy (6)for the period = 1, up(7) for the aircraft = [red, blue] to(8) if the aircraft = red then(9) Set the opponent's policy (10) Red Agent Neural Networks(11) while Winning Rate< Do(12) (12) agent using algorithm 1(13) to finish while(14) Save a well-trained agent, whose manoeuvre routing policy (15) is left (16) if the period = then(17) pause(18) remain (19) Set the policy of the opponent (20) Initialize the neural networks of the blue agent (21) while the rate of gain< do(22) Train agent using algorithm 1(23) ends until(24) Save a well-trained agent, whose policy of directing manoeuvres (25) is the end if(26) ends if(27) ends(28)end for Important Effect to be taken accounted for in this approach is the effect of the red queen. When one aircraft uses a DRL agent and its opponent uses a static strategy, the performance of the aircraft is absolute relative to the opponent. However, when both aircraft use DRL means, each agent's performance is associated only with the current adversary. As a result, a trained agent is suitable only for his latest opponent, but he can not cope with previous ones. Through periods of alternative learning freeze training, red agents and blue agents are getting ready in the training process. A league system is adopted in which these agents are considered players. Using a combination of multi-opponent strategies, the opponent's mixed strategy becomes smoother. In different initial scenarios, each agent leads the aircraft to face an aircraft guided by each adversary. The goal through the league is to choose one of our strategies to make the probability of victory high and the probability of defeat low. According to the result of the competition, the agent gets different points. The best agent on the league table has been selected as optimal.4. Simulation and results In this section, first, random air combat scenarios are initialized into simulation software for training and testing means for specifying manoeuvres. Second, agents of both parties with reward design are created and trained using an alternative game of freezing the DQN algorithm. Third, taking well-trained agents as players, the league system is adopted, and the main agent on the league table is selected. Finally, the selected means are evaluated and the maneuvering behavior of the aircraft is analyzed.4.1. Simulation Setup Parameters of air combat simulation are presented in Table 1. Adam 's optimizer [52] is used to learn neural network parameters with learning speed and discount . The size of the replay memory is. The baseline of in-greedy research is 1, and the final value is 0.1. For each simulation, the prize formatting parameters are set to 2, −2, −1 and −1. Conditions and are set at 0.98 and 0.01, respectively. Training period is 10.Red aircraft parameters Speed Maximum rolling speed Rolling speed Starting position and heading angleBlue parameters aircraft Speed of maximum rolling speed Rolling speed Rolling speedMap, north Starting policy ()Maximum overload turnsSimulation of parameters Position advantages: ; : ;: ; : Combat Area Simulation Time Simulation Time Step Training Time Step We evaluated three neural networks and minibatches. Each neural network has 3 hidden layers, and the number of units is 64, 64, 128 for small neural network (NN), 128, 128, 256 for medium and 256, 256, 512 for large. The sizes of mini-gables (MB) are 256, 512 and 1024, respectively. These neural networks and minibatches are used in pairs to train red agents and play against the initial blue

agent. The result of the simulation is shown on the 5th floor. First, a large minibatch can not make training successful for small and medium-sized neural networks, and the speed of training is slow for a large network. Second, using a small neural network, the average reward won will be lower than that of the other two networks. Thirdly, if the same neural network is adopted, the training speed using the middle minibatch is faster than using a small one. Finally, given the computer efficiency, the selected network has 3 hidden layers with 128, 128 and 256 units, respectively. The chosen minibar size is 512.In to improve the generality of one agent, the starting positions are randomized in the simulation of air combat. In the first iteration of the training process, the initial strategy is formed by a randomly paralysed neural network for the red agent, and the conservative strategy of turning the maximum overload is adopted by the blue one. In subsequent training, the training agent is trained from scratch, and his opponent adopts the strategy obtained from the latest training. Air combat geometry can be divided into four categories (from the perspective of red aircraft): offensive, defensive, neutral and frontal [7], as shown in Figure 6(s). Defining the angle