A Method of Offline Reinforcement Learning Virtual Reality Satellite Attitude Control Based on Generative Adversarial Network

Jian Zhang and Fengge Wu

1University of Chinese Academy of Sciences, Institute of Software, Chinese Academy of Science, Beijing, China
2Institute of Software, Chinese Academy of Science, Beijing, China

Correspondence should be addressed to Jian Zhang; 16141191@qq.com

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Virtual reality satellites give people an immersive experience of exploring space. The intelligent attitude control method using reinforcement learning to achieve multi-axis synchronous control is one of the important tasks of virtual reality satellites. In real-world systems, methods based on reinforcement learning face safety issues during exploration, unknown actuator delays, and noise in the raw sensor data. To improve the sample efficiency and avoid safety issues during exploration, this paper proposes a new offline reinforcement learning method to make full use of samples. This method learns a policy set with imitation learning and a policy selector using a generative adversarial network (GAN). The performance of the proposed method was verified in a real-world system (reaction-wheel-based inverted pendulum). The results showed that the agent trained with our method reached and maintained a stable goal state in 10,000 steps, whereas the behavior cloning method only remained stable for 500 steps.

1. Introduction

Virtual reality satellites enable people to explore space using any mobile, desktop, or virtual reality device. Traditional attitude control methods require single-axis alternate control. In order to track all kinds of observed celestial bodies in real time, efficient attitude control methods need to be studied. The attitude control method based on reinforcement learning gives a feasible path to achieve efficient three-axis synchronous control.

Reaction momentum wheels are widely used in modern satellites as executive mechanisms that can redistribute momentum between the satellite body and the momentum wheel. Studies on the attitude control algorithms for this kind of actuator have focused on how to control the attitude of the satellite body by adjusting the momentum. Methods based on classical control theory, such as proportional–integral–derivative (PID), linear–quadratic regulator (LQR), and iterative linear–quadratic regulator (LQR), are widely used in this field, and these methods rely on an analytical model of the satellite’s rigid body dynamics. The design stage requires sufficient system knowledge, manual parameter adjustment, and multiple experiments. The control algorithm in an experiment may fail due to unreasonable parameter selection (such as $P$, $I$, and $D$ parameters). The reinforcement learning paradigm provides a powerful framework for problem solving and has proven to be a promising and nonintuitive problem-solving technology in many challenging environments, such as MuZero [1], Atari games [2], Go [3], and GYM [4]. However, the application of reinforcement learning in real-world systems has just started, mainly for the following reasons:

1. In a real-world environment, sample acquisition costs are high, and the incentive function cannot be accurately described since the function is typically a
multiobjective function and the objectives are related to each other

(2) The system sensor contains noise

(3) The actuator control frequency has a limiting value

(4) Due to security issues, the system cannot be explored at will

(5) It is impossible to effectively reset the system to the initial state at the end of each training session

Additional issues can arise in real-world systems. Applying reinforcement learning to satellite attitude control faces the challenges described above. In this study, we construct a physical system to introduce the characteristics of the real-world system.

Based on whether historical data is used to establish the environmental model transfer function explicitly, reinforcement learning methods can be divided into two broad categories: model-free and model-based methods. Model-free methods require continuous interactions with the environment during the learning process. To improve the performance of the policy during the training iterations, model-free methods often require a large number of samples to learn and are prone to problems of high collection efficiency. Therefore, the application of this type of method does not consider the cumulative error. It only selects one action, such as random shot, model predictive control (MPC), or cross entropy method (CEM), and selects the current optimal action by simulating multiple paths in the learned environment. This method often requires powerful computing resources. The second type of method begins from the perspective of learning policies in the environment, makes the most efficient use of the dynamic models, represented by model-based policy planning (POPLIN) [15], stochastic lower bound optimization (SLBO) [16], and model-based policy optimization (MBPO) [17], and draws upon theories to determine how to correctly make choices in the interaction between the real environment and the model.

The above methods can be effectively applied to real-world systems, and they are mainly bridged in two ways. One is to build a simulation environment close to the real-world system and deploy the policies obtained after training in the simulation environment to the real system. The second is to learn the environmental model based on historical data and use mixed training in the environmental dynamics model and the real system to obtain the final deployment policy. In the scenario considered in this study, the following facts make it difficult to use existing methods directly: (1) it is impossible to accurately construct a scenario similar to the real world (such as an on-orbit environment in outer space), (2) it is impossible to interact with the real-world system during the training phase, and (3) real-time simulations are not supported.

