Airfoil Optimization with Q-Learning and Genetic Algorithms

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I. Problem Statement

AIRFOIL shape optimization is a fundamental challenge in aerodynamics due to the nonlinear and high-dimensional characteristics of fluid mechanics. The goal is to design two-dimensional airfoil shapes that maximize desirable aerodynamic metrics such as lift-to-drag ratio while minimizing penalties such as excessive drag. Traditional optimization methods, including gradient-based algorithms, genetic algorithms, and particle swarm optimization, have achieved varying degrees of success. However, these approaches are often computationally expensive when coupled with high-fidelity solvers, prone to convergence on local optima, and data-inefficient in that they do not build on prior evaluations to guide future optimization.

Geometric parameterization adds another layer of complexity. While classical families like the NACA 4-digit series provide simplicity, they confine optimization to a limited design space. Bézier curves, by contrast, provide a flexible and smooth representation of airfoil geometries, allowing for localized and interpretable shape modifications. This flexibility introduces a richer search space but also necessitates an optimization method capable of navigating it effectively.

Reinforcement learning (RL) is particularly well suited to this problem because it frames airfoil optimization as a sequential decision-making process. An RL agent can iteratively modify control points of a Bézier curve, evaluate aerodynamic performance using a solver, and use feedback to refine its policy. Unlike supervised learning, RL does not depend on pre-existing datasets that might bias outcomes or limit generative potential. Instead, it learns from direct interaction with the environment, building knowledge through trial and error. RL also naturally accommodates continuous action spaces, which is essential for smooth geometric modifications in Bézier curve parameterizations.

II. Motivation

Reducing aerodynamic drag and increasing efficiency are critical for improving aircraft performance and sustainability. Studies estimate that reducing drag can cut fuel burn by up to 20 to 25 percent, with substantial implications for both cost savings and carbon emissions in the aviation industry. In the context of the global push for sustainable aviation, efficient airfoil optimization is both timely and impactful.

Beyond aviation, efficient aerodynamic design benefits renewable energy systems such as wind turbines, where optimized blade profiles can significantly enhance power generation. The relevance of airfoil optimization therefore extends across multiple sectors where fluid–structure interactions play a central role.

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A. Learning Objectives

1) Environment Development: Develop a reinforcement learning environment that parameterizes airfoil geometry using Bézier curves.

2) Training RL Agents: Train an RL agent to optimize airfoil shapes under different aerodynamic objectives, including maximizing lift-to-drag ratio, maximizing lift coefficient, and minimizing drag coefficient.

3) Performance Benchmarking: Evaluate the efficiency of reinforcement learning compared to traditional optimization methods, focusing on convergence speed and solution quality.

4) Exploring Properties of RL: Explore the generative capabilities of RL in producing unconventional but high-performing geometries that may not emerge from traditional approaches.

III. Environment Details

A. State Space

The state space consists of the control points defining the Bézier curves that parameterize the airfoil geometry. Each state is a vector of coordinates describing the current airfoil shape. In addition, the state may include previously computed aerodynamic performance metrics such as lift and drag to provide richer context to the agent.

B. Action Space

The action space is continuous, reflecting the agent's ability to make small adjustments to the control points. At each step, the agent selects a control point along the chord line and applies a continuous displacement in the vertical direction. This action directly modifies local thickness or camber of the airfoil. Constraints will be applied to ensure physical plausibility, such as preventing self-intersecting curves or excessively thin trailing edges.

C. Reward Function

The reward function is tied to the optimization objective. For lift-to-drag maximization, the reward is defined as the change in L/D between the current and previous shape. Positive rewards encourage modifications that improve efficiency, while negative rewards penalize regressions. For objectives such as minimizing drag coefficient or maximizing lift coefficient, the reward will be adjusted accordingly. Solver failures due to unrealistic shapes will return large negative rewards, discouraging the agent from exploring impractical regions of the design space.

IV. Proposed Approach

A. Algorithms

1) Q-Learning: A fundamental value-based algorithm that estimates the expected cumulative reward for each state–action pair. To apply Q-Learning, the continuous action space of Bézier control point adjustments will be discretized into a finite set of possible movements. This approach provides a clear baseline for comparison and builds intuition for how reinforcement learning interacts with aerodynamic optimization.

2) Genetic Algorithm (GA): A population-based optimization method inspired by natural evolution. GA evolves airfoil shapes over generations through crossover, mutation, and selection. It has been widely used in aerodynamic optimization and serves as a strong baseline for evaluating the effectiveness of reinforcement learning approaches.

B. Implementation Plan

1) Airfoil Representation: Implement composite Bézier curves to represent airfoil shapes, starting with approximately 10 to 12 control points for balance between flexibility and stability.

2) Environment Construction: Build a custom RL environment in Python following the OpenAI Gym interface. The environment will integrate with XFOIL to compute aerodynamic metrics from generated airfoils.

3) Agent Integration: Implement Q-Learning with discretized control point actions. In parallel, implement a GA framework to optimize Bézier control points through population-based search.

4) Testing and Robustness: Compare the results of Q-Learning and GA, evaluating their convergence speed, quality of final solutions, and robustness when starting from symmetric, high-performance, and low-performance initial shapes.

V. Evaluation Metrics

A. Performance Measures

Performance will be measured by key aerodynamic metrics, including maximum achievable lift-to-drag ratio, maximum lift coefficient, and minimum drag coefficient. Learning curves showing progression of these metrics across training episodes will be analyzed to track the agent's improvement.

B. Success Criteria

1) Repeatability: Consistently improves airfoil performance compared to the initial baseline shape.

2) Benchmarking: Produces results comparable to or better than traditional optimization methods in terms of both performance and computational cost.

3) Convergence: Demonstrates robustness by converging on high-performing geometries from a variety of initial conditions.

4) Applicability: Generates airfoils with physical realism and identifiable aerodynamic features consistent with known high-performance designs.

VI. Preliminary Results

As a baseline, NACA 4-digit airfoil shapes will be simulated using XFOIL. These shapes typically exhibit modest lift-to-drag ratios under the chosen flow conditions, providing a clear benchmark for improvements achieved through reinforcement learning.

Preliminary studies in related research show that RL agents trained on parametric airfoil environments can reproduce geometric features of known high-performance designs. Bézier parameterizations with 10 to 12 control points have been shown to yield stable solver convergence and allow agents to achieve lift-to-drag ratios exceeding 100 within a few thousand training iterations. Similar behavior is expected by this implementation, with the agent learning to produce shapes with higher camber near the leading edge and drooped trailing edges, characteristics commonly associated with efficient airfoils.

References

[1] O. J. P. F. D. N. M. Thomas P. Dussauge, Woong Je Sung, "A reinforcement learning approach to airfoil shape optimization," *Scientific Reports*, 2023.

[2] A. N. Amanda Lampton and J. Valasek, "Reinforcement learning of morphing airfoils with aerodynamic and structural effects," *Aerospace Computing, Information, and Communication*, 2012.

[3] A. N. Dev Rajnarayan and J. Mehr, "Universal airfoil parametrization using b-splines," *Faculty Publications*, 2018.

[1] [2] [3]