

Two-Stage Reinforcement Learning-Based Upset Recovery Strategy for Aircraft

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Abstract—something anasdd

Index Terms—aircraft upset recovery, reinforcement learning, Twin Delayed Deep Deterministic Policy Gradient

I. INTRODUCTION

Aircraft upset incidents are the highest risk to civil aviation for decades ago to now [1]. To this end, several researchers have devoted to address the aircraft upset issue [?]. Yildiz et al. [2] describes a novel finite-state conditional switching structure that enables autonomous recovery for a large envelope of loss-of-control conditions. Cunis et al. [3] proposed a loss of altitude minimizing economic model predictive control strategy for deep-stall recovery. The problem of aircraft spin recovery is addressed by solving a trajectory optimization problem via direct multiple shooting method in [4]. Although the above-mentioned approaches are adequate to deal with nonlinear dynamics of aircraft, they may fail to address the high complexity of the upset situation [5].

Reinforcement Learning (RL) is an approach that can deal with high complexity problems without an explicit model of the problem [6], leading to recovery strategies for aircraft suffering complex upset situation [?]. Dutoi et al. combined robust control and RL to address spin recovery problem [?]. The spin recovery performance of the achieved strategy outperforms the strategy obtained based on skilled pilots in some cases. Nonetheless, this study compressed the action space to reduce the computation load, leading to a limitation on agile spin recovery. Kim et al. [5] developed an RL-based recovery strategy including 27 actions for angular rate arrest and nine actions for unusual attitude recovery for stable flat

spin. The performance of the proposed RL-based strategy was compared with an optimal solution. However, the training of the RL-based strategy was not detailed in [5]. Zhu et al. [7] applied deep Q-network (DQN) and deep deterministic policy gradients (DDPG) to achieve spin recovery strategies and propose an exploring mechanism that dynamically selects between deterministic and stochastic exploration for DDPG. Whereas this study did not consider the uncertainties of the aircraft and the environment.

In this paper, we proposed a method based on RL to recover the aircraft back to steady level flight swiftly. When the aircraft is in an upset state, control the aircraft through RL and adjust the aircraft attitude so that the aircraft can resume smooth flight within a limited time.

This paper has the following major contributions.

- A pretrained-fine tuned RL method is proposed for random upset state recovery. Using this method, the agent can be trained successfully and quickly.
- A novel reward function is proposed to improve the performance of the training efficiency.
- We provide a comparison between PID and our proposed method for LOA(loss of altitude)-minimal recovery, and proved our method is quite more excellent than PID.

The rest of this paper is organized as follows. Section II introduces the preliminaries of this paper, including typical upset situations of aircraft and Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm. In section III, a TD3-based upset recovery strategy is proposed. Section IV presents the simulations to illustrate the proposed strategy. Finally, section V summarizes this paper.

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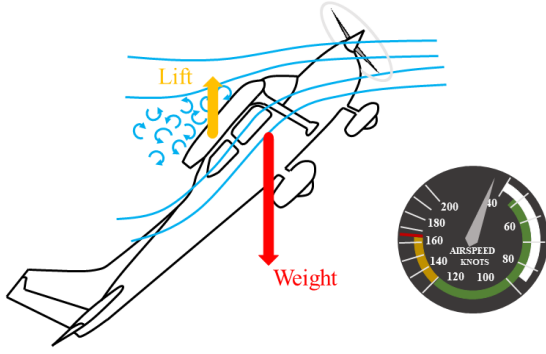


Fig. 1. The stall phenomenon of the aircraft

II. PRELIMINARIES

A. Upset Situations of Aircraft

An upset situation of aircraft refers to an abnormal mode of the nonlinear dynamics that shows significantly altered steady-state responses and usually immediately precedes wing stall [3], such as stall and spin.

Stall. A stall is a condition in aerodynamics and aviation such that if the angle of attack increases beyond a certain point, then lift begins to decrease. Stalls in fixed-wing flight are often experienced as a sudden reduction in lift as the pilot increases the wing's angle of attack and exceeds its critical angle of attack. The stall phenomenon is shown in Fig. 1.