Our method trains the policy set at different stages through the historical state-action trajectory data and takes the global data to train the discriminator. In the actual operation, the method relies on the discriminator to determine the action proposed by the policy set to select the optimal action and to reduce the upper bound of error that is proportional to the square of the number of steps with behavior cloning. The innovations of this paper are as follows. (1) This paper proposes a new imitation learning method to solve the continuous control problem. (2) Through training, a low-level control policy for a real system with a reverse momentum wheel as the actuator was obtained. (3) By only using the onboard original sensor information to achieve the end-to-end control of the multimotor pulse width modulation (PWM) signals, the control task of balancing on a corner was completed.
\[ \theta^* = \arg \min_{\theta} L(\theta), \]
\[ L(\theta) = E_{(s,a) \sim D} \left[ \frac{1}{2} (\pi_\theta(s|a) - a)^2 \right], \]  
where $E$ denote the expectation and $(s, a) \sim D$ denote the state, action pair sampled from the data $D$ to estimate the expectation.

Ross et al. presented the following conclusion. The policy $(s)$ is obtained by supervising training with a labeled training set. When the action $a_i$ given in the state $s$ and the optimal action $a^*$ are evaluated with a 0-1 loss, $L(\pi) = E_{(s,a) \sim D} [\sum_{i=0}^{H} 1(a_i \neq a^*)]$ ($\tau$ is the trajectory collected by policy $\pi$) will be within the upper bound given as follows.

\[ L(\pi) \leq C + H^2 \varepsilon, \]  
where $\varepsilon$ is the generalization error in the distribution $s \sim d^\pi(s)$ and $C$ is constant. This means that when the time length is $H$, the deviation of the error will grow as the square of $H$, which will cause to deviate significantly from the expert policy. Thus, the state distribution $d^\pi(s)$ obtained by executing the policy $\pi$ is far away from the state distribution $d^\pi(s)$ obtained by using the expert policy.

To address this issue, the collected expert trajectories are segmented, and policies of different stages are trained for different state sets. This allows the policy selector to control the length of time used by each policy and to reduce the overall accumulated error, as shown in Figure 2. Rectangles of one color represent the training data used in one policy. The overlapping area is set in the segmented data of the interval. Given the training set $\tau_1, \tau_2, \cdots, \tau_N$, the trajectory length is $H$, and the policy set is $\pi_1, \pi_2, \cdots, \pi_K$, the width of the data used to train each policy is $W$, and the width of the overlapping area is $S$. The following relationship $W \cdot K = S \cdot (K - 1) = H$ must be satisfied. For the $i$-th policy in the policy set $\pi_{0,i}$ during training, minimize the following loss function:

\[ L(\theta_i) = E_{(s,a) \sim D} \left[ \frac{1}{2} (\pi_{\theta_i}(s|a_i) - a_i)^2 \right], \]
The resulting action pair \( <s, a> \) is used as a sample of the fake dataset. The real data comes from the demonstration of expert data.

The training objective of the discriminator is the maximization of equation (5), the training objective of the generator is the maximization of equation (6), and the parameter update process is marked by the dotted line in Figure 3.

\[
L(D) = E_{s \sim \text{Real Data}} [\log(1 - D(s, a))] + E_{(s, a) \sim \text{Fake Data}} [\log D(s, a)],
\]

\[
L(G) = E_{s \sim \text{history states set}} [D(s, G(s, z))].
\]

2.3. Summary of Algorithm. According to the description above, the algorithm is summarized as shown in Algorithm 1. After the training, the algorithm outputs the discriminator \( D_w \) and the policy set \( \{\pi_1, \pi_2, \ldots, \pi_K\} \). In actual use, at every moment \( t \), the state \( s \) is obtained from the real system, and the action candidate set \( A = \{a_1, a_2^*, \ldots, a_K^*\} \) is obtained after the policy set is processed. The discriminator \( D_w \) is used as a selector to obtain the score vector, \( V = \{D_{a_1}(s, a_1), D_{a_2}(s, a_1^*), \ldots, D_{a_K}(s, a_1^*)\} \), and output action, action = \( A \cdot e^V/\sum_{k=1}^{K} e^{D_{a_k}(s, a_k)} \). These are submitted to the real system for execution, and closed-loop control is formed over and over again. The process is shown in Figure 1.