of deviation and angle of aspect from to , Figure 6(b) shows a diagram of the advantages where the distance is . Less means that the direction or gun of a red aircraft has a better goal towards the opponent, and the smaller one implies a greater possibility of a blue aircraft being shot or facing a deadly situation. For example, in an offensive scenario, the initial state value of the red asset is large due to small and , according to equations (14) and (16). Therefore, in the offensive initial scenario, the probability of our side winning will be greater than that of the opponent, while the defensive starting scenario is reversed. In neutral and first initial scenarios, the initial government values of both parties are almost the same. The performance of well-trained agents is checked according to the classification of the four initial situations in the league system. (a) (b) (a) (b)4,2. The results of the simulation of the Naming Conventions are either , meaning or a policy produced after the period. After every 100 episodes of training, test episodes are shown 100 times, and learning curves are shown at number 7. For the first period (vs.), due to the simple manoeuvring policy of the blue aircraft, the red aircraft can achieve almost 100% success through about 4000 episodes of training, as shown in Figure 7(s). At the outset, most games are due to the random initialization of the red agent and the strategy of evasion of the opponent. Another reason is that the aircraft often flies out of airspace in the early stages of training. Although the agent will get fined for it, the aerial combat episode will still get a draw. During the training process, the red aircraft seeks winning strategies in the airspace, and its winning rate is steadily increasing. However, due to its quest for offensive and neglect of defense, the winning rate of opponents is also rising. At a later stage of training, the red aircraft gradually understands the opponent's strategy and can achieve a very high winning rate. (a) (b) -c) (a) (b) -c) With iterations in games, both agents have learned an intelligent manoeuvring strategy, which can guide aircraft in a chase avoidance game. Figure 7(b) shows a typical example of what a coach and his opponent are. After about 5,000 episodes of training, a blue aircraft can reduce the loss rate to a lower level. Because the Red adopts an intelligent strategy of directing maneuvers, the blue agent can't learn a winning strategy in a short time. After about 20,000 episodes, the agent gradually understands the strategy of maneuvering the opponent, and his winning rate increases. The final winning rate is stable between 50% and 60%, and the rate of loss is below 10%. The iteration of the training process in relation to this is shown in Figure 7(c). Since the blue aircraft manoeuvring strategy is an intelligent strategy that is iteratively trained, training for a red agent is much more difficult than that in the first iteration. A well-trained agent can win more than 60% and lose less than 10% in a game against. It 's hard to get a higher win rate at every training session except for the scenario that he 's an opponent . This is because both aircraft are homogeneous, initial situations are randomized, and the opponent in the training environment is intelligent. In some situations, as long as the opposing strategy is intelligent enough, a trained agent is almost impossible to conquer. Interestingly, in some scenarios where the opponent is intelligent enough and the aircraft cannot defeat him regardless of how the agent operates, the agent will guide the aircraft out of the airspace to get a draw. It gives us inspiration, that is, in a scenario where you can't win, that's maybe the best way to get out of the combat area. For the four initial aerial combat situations, the two aircraft are led by agents trained at each stage of the iteration. Typical flight paths are shown on the 8th floor. Being a static strategy, it can easily win offensive, frontal and neutral situations, as shown in Figures 8(a), 8(c) and 8(d). In a defensive situation, the red aircraft first turns away from the advantaged rival and then looks for opportunities to establish an advantage situation. There are no fierce rivalries in the fight process, as shown Figure 8(b). (a) (b) -c) (d) (e) (g) (g) (h) (i) (j) (k) (l) (a) (b) -c) (d) (e) (g) (g) (i) (j) (k) (l) Although intelligent strategy, well-trained can still gain an advantage in combat, as shown in Figures 8(e)–8(h). In an offensive situation (from the perspective of a red aircraft), a blue aircraft can not easily get rid of a red follower, and after a fierce conflict can establish a situation of advantage, as shown in Figure 8(s). Figure 8(f) shows the defensive situation that a blue aircraft can