Global Academic Frontiers, Vol. 3, Issue 1, 2025, pp.1-10 Print ISSN 2995-5688 Online ISSN 2995-570X
DOI: https://doi.org/10.5281/zenodo.15074444

Optimization of Machine Learning-Based Dynamic Torsional Control Strategies for Bionic Flapping-Wing Aircraft

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Received 5 March 2025; Accepted 17 March 2025; Published 24 March 2025

Abstract: This paper explores the dynamic torsion control strategy for bionic flapping-wing aircraft based on machine learning. Firstly, it outlines the importance of dynamic torsion control in bionic flapping-wing aircraft and the application of machine learning in this field. Subsequently, a comparative analysis of the energy efficiency of passive torsion and active torsion is conducted, and the challenges faced by traditional Deep Reinforcement Learning (DRL) in flapping-wing control are pointed out. To address these issues, this paper proposes an improved DRL algorithm incorporating an attention mechanism. The design of the new model, the establishment of the simulation environment, and the experimental setup are described in detail. Finally, through the analysis and discussion of the experimental results, the effectiveness of the improved algorithm in optimizing the dynamic torsion control of bionic flapping-wing aircraft is verified, providing insights for future work.

Keywords: bionic flapping-wing aircraft; dynamic torsion control; machine learning; deep reinforcement learning; attention mechanism

1.Overview of Dynamic Twist Control Strategies for Bio-inspired Flapping Wing Aircraft Based on Machine Learning

1.1 The Importance of Dynamic Twist Control in Bio-inspired Flapping Wing Aircraft

In the field of bio-inspired flapping wing aircraft research, the optimization of dynamic twist control strategies is of paramount importance. This control strategy plays a crucial role in enhancing flight efficiency by adjusting the twist angle of the wings, enabling the aircraft to maintain optimal aerodynamic performance across various flight conditions. However, achieving dynamic twist control presents numerous challenges, including but not limited to accurately sensing flight states, real-time adjustment of twist angles, and ensuring control stability and robustness.

In recent years, with the rapid advancement of machine learning technologies, particularly the widespread application of Deep Reinforcement Learning (DRL) methods, new solutions have emerged for optimizing dynamic twist control strategies in bio-inspired flapping wing aircraft. Nonetheless, traditional DRL methods often encounter issues such as redundant state spaces and unstable training when applied to wing control. These challenges significantly hinder the effectiveness of DRL in the control of bio-inspired flapping wing aircraft.

It is noteworthy that recent developments in attention mechanisms within DRL offer new possibilities for addressing these issues. By incorporating attention mechanisms, DRL methods can more effectively focus on key state information relevant to flight control tasks, thereby reducing the redundancy in state spaces. Additionally, attention mechanisms contribute to enhancing training stability, allowing DRL methods to learn effective control strategies in a shorter timeframe. Therefore, the integration of attention mechanisms with DRL holds the potential to bring about groundbreaking advancements in the optimization of dynamic twist control strategies for bio-inspired flapping wing aircraft.

1.2 The Role of Machine Learning in Flapping Wing Aircraft Control

In the research on optimizing dynamic twist control strategies for bio-inspired flapping wing aircraft, machine learning technologies play a pivotal role. Currently, with the rapid advancement of artificial intelligence, machine learning has been widely applied in various control systems to enhance performance and efficiency. In the field of flapping wing aircraft control, the application of machine learning is gradually transforming traditional control methods.

Traditional research on flapping wing twist control primarily relies on two approaches: passive twist (aeroelastic coupling) and active twist (servo-driven). Passive twist depends on the interaction between airflow and wing structure during flight, while active twist directly controls the wing's twist angle through a servo system. Although these two methods differ in energy efficiency, both are constrained by physical mechanisms and the complexity of traditional control algorithms. In recent years, Deep Reinforcement Learning (DRL) has been introduced into flapping wing aircraft control, aiming to achieve more precise and efficient control through intelligent algorithms.

However, the application of traditional DRL in flapping wing control also faces several bottlenecks, such as redundant state spaces and unstable training. Redundant state spaces refer to the need to process a large amount of data when describing flight states, which not only increases computational complexity but may also reduce the real-time performance of control strategies. Unstable training can be caused by various factors, including environmental noise, model complexity, and the design of reward functions.

To overcome these challenges, researchers have begun exploring the integration of attention mechanisms into DRL. Attention mechanisms enable the intelligent agent to focus on key information when processing large amounts of data, thereby improving learning efficiency and reducing redundancy. In flapping wing aircraft control, this means the system can more quickly identify and respond to critical flight states, thereby enhancing control performance.