Spin. A spin is defined as an aggravated stall, which results in auto-rotation of an aircraft while descending in a helical pattern about the vertical spin axis, as shown in Fig. 2. In an aggravated stall, one wing is stalled more than the other. The more stalled wing experiences less lift and more drag as compared to the other and this imbalance of forces initiates auto-rotation and subsequent rapid decent of the aircraft [?]. Spin is a nonlinear post-stall phenomena in which an aircraft develops a high rotational-rate and descends almost vertically in a helical trajectory.

B. Loss of Altitude

Loss of altitude (LOA) [3] is an important performance metric for upset recovery maneuvers and it can be exploited to enlarge the operational envelope during and after the maneuver, particularly at low altitudes. The LOA has been used in several previous researches [?] to evaluate control strategies of aircraft. In this study, the LOA is an significant index to measure the performance of the proposed strategy.

C. Reinforcement Learning and Twin Delayed Deep Deterministic Policy Gradient Algorithm

Reinforcement learning studies the paradigm of an agent interacting with the environment aiming to learn behaviors that maximize accumulated rewards. At time step t , the agent selects an action $a \in \mathcal{A}$ based on the current state $s \in \mathcal{S}$ with respect to its policy $\pi : \mathcal{S} \mapsto \mathcal{A}$. The agent receives a reward r and the state transfers to a new state s' . The agent aims to

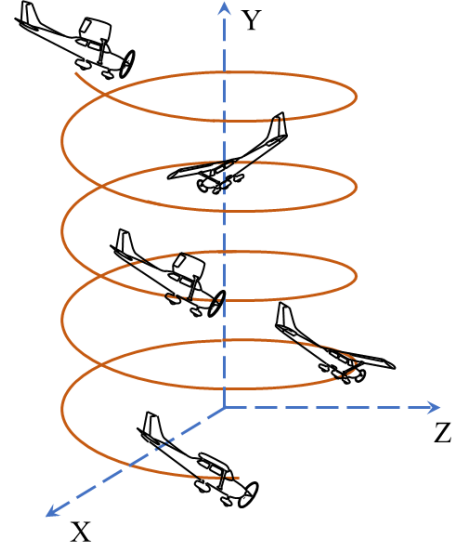


Fig. 2. The spin phenomenon of the aircraft

maximize the accumulated rewards $R_t = \sum_{i=t}^T \gamma^{i-t} r(s_i, a_i)$, where γ is a discount factor.

Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm [8] is a RL algorithm proposed for agents with continuous states and actions. TD3 is based on an actor-critic architecture taking the interplay between function approximation error in both policy and value updates into account. TD3 applies three novel approaches to address the overestimation issue of the critic network.

Smooth target policy. In order to reduce the variance caused by over-fitting, TD3 uses a regularisation technique known as target policy smoothing. Ideally there would be no variance between target values, with similar actions receiving similar values. TD3 reduces this variance by adding a random noise to the target and averaging over mini batches. The range of noise is clipped in $(-c, c)$ in order to keep the target value close to the original action. After adding the clipped noise, the target action is then clipped to lie in the valid action range. The target actions are thus:

$$a'(s') = \text{clip}(\pi_{\theta_{\text{target}}}(s') + \text{clip}(\epsilon, -c, c), a_{\text{Low}}, a_{\text{High}}) \quad (1)$$

where $\pi_{\theta_{\text{target}}}$ is the target policy, action a satisfy $a_{\text{Low}} \leq a \leq a_{\text{High}}$, $\epsilon \in \mathcal{N}(0, \sigma)$.

