
A Reinforcement Learning Approach to Optimizing Autonomous Kite-Powered Vessel Control

A Novel Approach

By

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ABSTRACT

Here goes the abstract

DEDICATION AND ACKNOWLEDGEMENTS

Here goes the dedication.

AUTHOR'S DECLARATION

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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INTRODUCTION AND MOTIVATION

Maritime travel has been a cornerstone of human civilization, facilitating the exchange of goods, ideas, and cultures across vast expanses of water. The annals of history are replete with instances of seafaring civilizations harnessing the power of wind to propel their vessels across the oceans. It is posited that ancient Neanderthals embarked on maritime voyages in the southern Ionian Islands between 110 to 35ka BP [1]. The quintessence of maritime travel has predominantly been wind-powered sails, which remained unchallenged until the industrial revolution ushered in the era of fuel-powered engines.

The art and science of sailing have evolved significantly over millennia, from rudimentary rafts and canoes to sophisticated sailing ships with complex rigging systems. Ancient civilizations, including the Egyptians, Phoenicians, and Polynesians, made remarkable advancements in sailing technology, enabling them to explore and trade over larger swathes of the ocean [2]. The medieval period saw the advent of the compass and the astrolabe, which further facilitated maritime navigation and exploration. The Age of Discovery, epitomized by the voyages of Columbus, Vasco da Gama, and Magellan, was propelled by advancements in sailing technology, which enabled transoceanic voyages and the establishment of maritime empires.

The industrial revolution in the 18th and 19th centuries marked a significant turning point in maritime propulsion. The invention of the steam engine heralded the decline of wind-powered sailing and the ascendancy of fuel-powered propulsion systems. Steamships and later, diesel-powered ships, offered greater reliability, speed, and capacity compared to their wind-powered predecessors, thus becoming the preferred mode of maritime transportation [3]. The transition to fuel-powered engines also mirrored the broader industrial and technological advancements of the era, which prioritized speed and efficiency over traditional methods.

1.0.1 A Renewed Interest in Wind Propulsion

However, the environmental costs of fuel-powered maritime transportation have become increasingly apparent in the modern era. The shipping industry is a notable contributor to global carbon emissions, and the deleterious effects of pollution on marine ecosystems are well-documented [4]. These challenges have rekindled interest in wind propulsion as a sustainable alternative, prompting a re-examination of the principles that guided ancient and medieval sailors. The modern iteration of wind propulsion seeks to amalgamate the age-old wisdom of harnessing wind power with contemporary technological advancements to create eco-friendly and efficient maritime transportation systems.

Contemporary wind propulsion technologies like Flettner rotors, wing sails, and kite systems are being revisited to mitigate the environmental impact of maritime travel [3]. Among these, kite-powered vessel technology stands out due to its potential for higher efficiency and lower operational costs. Kites offer two main advantages over traditional sails: they can move relative to the vessel and can be flown at higher altitudes, accessing different wind systems.

The relative movement of kites generates apparent wind, allowing for maximum potential force even when the vessel is stationary. This enhanced apparent wind results in a larger force compared to a sail of equivalent area. Flying kites at higher altitudes taps into stronger and more consistent wind currents, making wind a more reliable energy source for propulsion [6].

However, the effective operation of kite-powered vessels requires precise control, which is skill-intensive. To leverage the full benefits of kites as a scalable propulsion method, implementing autonomous control is crucial.

1.0.2 Reinforcement Learning for Autonomous Control

Reinforcement Learning (RL), a subset of artificial intelligence, presents a compelling avenue for optimizing the autonomous control of kite-powered vessels. The paradigm of RL, predicated on the principles of learning from interaction with the environment, holds promise for devising sophisticated control strategies that can significantly enhance the energy efficiency and operational efficacy of kite-powered vessels [4].

Talk about what we are going to investigate in the paper

Aims and Objectives

Overall aim : Develop a RL algorithm for autonomous control of kite-powered vessels

Along the way:

BACKGROUND

This chapter delves into the application of machine learning in sailboat control, with a particular emphasis on utilizing kites as a means of propulsion. The exploration of kite-powered vessel technologies presents a novel avenue to enhance the efficiency of sailboats, transcending the limitations inherent in traditional sail systems. The fusion of machine learning, specifically Reinforcement Learning (RL), with kite propulsion systems, opens up a realm of possibilities for autonomous sailboat control, optimizing the harnessing of wind power in a dynamic and adaptive manner. Through a meticulous review of existing technologies, RL principles, and related work in this domain, this chapter aims to lay a solid foundation for the ensuing discussion on the proposed RL approach to optimizing the autonomous control of kite-powered boats.

The subsequent sections will provide an in-depth examination of kite-powered vessel technologies, introduce the core concepts of RL, discuss relevant literature, identify gaps in current research, and highlight the novelty and potential contributions of the proposed work.