maintain its advantage until it wins. In the other two scenarios, the blue aircraft performs well, especially in the initial situation of neutral, which adopts delayed turning tactics and successfully wins in the air combat.is intelligent strategy, and well-rehearsed can achieve more than half of the victory and less than 10% failure. However, unlike vs. , it cannot win easily, especially in frontal situations, as shown in Figures 8(i)–8(l). In an offensive situation, the blue aircraft tries to get rid of the red by constantly adjusting its bank angle, but is finally caught by the red one. In a defensive situation, the Reds aircraft cleverly adopted the tactic of circling the back and quickly caught its opponent. In a frontal situation, red and blue aircraft take turns taking advantage of the situation, and after a fierce manoeuvring conflict, the red plane finally wins. In a neutral situation, the Reds constantly adjust their bank angle to the opposing position and win. For the above three pairs of strategies, initial situations are taken as examples to analyze the advantages of both sides in the game, as shown in Figure 9. For a vs. scenario, as it lacks intelligent manoeuvrability, although both sides are equally competitive in the first half, the red aircraft continues to expand its strengths until it wins, as shown in Figure 9(s). When a blue agent learns an intelligence strategy, he can beat red, as shown in Figure 9(b). For a vs. scenario, the two sides took turns establishing a position of advantage, and the red aircraft did not win easily, as shown in Figure 9(c). Combining with the trajectories shown in Figures 8(c), 8(g) and 8(k), both sides' maneuvering strategies have been improved using an alternative freezing game of the DQN algorithm. The approach benefits from the unveiling of new manoeuvre tactics. (a) (b) -c) (a) (b) (c)4.3. League results The goal of the league system is to select a red agent who generates instructions for maneuvering according to his strategy, in order to achieve the best results without knowing his opponent's strategy. There are ten agents on each side who are saved in the iteration of the games. Each red agent fights each blue agent 400 times, including 100 times for each of the four initial scenarios. Detailed league results are shown in Table 2. Results with a win-loss ratio of more than 1 are highlighted in bold. Where, he trained in an environment with as his opponent, and he trained against. The result of the fight is ideal. However, because it is a static strategy rather than an intelligent strategy, it does not work well in the game with other intelligent blue agents. For , although there is no special training against , performance is still very good because it is a static strategy. In the process of iterative play, trained agents can get good results in conflict with frozen assets in the environment. For example, it has a huge advantage over, so and. Due to the effect of the red queen, although she has the advantage against, she is in a weak position against early blue agents, such as, and. The league table is shown in Table 3, in which they are 3 points to win, 1 point for draws and 0 points for defeat. In the early stages of training, the performance of trained agents will gradually improve. Later trained agents are better than exes, such as. As alternative freeze training continues, performance is not getting better, such as . The top of the scorecard is , which not only has the highest score, but also has advantages when playing with all blue agents except , as shown in Table 2. In competition with all opponents he can win 44% and remain unbeatable at 75%. RankAgent (strategy)WinDrawLossScore1113713711471218581323121968973187112761253688941877122612976857518631230130768196189610811423676971860116013806740816541263148362591587123615775997101362133217065418 In the order to verify the performance of this agent, he faces opposing agents trained by ADP [20] and Minimax-DQN [44]. Each of the four typical initial situations is performed 100 times for both opponents, with the results shown in Table 4. The cost of time to generate an action for each algorithm is shown in Table 5. It can be taken into account that the effectiveness of the means presented in this paper is comparable to the performance of ADP, and the computer time is slightly reduced. However, ADP is a model-based method, which is assumed to know all information such as the rolling rate of the opponent. Compared to Minimax-DQN, the agent has an overall advantage. This is because Minimax-DQN assumes that the opponent is rational, while the opponent in this work is not, which is closer to the real world. In addition, compared to minimax-DQN, the computational efficiency of the proposed algorithm is significantly improved