Apply a pair of critic networks. TD3 learns two Q-functions Q_{ϕ_1} , Q_{ϕ_2} , and uses the smaller of the two Q-values to form the targets in the Bellman error loss functions.

$$y(r, s', d) = r + \gamma(1 - d) \min_{i=1,2} Q_{\phi_i, \text{target}}(s', a') \quad (2)$$

where $d = 0$ or 1 . Then the parameters of both Q-value function ϕ_1 and ϕ_2 are updated by one step of gradient descent using:

$$\nabla_{\phi_i} \frac{1}{B} \sum_{(s, a, s', r, d) \in B} (Q_{\phi_i}(s, a) - y(r, s', d))^2 \quad (3)$$

where $i = 1, 2$ and \mathcal{B} is a mini-batch sampled from the replay buffer \mathcal{D} . Using the smaller Q-value for the target, and regressing towards that, helps decrease overestimation in the Q-function.

Delay policy updates. TD3 updates the policy and target networks less frequently than the Q-function, and we define the delayed frequency as p_d . The parameter θ of the policy network π_θ is updated by one step of gradient ascent to maximize the Q-value using:

$$\nabla_\theta \frac{1}{\mathcal{B}} \sum_{s \in \mathcal{B}} Q_{\phi_1}(s, \pi_\theta(s)) \quad (4)$$

III. TWO-STAGE REINFORCEMENT LEARNING-BASED UPSET RECOVERY STRATEGY

In this section, a two-stage reinforcement learning-based upset recovery strategy is proposed for aircraft.

A. Problem Formulation

In the context of aviation, the term upset can be used to describe a variety of abnormal situations. A upset recovery strategy is expected to recover aircraft from an upset state with minimum LOA within the shortest time in practice. Assume an aircraft can adjust its state by aileron, elevator, rudder, and throttle, as shown in Fig. 3. The problem addressed by a upset recovery strategy can be expressed as

$$\begin{aligned} & \arg \min_{\delta_e, \delta_a, \delta_r, \delta_t} ||LOA|| \\ \text{s.t.} \quad & -1 \leq \delta_e, \delta_a, \delta_r \leq 1 \\ & 0 \leq \delta_t \leq 1 \end{aligned} \quad (5)$$

where $\delta_e, \delta_a, \delta_r, \delta_t$ denote elevator, aileron, rudder, throttle, respectively.

We noticed that our goal had no dependence on its location, so latitude and longitude can be ignored. Under comprehensive consideration, we define our state space \mathcal{S} as a set of states corresponding to the following: $\{\omega, \kappa, \xi, p, q, r, h, v\}$:

$$\mathcal{S} = \{s | s = [\omega, \kappa, \xi, p, q, r, h, v]\} \quad (6)$$

Where $\omega, \kappa, \xi, p, q, r, h, v$ denote pitch, roll, heading, rotational velocity of pitch, rotational velocity of roll, rotational velocity of heading, altitude, indicated airspeed of the aircraft, respectively.

B. Two-Stage RL-Based Upset Recovery Strategy

The dynamics of an aircraft is with complexity and uncertainty caused by aerodynamics, weather, fuel, and payload. Upset recovery strategies based on robust control and the knowledge of dynamics of the aircraft cannot achieve the optimal performance. RL is a promising upset recovery scheme in the sense of complexity and uncertainty handling. In view of the uncertainties of upset recovery for aircraft such as aerodynamics, weather, fuel, and payload, a two-stage, namely pre-train stage and fine-tuning stage, upset recovery strategy is proposed.

In the pre-train stage, a general upset recovery strategy is learned based on RL for an aircraft with parameters (e.g.,