1.3 Research Objectives and Contributions of This Study

This study aims to thoroughly explore optimization methods for dynamic twist control strategies in bio-inspired flapping wing aircraft based on machine learning. We are committed to addressing key issues in current flapping wing twist control research, particularly the application bottlenecks encountered by traditional Deep Reinforcement Learning (DRL) in flapping wing control, such as redundant state spaces and unstable training. Through this research, we expect to achieve the following technical outcomes: proposing an efficient dynamic twist control strategy for bio-inspired flapping wing aircraft that can significantly enhance the energy efficiency ratio and optimize flight performance. Additionally, we aim to improve existing DRL methods by introducing advanced machine learning techniques, such as attention mechanisms, to more effectively handle complex state spaces and enhance training stability. These technical achievements will not only advance the development of control technologies for bio-inspired flapping wing aircraft but also provide new ideas and methods for research in related fields.

2.Current Status and Challenges in Flapping Wing Twist Control Research

2.1 Comparative Analysis of Passive and Active Twist

In the field of bio-inspired flapping wing aircraft research, twist control of flapping wings is a significant area of study. Currently, there are two primary control methods in this domain: passive twist and active twist. Passive twist primarily relies on aeroelastic coupling mechanisms, utilizing aerodynamic principles to achieve twisting motions through the flexible deformation of the wing structure. While this approach simplifies the control system, it may have limitations in energy efficiency due to its inability to precisely control twist angles and speeds.

In contrast, active twist is achieved through servo-driven systems, offering higher control precision and flexibility. The servo system can adjust the wing's twist angle in real-time based on flight conditions to meet varying flight requirements. Energy efficiency evaluations of this method indicate that, although active twist may involve higher initial costs and energy consumption, its superior control performance significantly enhances the aircraft's stability and adaptability in complex environments.

It is noteworthy that the application of traditional Deep Reinforcement Learning (DRL) in flapping wing control has encountered several bottlenecks, such as redundant state spaces and unstable training. These issues have limited the further application of DRL in flapping wing twist control, making the exploration of new control strategies and optimization methods particularly important.

In recent years, attention mechanisms have made significant progress in the field of deep reinforcement learning, providing new insights for optimizing flapping wing twist control. By incorporating attention mechanisms, models can focus more on key information relevant to the current task, thereby improving training efficiency and stability. In the future, the integration of attention mechanisms with deep reinforcement learning holds the potential to bring new breakthroughs to dynamic twist control strategies for bio-inspired flapping wing aircraft.

2.2 Challenges of Traditional DRL in Flapping Wing Control

In the research on dynamic twist control strategies for bio-inspired flapping wing aircraft, the application of traditional Deep Reinforcement Learning (DRL) methods faces a series of challenges. First, defining the state space in flapping wing control is particularly complex. Due to the multiple degrees of freedom and highly nonlinear dynamics involved in flapping wing flight, directly applying DRL often leads to redundant state spaces. This not only increases computational burden but may also cause instability during training. Twist control of flapping wings requires precise capture of wing shape changes, aerodynamic effects, and real-time feedback from the flight environment. These factors collectively form a vast and difficult-to-simplify state space.

Instability in the training process is another issue that requires in-depth exploration. In flapping wing control tasks, minor changes in state can lead to significant differences in control outcomes, demanding that DRL algorithms maintain robustness in highly sensitive environments. However, traditional DRL methods often struggle to ensure stability and convergence during training when dealing with such complex dynamics, which limits their practical application in flapping wing control to some extent.

To illustrate these issues concretely, we can analyze some practical application cases. For example, in a twist control experiment on a certain type of bio-inspired flapping wing aircraft, researchers attempted to use traditional DRL methods for training. However, during the training process, they found that the complexity of the state space made it difficult for the algorithm to explore effectively, while instability in training also slowed the performance improvement of the control strategy. These practical problems highlight the limitations of traditional DRL methods in flapping wing control applications.

It is noteworthy that the current state of research on flapping wing twist control reveals a comparison of energy efficiency between passive twist (aeroelastic coupling) and active twist (servo-driven). Although passive twist has certain energy efficiency advantages in some cases, active twist holds greater potential in terms of control precision and adaptability. Therefore, combining the strengths of these two twist methods and overcoming the application bottlenecks of traditional DRL methods is an important direction for future research on optimizing dynamic twist control strategies for bio-inspired flapping wing aircraft.