because linear programming is used to choose optimal action at every turn in minimax-DQN, which is time consuming. vs. ADP [20]vs. Minimax-DQN [44]OffensiveWin5766Draw2821Los1513DefensiveWin1920Draw3142Loss5038Head-onWin4346Draw1626Loss4128NeutralWin3243Draw3222Loss3635AlgorithmTime Cost (ms)Suggested Algorithm13.8ADP14.2Minimax-DQN7864.4. Agent Evaluation and Behavioral Analysis Evaluating the performance of an agent in an air combat is not just a matter of win or loss. in addition and loss rate, two criteria are added that represent the level of success: average win time (ATW) and average disadvantage time (ADT). ATW is measured as the average time required to manoeuvre to a position of advantage in a scenario where our aircraft wins. A smaller ATW is better than a bigger one. ADT is the average accumulated time that the value of the advantage function of our aircraft is less than that of the adversary, which is used as a criterion for assessing exposure to the risk of opposing weapons. A thousand aerial combat scenarios are generated into simulation software, and the opponent is randomly selected between ten blue agents in each scenario. Each well-trained red agent is used to perform these conflicts, and the results are shown on the number 10. Agent number means rules trained after a period. From to - the performance of agents gradually improves. After that, their performance is stabilized, and each agent has different characteristics. Compared to , the rates of gain and loss are almost the same as those in Table 3. The winning rate of six agents is similar, with the highest gain of 6% higher than the lowest , as shown in Figure 10(s). However, is the agent with the lowest rate of loss, and his rate of loss is more than 10% lower than that of other agents, as shown in Figure 10(b). For the ATW, it is less than 100 s, is 108.7 s, and other agents are more than 110 s, as shown in Figure 10(c). For ADT, and less than 120 s, it is above 130 s, and between 120 and 130 s, as shown in Figure 10(d). (a) (b) -c) (d) (a) (b) -c) (d) In short, with the number of iterations increasing, the red queen effect appears. Performance, and it's no better than performance and. Although the winning rate is not high and has more time at a disadvantage, it can always win quickly. It is an aggressive agent and can be used in scenarios where our aircraft needs to beat the opponent quickly. The winning rate is similar to other agents, while its loss rate is the lowest. Its ATW is only higher than and ADT is the lowest. In most cases, it can be selected to achieve more wins while preserving it. is an agent with a good comprehensive performance, which means that the method of selecting a league system is effective. For the four initial scenarios for behavioral analysis, a simulation of air combat was selected, as shown in Figures 11 and 12. In an offensive scenario, the opponent tried to escape by turning in the opposite direction. Our spacecraft used the tactic of searching for delays, which is simple but effective. In the 1st second, our plane did not go up with the opponent, but decided to fly straight. In the 9th second he gradually turned to the opponent, established himself and maintained the advantage and eventually won, as shown in Figure 11(s). (a) (b) -c) (d) (d) (e) (g) (g) (h) (a) (b) -c) (d) (e) (g) (h) In the defensive scenario, our aircraft was at a disadvantage and the opponent was trying to lock us in with delay-search tactics, such as in Figure 11(b). In the 30th second, our aircraft adjusted the rolling angle to the right to avoid being locked by the opponent, as shown in Figure 11(c). After that, he continued to adjust the rolling angle, and when the opponent noticed that our strategy had changed, our aircraft had already flown out of the sector. In situations where it is difficult to win, the agent will use a safe manoeuvre strategy to get a draw. In the frontal scenario, both sides adopted the same manoeuvring strategy in the first 50s, i.e. maximum overload and waiting for opportunities, as shown in Figure 11(d). The key decision was made in the 50th opponent was still hovering and waiting for the opportunity, while our aircraft stopped hovering and reduced the speed of turning to fly towards the opponent. In the 90th second, the aircraft came to a situation of advantage over the opponent, as shown in Figure 11(s). In the final stage, our aircraft adopted lead chase tactics to establish and maintain the advantage and win, as shown in Figure 11(f). In a neutral scenario, our initial strategy was to turn away from opponents to find opportunities. The opponent's strategy was to lag behind in the chase and successfully reached the rear of our aircraft in the 31st second, as shown in Figure 11(g). However, after the 40th second, our