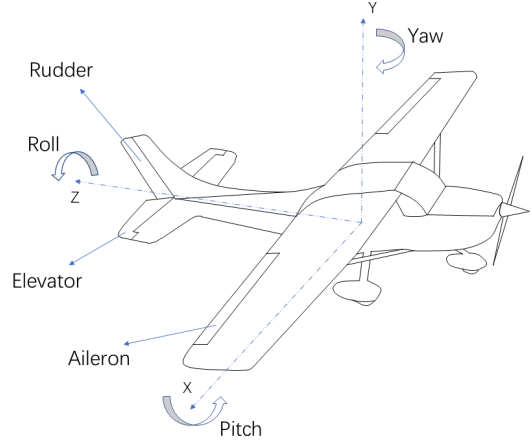


Fig. 3. Aircraft control surfaces

aerodynamics, weather, fuel, and payload) disturbed in certain ranges randomly. The general upset recovery strategy is sub-optimal but is with the adaptability to aircraft with parameter uncertainties. In the fine-tuning stage, a specific upset recovery strategy is learned via RL by the current aircraft whose aerodynamics, fuel, and payload are determined, based on the general upset recovery strategy. Based on the general upset recovery strategy achieved in the pre-train stage, rather a random initial strategy, the training of the specific upset recovery strategy for the current aircraft can speed up.

We shape the reward function using the method as described in Section III-C. The overall framework of training algorithm is shown in Fig. 4.

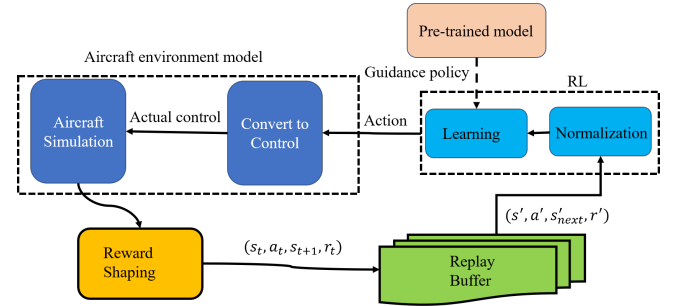


Fig. 4. The overall framework of training process.

C. Reward Function

The design of reward function is crucial for RL since it affects not only the convergence but also the quality of the convergent point of the RL.

With the idea of rewarding shaping [9], we define the reward function as follows:

$$R(s, a, s') = T(s') + F(s, a, s') \quad (7)$$

where $T(s')$ is the termination reward and $F(s, a, s')$ is a bounded function.

The termination reward is the reward obtained when the next state is crashed or is successful to recover. It is defined as:

$$T(s') = \begin{cases} T_1, & \text{if the aircraft is crashed} \\ T_2, & \text{if the aircraft is successful to recover} \\ 0, & \text{else} \end{cases} \quad (8)$$

where T_1 is a very small negative value while T_2 is a large positive value. When the steady state of aircraft hold for more than n time steps, the aircraft is successful to recover.

$F(s, a, s')$ has the form:

$$F(s, a, s') = C(s, a, s') + P(s) \quad (9)$$

where $C(s, a, s')$ is the action reward which is related to the elevator and aileron, and it is a function whose values are integers. It links the current action and expected action with the current attitude change. When the current action is consistent with the expected action, $C(s, a, s')$ will increase, otherwise it will decrease.

$P(s)$ is the aircraft attitude reward, it is given by (10):

$$P(s) = \sum_{j=1}^8 p_j |s_{norm}[j] - s_{targ,norm}[j]| + p_0 |LOA_{norm}| \quad (10)$$

where $p_j (j = 0, \dots, 8)$ are non-positive weight coefficients, and p_0 is much smaller than $p_j (j = 1, \dots, 8)$. s_{norm} , $s_{targ,norm}$, LOA_{norm} are the normalization of state s , target state s_{targ} , the LOA of aircraft, respectively.

D. Two-Stage TD3-Based Upset Recovery Strategy

Based on the two-stage RL-based upset recovery strategy framework presented in section III-B and the reward function presented in section III-C, we can develop a two-stage TD3-based upset recovery strategy by applying TD3 in both the pre-train stage and in the fine-tuning stage. The pseudo-code of the TD3 algorithm applied for upset recovery is shown in Algorithm 1.

Although the TD3 algorithm is used in both the pre-train stage and in the fine-tuning stage, applications of the TD3 algorithm are different from two aspects - initialization and parameter uncertainty. For the initialization aspect, the strategy is initialized randomly in the pre-train stage while, in the fine-tuning stage, the strategy is initialized to the general strategy achieved in the pre-train stage. For the parameter uncertainty aspect, the environment is with parameters distributed randomly in certain ranges in the pre-train stage, but the environment is with parameters determined by the current aircraft.