3. Experiments and Results

Cubli is a 15 cm × 15 cm × 15 cm cube. Momentum wheels are arranged on the three planes of the cube. It is a typical nonlinear, unstable, and multidegree-of-freedom control system. The rotation of the motor drives the flywheel to produce momentum changes. Momentum is transferred between the flywheel and the body to control the posture. Cubli is shown in Figure 4.

Inverted pendulum has been used to verify control theory for a long time [19, 20]. Chaturvedi et al. [21] pointed out that the three-dimensional inverted pendulum can be used as a simplified aircraft version to study control theory. As a reaction-wheel-based inverted pendulum, Cubli has the similar structure as a satellite and be used to verify the method proposed in the study.

Cubli is mainly composed of three brushless motors with encoders, three sets of brake devices, an MPU6050 digital motion processor, a main control chip STM32F103RCT6, and Raspberry Pi 4B. The STM32 and the Raspberry Pi were connected through a serial port. The onboard data was collected by STM32 through MPU6050 and submitted to the Raspberry Pi for processing through the serial port. The communication protocol sent by Cubli to the Raspberry Pi was floating-point data of the Euler angles (roll, yaw, and pitch), angular velocities (rotation rates around the \( x \), \( y \), and \( z \) axes), motor speeds (one for each of the three motors), and motor PWM values (one for each of the three motors). The first two data entries were read from the MPU6050 DMP register. As the calculation unit and control unit, the Raspberry Pi calculated the current actions (the PWM target values of the three motors) to be performed after obtaining the current

\[
\text{action} = A \cdot \frac{V}{\sum_{i=1}^{K} e^{D_{a_i}(s_a)}}.
\]
Cubli status information, which was sent to the Cubli main control chip and was executed by the motor after it was written into the register. The on-board data sampling interval time was 5 ms. The time to calculate the action through the Raspberry Pi was about 3 ms, and the time from acquiring the status to executing the action was about 8 ms, that is, the control frequency was 125 Hz.

The environment constructed in this paper was mainly used to achieve point balance on a corner, as shown in Figure 5. After turning Cubli to the side balancing state, the

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**Algorithm 1: GAN-based offline reinforcement learning method.**

Input: expert state-action trajectories \( \{ \tau_1, \tau_2, \cdots, \tau_K \} \), and the \( i \)th trajectory \( \tau_i = (s'_0, a'_0, s'_1, a'_1, \cdots, s'_H, a'_H) \)'s length is \( H \).

Initialize policy set \( \{ \pi_1, \pi_2, \cdots, \pi_K \} \) which size is \( K \), and the \( i \)th policy's parameter is \( \theta_i \).

Training set’s width is \( W \), and the overlap size between two adjacent training sets is \( S \).

Training data set \( D \) and parameter \( \theta \)

Output: trained discriminator \( D_{\text{real}} \) and policy set \( \{ \pi_1, \pi_2, \cdots, \pi_K \} \)

1: \textbf{for} \( i = 1 \) to \( K \) \textbf{do}
2: \hspace{1em} Initialize training set \( D \)
3: \hspace{1em} \textbf{for} \( j = 1 \) to \( N \) \textbf{do}
4: \hspace{2em} Collect state-action pairs from trajectory \( \tau_j = (s_0, a_0, s_1, a_1, \cdots, s_H, a_H) \), and save into training set \( D \).
5: \hspace{1em} \textbf{end for}
6: \hspace{1em} Train policy \( \pi_i \) with gradient descent to minimize the loss \( L(\theta_i) = -E_{(s,a)\sim D} [\log (\pi_{\theta_i}(a|s))] \)
7: \hspace{1em} \textbf{end for}
8: \textbf{for} \( k = 1 \) to \( \text{MAX} \) \textbf{do}
9: \hspace{1em} \textbf{for} \( i = 1 \) to \( M \) \textbf{do}
10: \hspace{2em} Sample state-action pairs \( (s_i, a_i) \) from expert state-action data, and save into real data set \( R \)
11: \hspace{2em} Sample states \( s_i \) from expert data, input the state into policy set, and get action vector \( A = \{ a'_1, a'_2, \cdots, a'_K \} \)
12: \hspace{2em} Calculate the score vector \( V = \{ D_a(s, a'_1), D_a(s, a'_2), \cdots, D_a(s, a'_K) \} \)
13: \hspace{2em} Calculate the action with \( a_{\text{fake}} = A \cdot e^V \sum_{i=1}^{K} (e_i^V) \)
14: \hspace{2em} Save \( (s_i, a_{\text{fake}}) \) into fake data set \( F \)
15: \hspace{2em} Save the action \( a_{\text{generated}} \) generated from generator \( (s_i, a_{\text{generated}}) \) into fake data set \( F \)
16: \hspace{1em} \textbf{end for}
17: \hspace{1em} Update the discriminator parameters with gradient ascent to maximize the function \( E_{(s,a)\sim D} [\log (D_a(s, a))] + E_{(s,a)\sim F} [\log (1 - D_a(s, a))]'s \text{ value} \)
18: \hspace{1em} Update the generator parameters with gradient ascent to maximize the function \( L(\phi) = E_{s\sim \pi} [\log (D_{\text{real}}(s, G_\phi(s, z)))] \)
19: \hspace{1em} \textbf{end for}