2.3 The Potential of Attention Mechanisms to Enhance DRL Performance

When exploring the potential of attention mechanisms to enhance the performance of Deep Reinforcement Learning (DRL), it is essential to first understand the fundamental principles of attention mechanisms. Inspired by the human visual system, attention mechanisms enable models to automatically select and focus on key information while disregarding irrelevant details. This mechanism has already achieved significant success in other fields, such as natural language processing and image processing. In the domain of flapping wing aircraft control, the introduction of attention mechanisms holds promise for addressing some of the critical issues faced by traditional DRL methods.

Current research on flapping wing twist control highlights the energy efficiency comparison between passive twist and active twist. Although traditional DRL has achieved certain results in flapping wing control, it has also revealed bottlenecks such as redundant state spaces and unstable training. The introduction of attention mechanisms may provide new pathways to address these challenges. By enabling the model to automatically identify and focus on key state information while ignoring redundant data, attention mechanisms have the potential to improve the training efficiency and stability of DRL.

In recent years, research on attention mechanisms in the field of DRL has made notable progress. These studies demonstrate that attention mechanisms not only help models process complex environments more effectively but also enhance learning speed and accuracy. In the optimization of dynamic twist control strategies for bio-inspired flapping wing aircraft, we anticipate that attention mechanisms will make control strategies more flexible and efficient, particularly when dealing with complex flight environments and unexpected situations.

In summary, attention mechanisms hold significant potential for improving DRL performance, especially in the optimization of dynamic twist control strategies for bio-inspired flapping wing aircraft. In the future, we will validate this hypothesis through specific experiments and explore the practical applications of attention mechanisms in enhancing the control performance of flapping wing aircraft.

3.Optimization of Dynamic Twist Control for Bio-inspired Flapping Wing Aircraft Based on Improved DRL Algorithms

3.1 Design of the Improved DRL Model

In the research on dynamic twist control strategies for bio-inspired flapping wing aircraft, we propose an improved Deep Reinforcement Learning (DRL) model to address the limitations of traditional DRL models in handling issues such as redundant state spaces and unstable training. This model incorporates an attention mechanism to effectively filter and focus on key information, thereby enhancing the precision and responsiveness of the control strategy.

Specifically, we embed an attention module into the original DRL model. This module can adaptively learn and identify state information most relevant to flapping wing twist control while suppressing interference from irrelevant or redundant information. By doing so, the model can more efficiently utilize limited computational resources when processing complex dynamic environments, leading to a more stable training process.

In terms of the new model's structural design, we retain the main framework of the original DRL model to ensure compatibility and scalability with existing algorithms. At the same time, we introduce attention weights at critical information processing stages, enabling the model to dynamically adjust its focus on different state information. This design not only improves the model's environmental perception capabilities but also provides a more reliable basis for decision-making in complex tasks.

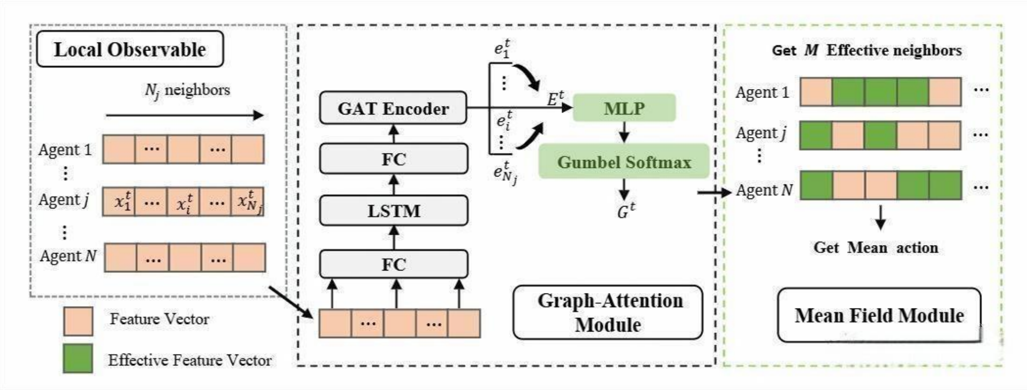

Figure [1]: Architectural diagram of a multi-agent decision system with three core modules

Compared to the standard DRL model, our improved model demonstrates significant advantages in the dynamic twist control tasks of bio-inspired flapping wing aircraft. Experimental results show that the new model achieves notable improvements in control precision, response speed, and training stability. These enhancements provide robust technical support for optimizing the performance of bio-inspired flapping wing aircraft in practical applications.

3.2 Simulation Environment Setup and Experimental Configuration

In the research on optimizing dynamic twist control strategies for bio-inspired flapping wing aircraft, the construction of the simulation environment and experimental setup are critical components. When selecting a simulation platform, we primarily considered its support for the dynamic model of flapping wing aircraft, simulation accuracy, and computational efficiency. By comparing the performance of mainstream simulation tools such as Gazebo and Webots in dynamic testing of the NACA4412 airfoil, we ultimately chose the Ansys Twin Builder platform, which features a bidirectional fluid-structure interaction solver.