IV. EXPERIMENTS

A. Environment Set Up

To evaluate the proposed two-stage upset recovery strategy, we conduct experiments based on X-Plane 11, a flight simulation environment. X-Plane 11 is a professional flight simulation environment, involving various types of aircraft

Algorithm 1: TD3-based upset recovery algorithm for aircraft

Input: initial policy parameters θ , Q-function parameters ϕ_1, ϕ_2 , empty replay buffer \mathcal{D}

- 1 Set target parameters equal to main parameters
 $\theta_{targ} \leftarrow \theta, \phi_{targ,1} \leftarrow \phi_1, \phi_{targ,2} \leftarrow \phi_2$;
- 2 **if** *Pre-train stage* **then**
- 3 Set Pre-train aircraft model parameters and environment parameters randomly;
- 4 **if** *Fine-tuning stage* **then**
- 5 Set the pre-train agent as the baseline agent and obtain the guidance policy;
- 6 Reset aircraft model parameters and environment parameters;
- 7 **for** $episode=1$ **to** M **do**
- 8 Receive initial observation state s_1 ;
- 9 Normalize the initial state s_1 ;
- 10 **for** $t=1$ **to** T **do**
- 11 **if** *Pre-train stage* **then**
- 12 Select and clip action a with exploration noise ϵ ;
- 13 **if** *Fine-tuning stage* **then**
- 14 Select and clip action a according to the guidance policy;
- 15 Convert the action into the aircraft control;
- 16 Execute action a in aircraft environment, and obtain **shaped reward** r and new state s' ;
- 17 Normalize the state s' ;
- 18 Store transition (s, a, r, s', d) in \mathcal{D} ;
- 19 Sample a mini-batch of transitions:
 $\mathcal{B} = \{(s, a, r, s', d)\}$ from \mathcal{D} ;
- 20 Compute target actions with (1);
- 21 Compute targets $y(r, s', d)$ according to (2);
- 22 Update Q-functions using (3);
- 23 **if** $t \bmod p_d=0$ **then**
- 24 Update policy using (4);
- 25 Update the target network:
 $\phi_{targ,i} \leftarrow \tau \phi_{targ,i} + (1 - \tau) \phi_i, \quad i = 1, 2$
 $\theta_{targ} \leftarrow \tau \theta_{targ} + (1 - \tau) \theta$

ranging from general aircraft to commercial aircraft. X-Plane has been used by several researchers [?] to study the design, control, and guidance of aircraft. X-Plane 11 is integrated to Tensorflow-gpu 2.4 in this study. A PC with 64-bit Windows 10 operation system, 32G Memory, a 3.4GHz Core i7 CPU, and a RTX 3070 GPU is used to validate the proposed strategy.

A Cessna172SP is included in experiments to study the performance of the proposed two-stage upset recovery strategy, as shown in Fig. 5. Moreover, the wind condition in the experiments is adjusted to achieve a general strategy in pre-train stage.



Fig. 5. Aircraft included in experiment - Cessna172SP

B. Algorithm Set Up

With the above-mentioned environment set up, we set the TD3 algorithm included in the proposed upset recovery strategy as follows. The learning rate is 1.0×10^{-4} . The discount factor γ is set to 0.99. The actor network has three hidden layers that have 64, 64, and 32 units, respectively. The critic network has two hidden layers with 64, 64 units, respectively. The time step T is defined as 500 and the minibatch size \mathcal{B} is 64.

The number of episodes M is 100 under both non-wind and windy conditions.

The values range of the state space and the coefficients of the reward function are set as Table I.

Table I. The values range of the state space and the coefficients of the reward function

variable	value	variable	value
ω, κ	$[-180^\circ, 180^\circ]$	ξ	$[0^\circ, 360^\circ]$
p, q, r	$[-90^\circ/s, 90^\circ/s]$	h	$[0\text{ m}, 5000\text{ m}]$
v	$[0\text{ m/s}, 160\text{ m/s}]$	n	60
T_1	-1000	T_2	500
initial $C(s)$	1	p_0	-1.0
p_1, p_2, p_3, p_6	-0.1	p_4, p_5, p_7, p_8	-0.5

When the current action is consistent with the expected action, $C(s, a, s')$ will increase 1, otherwise it will decrease 1.