2.1 Reinforcement Learning (RL)

2.1.1 Introduction to RL

2.1.2 Application of RL

2.2 Related Work

2.2.1 Autonomous Control of Kite-Powered Vessels

2.2.2 Limitations and Challenges

METHODOLOGY

This section will investigate the approach taken to create an autonomous kite-powered vessel. - We need a physics engine -we need to model a boat so that it behaves with realistic movements - need to be able to run machine learning in the physics simulations

3.1 A Simulation Environment

In the endeavor to establish a robust and realistic simulation environment, that would act as that platform for training a reinforcement learning model, an appropriate simulation environment had to be chosen.

3.2 Training Environment

Unity has a comprehensive physics engine built in, it allows for easy creation of mesh bodies and colliders, rigid bodies and configurable joints. These would all come in very handy in while trying to model the complex system of a kite-boat, significantly reducing the development time while still maintaining a complex and realistic system. Another feature of the game engine that became the starting point for the physics model was the Unity HDRP Water System 16.0.3 [cite], that is available in the latest beta version Unity 2023.2.0b9 [cite]. The first steps to creating a comprehensive model ready for training is to model Buoyancy and a rudder, making a controllable playable boat.

3.2.1 Buoyancy

To model buoyancy accurately, first the maths had to be reviewed. When a body is submerged in a fluid the fluid exerts a force on the surface of the body, due to the pressure in the fluid. Archimedes Principal states that "The upward buoyant force that is exerted on a body immersed in a fluid, whether partially or fully submerged, is equal to the weight of the fluid that the body displaces and acts in the upward direction at the center of mass of the displaced fluid", shown in equation 3.1. In order to model the buoyancy of a complex object, such as a boat hull, the 'amount' of boat below the water needed to be calculated. In Unity the boat hull was a 'mesh' with a 'mesh collider' attached to it, this was incredibly helpful as it takes on the complex challenge of splitting the surface of the hull into many small triangles or Voxels

$$(3.1) \quad F_B = \rho_w g V$$

The total Archimedes force (AF) of the entire boat was calculated using equation 3.1, followed by a local AF at each Voxel. The water level, y component, was then computed at each voxel's (x,z) coordinates to determine if it was above or below the surface. If below the surface the component of the AF was applied vertically at each voxel.

3.2.2 Rudder

The rudder was created as a rigid body and modeled as a simple symmetric foil using the force diagram in figure 3.1. The lift and drag forces were calculated using equations 3.2 and 3.3, where C_l is the lift coefficient, C_d is the drag coefficient, A is the sing surface area, V is the velocity of the water and ρ is the density of the water.

$$(3.2) \quad L = C_l A \rho \frac{V^2}{2}$$

$$(3.3) \quad D = C_d A \rho \frac{V^2}{2}$$

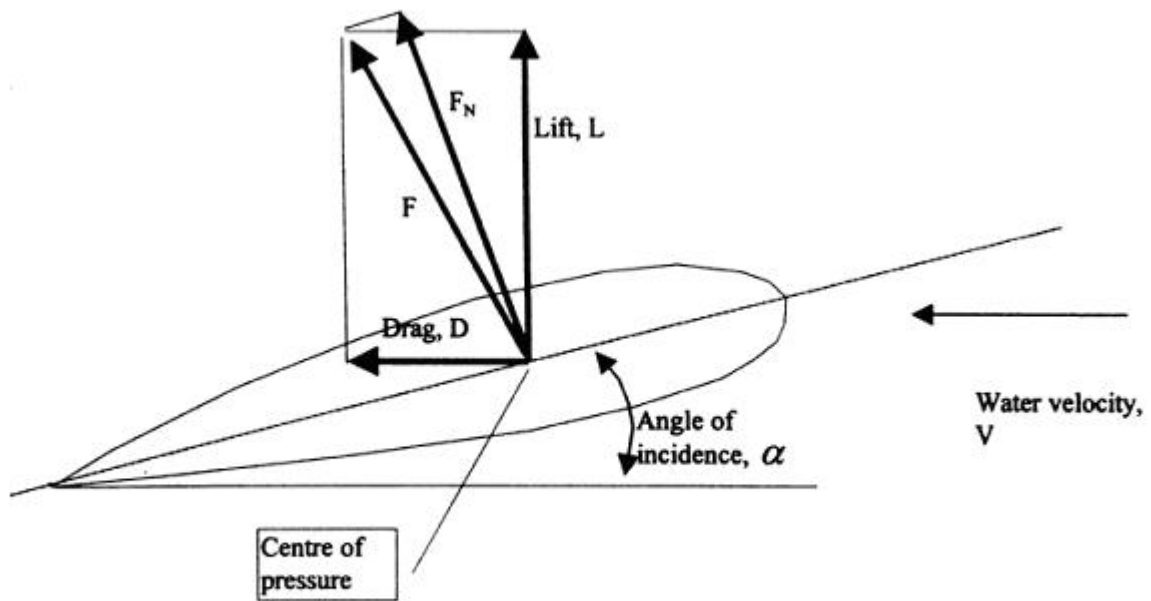


Figure 3.1: Force Diagram of a boat rudder

3.2.3 Course Generation

3.2.4 Mark Roundings

3.3 MLAgents

3.4 The Boat Agent

3.5 Initial Training

3.6 Optimization

APPENDIX



APPENDIX A

Begins an appendix

BIBLIOGRAPHY