spacecraft made the wise decision to reduce the rolling angle, thereby increasing the turning radius. In the 60th second, the situation at a disadvantage was interrupted, as shown in Figure 11(h). After that, our aircraft increased its rolling angle, and the opponent was in a state of maximum overload with a right turn, which is why he could not get rid of our aircraft, and in the end, lost. It can be seen that trained by alternative freezing games using the DQN algorithm and selected through the league system, the agent can learn tactics such as lead chase, search for delays and hovering and can use them in aerial combat.5. Conclusion In this paper, a middleware is developed that connects the software for simulation of air combat and a means of learning reinforcement. It provides an idea for researchers to design a variety of medium necessities to turn existing software into a reinforcement learning environment, which can expand the scope of reinforcement learning. Agents have been designed to list the manoeuvres with the reshaping of rewards. Through environmental training, an agent can guide an aircraft to fight its opponent in an air combat and get to a situation of advantage in most scenarios. An alternative freezing game algorithm is proposed and combined with RL. It can be used in situations of non-habitability where other players' strategies are variable. Through the league system, an agent with improved performance is selected after iterative training. The league results show that the quality of the selected agent's strategy is better than that of the other agents, and the Red Queen effect is avoided. Agents can learn some typical angular and behaviors in the horizontal plane and perform tactics by directing the aircraft to manoeuvre in a one-on-one air combat. In future works, the problem would extend to 3D manoeuvring with less restrictive vehicle dynamics. The 3D formulation will lead to more government space and more complex actions, and the learning mechanism would be improved to cope with them. In addition to expanding to 3D maneuvering, a 2-vs-2 aerial combat scenario would be established, in which there are associates as well as opponents. One option is to use a centralized controller, which turns to the PROBLEM of DRL with one agent to obtain joint action by both aircraft to execute in each time step. Another option is to adopt a decentralised system, in which both agents make a decision for themselves and could co-operate to achieve a common goal. In theory, it is necessary to analyze the convergence of an alternative algorithm for freezing the game. Furthermore, to improve the diversity of potential opponents in a more complex aerial combat scenario, the league system would be refined. Nomenclature:3-dimensional aircraft coordinates:Speed:Flight path angle:Direction:Angle of attack:Bank angle:Weight of aircraft:Acceleration due to gravity:Force thrust:Lift force:Pull force:Turn speed:Rolling speed:Distance between aircraft and target in time :Minimum position distance advantage:Maximum position distance advantage:Time deviation angle :Maximum deviation angle of advantage position:Aspect angle at time :Maximum angle of advantage position aspect:State space:State vector in time :All countries in the state space:Action space:Action on time :All actions in action space:Politics:Reward function:Scalar award received on time :Value function:Action value function:Optimal function of action value:Estimated function of action value in time :D responsible factor :Learning rate:Maximum simulation time in each episode:Training time step size:Time simulation step size:Shaping reward function:Real-value reward function in countries:Break reward function:Distance reward function:Orientation reward function:Number of training periods. Availability of data Data used to support the findings of this study are available from the appropriate author on request. Conflict of interest Authors declare that they have no conflict of interest. RecognitionsThis work is partially supported by the National Foundation for Natural Sciences of China under grants 91338107 and U1836103 and the Sichuana Development Program in China, as part of grants 2017GZDZX0002, 18ZDYF3867 and 19ZDZX0024. Complementary Dynamics of MaterialsAircraft: Derivation of Kinematic and Dynamic Equations of Aircraft. Code: Simplified version of the environment used in this paper. It has no commercial software and middleware, but its aircraft model and other functions are the same as those proposed in this paper. This environment and RL agent are packed complementary material. Through this material, an alternative freeze game DQN algorithm suggested suggested this work can be reproduced. (Additional materials) Materials)

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