C. Training

Based on the environment set up and the algorithm set up demonstrated above, we conduct the training of two-stage TD3-based upset recovery strategy. In the pre-train strategy, it is assumed that the fuel and payload of aircraft and the weather are not determined. Thus, the weight of the aircraft distributes randomly from to and the wind speed ranges from to. In the fine-tuning stage, it is assumed that the fuel and payload of aircraft and the weather are determined by the current aircraft. The initial upset recovery strategy is the strategy achieved in the pre-train stage. The accumulated rewards achieved in the

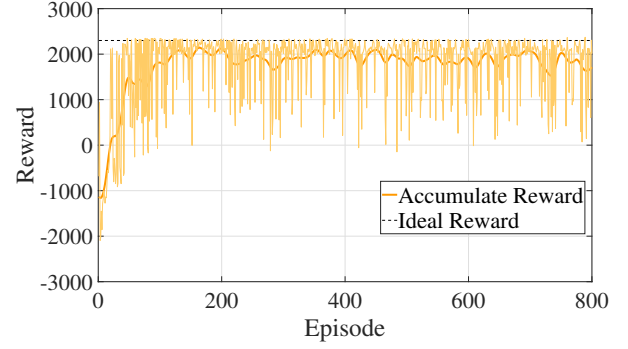


Fig. 6. Rewards achieved in the pre-train stage

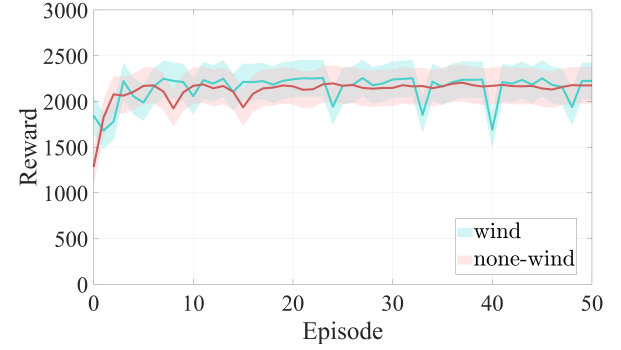


Fig. 7. Rewards achieved in the fine-tuning stage

pre-train stage and in the fine-tuning stage are shown in Fig. 6 and Fig. 7.


In the pre-train stage, about 180 episodes begin to converge, the average reward of the simulation results is approximately 2000. It can be seen from the simulation results that the pre-train model has obtained a sub-optimal policy since there are still sometimes unstable flight situations. This is also in line with the results we expected. it is almost impossible to obtain the optimal policy in the pre-trained phase, but the sub-optimal policy obtained assist the subsequent tuning.

In the fine-tuning phase, based on the pre-train model, We trained our agent in windy and non-wind conditions. As shown in Fig. 7, only less than 5 iterations are needed to make the training successful in both windy and non-wind conditions, which greatly improves the training efficiency. Besides, the training speed of non-wind performs better than the training speed of windy. Each of them has obtained the optimal policy.

D. Evaluation of Upset Recovery Strategy


the performance of our method is compared with a traditional PID controller with windy and non-wind interference under stall and spin states.

Stall recovery. The well-trained agent and the traditional PID controller are tested for 10 simulations under the stall state. The corresponding attitude changes and airspeed changes are shown in Fig. 8 - Fig. 10. All of angles are regulated to the target region which stands for steady state of the aircraft




roll_stall-eps-converted-to.pdf

Fig. 8. The roll angle changes under stall changes




speed_stall-eps-converted-to.pdf

Fig. 10. The airspeed



pitch_stall-eps-converted-to.pdf

Fig. 9. The pitch angles changes under stall changes



altitude_stall-eps-converted-to.pdf

Fig. 11. The altitude angle changes

and the airspeed has returned to the normal controllable range. But the performance of PID controller is worse than the well-trained agent especially in the windy condition. For the loss of altitude(LOA) shown in Fig. 11, the performance of the well-trained agent is better than PID and the recovery speed of the well-trained agent is also faster than PID.