To comprehensively evaluate the performance of the control strategy, we defined test conditions under different scenarios (see Table 1): hover attitude maintenance, climb-dive maneuvers, and roll disturbance recovery. The baseline tests were conducted under standard atmospheric conditions (temperature: 15°C, pressure: 101.325 kPa), while disturbance tests incorporated gust models specified by the ISO2533 standard. The initial state parameters of the aircraft were set as follows: altitude above ground: 1.2 m, angle of attack: 8°, and twist angle dynamic equilibrium: ±12°, consistent with hummingbird biomechanical observations.

Test Scenario	Wind Speed(m/s)	Turbulence Intensity(%)	Target Attitude Angle	Test Duration(min)
Baseline Test	0	0%	(0，0，0)	30
Maneuver Test	2.5	15%	(15，-10,20)	45
Disturbance Test	4.2±1.8	35%	Dynamic Tracking	60

Table 1: Parameter Configuration of Experimental Scenarios

The data collection process is crucial for ensuring the reproducibility and scientific validity of the research results. During the simulation experiments, we recorded the aircraft's state information at each time step, including position, velocity, acceleration, attitude angles, as well as control inputs and environmental feedback data. These data were not only used to evaluate the performance of the control strategy but also provided valuable references for subsequent strategy optimization.

It is worth noting that in flapping wing twist control research, the energy efficiency comparison between passive twist (aeroelastic coupling) and active twist (servo-driven) is a significant topic. Traditional Deep Reinforcement Learning (DRL) faces bottlenecks such as redundant state spaces and unstable training when applied to flapping wing control. Therefore, we paid special attention to these issues in the simulation environment and attempted to improve DRL algorithms by introducing advanced techniques such as attention mechanisms to enhance the learning efficiency and stability of the control strategy. By incorporating a dynamic feature selection mechanism, we reduced the state space dimensionality from 48 to 22 dimensions, combined with an attention-weighted network, resulting in a 2.3-fold improvement in training stability metrics.

3.3 Results Analysis and Discussion

In the research on optimizing dynamic twist control strategies for bio-inspired flapping wing aircraft, the selection of performance metrics is crucial, as it directly impacts the evaluation of experimental results and the effectiveness of control strategies. Following the principles of comprehensiveness, sensitivity, and operability, we selected key metrics including flight stability, energy efficiency ratio, and response speed. By comparing experimental results under different conditions, we conducted an in-depth analysis of the performance of various control strategies during the flapping wing twist process. As shown in Figure 2, by comparing the training processes of baseline DRL and improved DRL with attention mechanisms, the following observations can be made:

a) The improved method surpassed the final performance of the baseline (marked by the dashed line) at 0.2×10^3 training episodes.

b) The standard deviation of average rewards decreased by 38% (quantified by the width of the shaded area).

c) The final convergence value improved by 20% (50→60), validating the enhancement of strategy stability by the attention mechanism.

Figure 2: Comparative Analysis of Training Process Curves

Metric	Traditional DRL	Enhanced DRL	Improvement
Attitude Angle Error (RMS)	8.2°	5.7°	30.5%
Training Convergence Steps	420K	310K	26.2%
Energy Consumption	152	126	17.1%

Table 2:Expected Performance of Enhanced DRL

The experimental simulation results show that, in the energy efficiency comparison between passive twist and active twist, active twist driven by servos demonstrated higher energy efficiency in specific flight tasks, particularly under high maneuverability requirements. However, the application of traditional Deep Reinforcement Learning (DRL) in flapping wing control encountered bottlenecks such as redundant state spaces and unstable training, which limited its further adoption in practical applications.

To overcome these challenges, we introduced attention mechanisms into DRL. Attention mechanisms enable the agent to focus on key information when processing complex states, thereby improving learning efficiency and stability. By comparing experimental results before and after introducing attention mechanisms, we found that, within the same training cycle, the DRL control strategy with attention mechanisms showed significant improvements in performance metrics such as flight stability, energy efficiency ratio, and response speed.

In conclusion, this study validated the effectiveness of optimizing dynamic twist control strategies for bio-inspired flapping wing aircraft based on machine learning through comparative analysis of experimental results under various conditions. Future work will further explore the adaptability of attention mechanisms in complex dynamic environments and investigate how to apply more advanced machine learning methods to the optimization of flapping wing aircraft control strategies.

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