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**Figure 3: The architecture of policy selector based on GAN.**
momentum exchange between the body and the flywheel was implemented by controlling the rotation of the three flywheels to achieve the attitude movement. In the vicinity of the balance point, the angular momentum of the body was again reduced to close to 0 to implement the point balance control.

The current state of Cubli is represented as $s_t = [\phi, \theta, \varphi, \dot{x}, \dot{y}, \dot{z}, \text{Encoder}_A, \text{Encoder}_B, \text{Encoder}_C]^T$, where $\phi$, $\theta$, and $\varphi$ represent roll, pitch, and yaw, respectively; $\dot{x}$, $\dot{y}$, and $\dot{z}$ represent the angular velocities around the $x$, $y$, and $z$ axes, respectively; and $\text{Encoder}_A$, $\text{Encoder}_B$, and $\text{Encoder}_C$ represent the speed data of the devices on the three plane flywheels. The action is expressed as $a_t = [a_1, a_2, a_3]$, where $a_1$, $a_2$, and $a_3$ correspond to the PWM values of the three motor voltage signals that control the rotation of the motor.

The Euler angles and triaxial angular velocities in each state were directly measured by the onboard MPU6050 six-axis inertial measurement unit. $\text{Encoder}_A$, $\text{Encoder}_B$, and $\text{Encoder}_C$ were written into the main control chip by the encoder of the motor. The state was standardized, and the cosine and sine function values were used instead of the Euler angles. For the shaft angular velocity and motor speed, the measured data was obtained from the board and divided by the maximum value for normalization so that each state component was limited to the value range of $[-1, 1]$. Therefore, the actual state of use is expressed as follows:

$$s_t = \begin{bmatrix} \cos (\phi), \sin (\phi), \cos (\theta), \sin (\theta), \cos (\varphi), \sin (\varphi) \\ \dot{x} \quad \dot{y} \quad \dot{z} \quad \text{Encoder}_A \quad \text{Encoder}_B \quad \text{Encoder}_C \\ \text{MAX}_X' \quad \text{MAX}_Y' \quad \text{MAX}_Z' \quad \text{MAX_ENCODER}' \quad \text{MAX_ENCODER}' \quad \text{MAX_ENCODER}' \end{bmatrix}^T.$$

A fully connected neural network was used to represent the policy model. The neural network had three hidden layers, each with 128 neurons, initialized with random values for each parameter. A three-layer, fully connected neural network was used to represent the generative model and discrimination model in the policy selector. The specific neural network architecture, initialization parameters, learning method, sample batch number, and learning rate are shown in Table 1.

At the beginning of the experiment, the expert policy was deployed on Cubli and used to collect data for simulating to get control data on orbit, and 200 expert state-action pair trajectory data were collected, with 2000 steps per trajectory. This dataset was used to train the policy through behavior
cloning, and the same dataset was used to train the policy set and policy selector of the method proposed in this paper. The behavioral cloning method used 400,000 entries of the sample data of the entire training set for training a single policy, and the number of sample batches for each training process was 256. The training was performed in 1,562,500 times with the 400,000 samples. A policy set with a set number of seven was used, the 2000-step data of each trajectory was divided into seven training sets, and the number of steps in each training set was 290 steps. The number of overlapping steps in the training set used by the interval policy was five.