Spin recovery. The same as the stall state, the well-trained agent and the traditional PID controller are tested for 10 simulations under the spin state. Fig. 12 - Fig. 14 showed

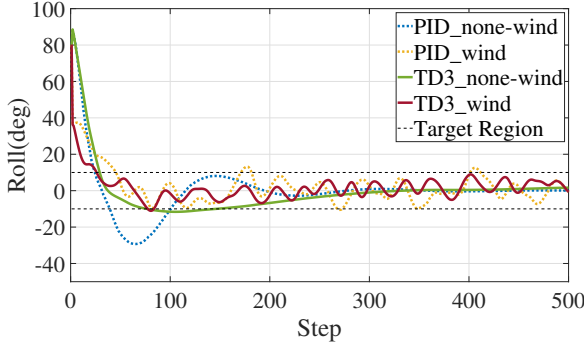


Fig. 12. The roll angle changes under spin situations

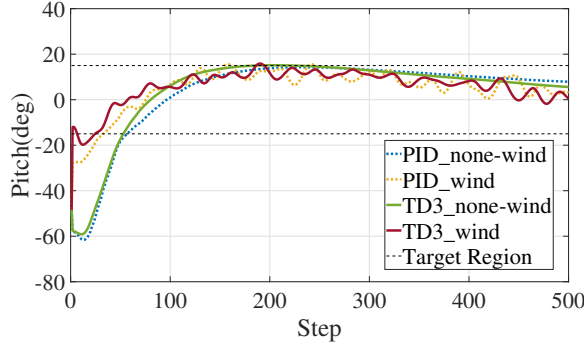


Fig. 13. The pitch angles changes under spin situations

the angles and airspeed changes. We can easily know all of angles and airspeed are regulated to the target region, but relatively speaking, the well-trained agent is more robust than PID controller. As expected, for the LOA shown in Fig. 15, the performance of the well-trained agent is also better than PID.

The simulation results show that our proposed method performs more efficiently and excellently than PID. It is very useful to return the aircraft to a steady state from any upset state.

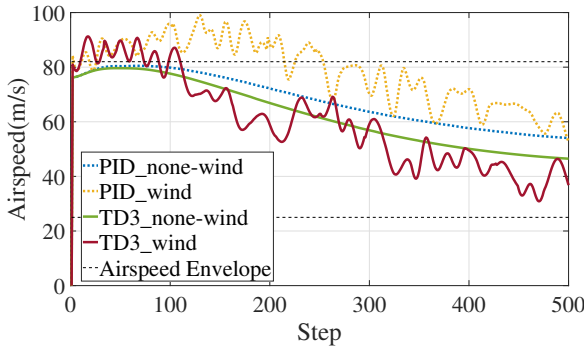


Fig. 14. The airspeed changes under spin situations

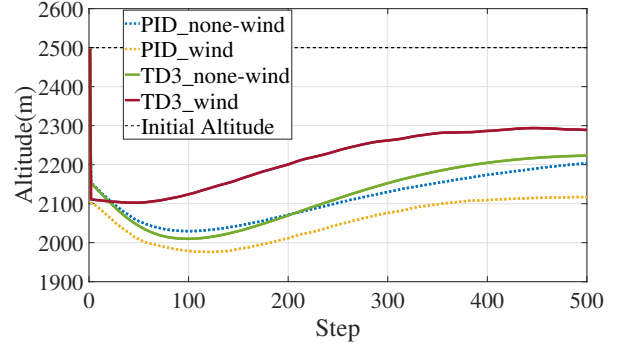


Fig. 15. The altitude changes under spin situations

V. CONCLUSION

In this paper.

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