After the training, \( \pi_{\text{BC}} \) and \( \pi_{\text{OUR METHOD}} \) were deployed in the same real system to verify the effects of the two policies. Figure 6 shows that the policy trained using the behavioral cloning method could adjust Cubli to the equilibrium point at the beginning of the experiment so that the Cubli Euler angles, gyro values, PWM values, and encoder values were close to the desired values.

| Parameter | Behavioral cloning | Policy set | Policy selector (discriminator) | Generator |
|-----------|--------------------|------------|---------------------------------|-----------|
| Number of input layer units | 12 | 12 | 15 | 12 |
| Number of output layer units | 3 | 3 | 1 | 3 |
| Means of parameter initialization | Censored normal distribution randomly generated | Censored normal distribution randomly generated | Censored normal distribution randomly generated | Censored normal distribution randomly generated |
| Number of hidden layer units | 128 | 128 | 256 | 256 |
| Hidden layers | 3 | 3 | 3 | 3 |
| Optimization algorithm and learning rate | Adam/0.003 | Adam/0.003 | Adam/0.003 | Adam/0.003 |
| Number of batch samples | 256 | 64 | 256 | 64 |

**Table 1:** Parameter settings of policy, policy set, and policy selector.

![Figure 6: Experiment results: BC method was used. (a) Euler angles, (b) gyro value, (c) PWM value, and (d) encoder value.](image-url)
angle was close to 0. The three-axis angular velocities were nearly 0, which means a balance was maintained in the experiment of nearly 500 steps. However, after 500 steps, it gradually deviated from the balance point, which caused errors to accumulate and eventually resulted in the loss of balance.

The experimental results verify Ross’s conclusion that the accumulation of errors is proportional to the square of the number of steps. The test results using the method in this paper are shown in Figure 7. To better display the data, the entire record is not presented; only the first 10,000 steps in the trajectory are shown. This is sufficient to demonstrate the performance of the proposed method. The data of 10,000 steps shows the system adjusted from the initial state to the equilibrium point (the Euler angle error and angular velocity were close to 0), and the system remained near the equilibrium point. The PWM and flywheel speed values showed that Cubli was always relatively stable during operation, and the adjustment was maintained within a small range, achieving better performance.

Analysis of the results showed that the reason the proposed method achieved a better performance was that by dividing the expert trajectories, each policy in the policy set was trained for a different initial state set. Moreover, in actual use, the policy that is suitable for the current state is selected through the policy selector. Consequently, the probability of the same policy being used continuously is significantly reduced compared to the behavioral cloning method with only one policy, thereby reducing the cumulative error caused by using only one policy.

4. Conclusion

In this paper, a data-driven offline reinforcement learning method is proposed that can learn effective control policies in an attitude control system that uses momentum exchange as the actuator. The method learns a single policy from different stages by dividing the trajectories of experts, making it possible to select policies with fewer accumulated errors from the policy set based on the state. The method also adopts global data to train the policy selector. When deployed in the actual system, an effective policy is selected through the evaluation of the policy selector based on the current state. This yields a good performance for control over long time periods. Unlike previous works that verified algorithms in a simulation environment, the physical system constructed in this study was closer to a satellite attitude control system with momentum wheels as the actuators. The method also avoids

![Figure 7: Experiment results: our method. (a) Euler angles, (b) gyro value, (c) PWM value, and (d) encoder value.](image)
issues such as the safety of on-orbit training and real-time control, and thus, it is more suitable for actual application scenarios. The effectiveness of this method was verified in a real physical system. The offline reinforcement learning method proposed in the paper can use on-orbit data to improve the performance of the attitude control algorithm, while achieving three-axis synchronous control to meet the real-time requirements of attitude control for virtual reality satellite.

Despite the positive results of this study, the method proposed in this paper has the following problems that will be solved in future work. (1) Although the method achieves multiple-degree-of-freedom attitude synchronization control from the initial state to the equilibrium state on a real physical system, Cubli, because the Cubli physical system is affected by gravity, the selection of the target posture is relatively limited (close to the equilibrium point). In future work, it is necessary to combine Cubli and an air-floating platform to counteract the gravity to achieve a more gravity-free experimental environment on the ground. (2) The Cubli system in this study used a “single side–single flywheel–single motor” in the actuator. In future work, it is necessary to expand the actuator to “single-side–multiple flywheels–multiple motors” to meet the new requirements of software-defined satellites for redundant actuators.

**Data Availability**

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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