CITY UNIVERSITY LONDON

Project Proposal for MSc in Artificial Intelligence

Name: Laerte Adami
E-mail address: laerte.adami@city.ac.uk
Project Title: Aerodynamic control via Deep Reinforcement Learning
Supervisor: Michael Garcia Ortiz

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1 Introduction

The aim of this work is to extend the capabilities of applying reinforcement learning techniques to fluid dynamics. The domain of the problem will be a wing section immersed in a current at a given angle of attack. On the back of the airfoil will be hinged a moving surface whose movement is controlled by a reinforcement learning algorithm. This control will be aimed at optimising the aerodynamic performance of the wing section. The fluid-dynamic environment will be simulated with an aerodynamic solver in order to create a realistic simulation framework.

The products of this study can therefore be listed as:

- a greater understanding and analysis of the usefulness of new control logic for improving the aerodynamic performance of a wing;
- the development of a control logic tested using an aerodynamic simulator;
- an assessment of the feasibility and importance that this study could have in extending the field of action of artificial intelligence techniques to the field of fluid dynamics.

2 Critical Context

The combination of artificial intelligence and fluid dynamics is an area that has only recently gained interest, despite its many possible applications and great potential [3].

In particular, the most popular and promising developments concern flow control, i.e. the practice of controlling a body (such as a wing or a structure) through direct action on the fluid in which it is immersed, or shape optimisation, i.e. the optimisation of an aerofoil shape to enhance the aerodynamic performances.

Focusing on the problem of control, a passive flow control device (flap) inspired by self-actuating covert feathers of birds has been shown to improve lift [4]. This lift improvement, tested through numerical analysis, is explained by the step in the pressure distribution (or pressure coefficient as shown in figure 1), over the airfoil [2].

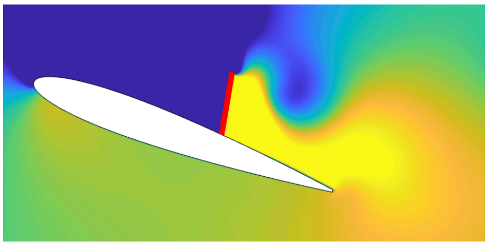

Figure 1: Pressure coefficient over bio-inspired flap (in red) [4]

The approach proposed by [4] presents a step forward. In this case, the bio-inspired flap is no longer passive but connected with a control logic developed with a deep reinforcement learning algorithm.

Deep reinforcement learning (DRL) has recently been adopted in a wide range of physics and engineering domains for its ability to solve decision-making problems that were previously out of reach due to a combination of non-linearity and high dimensionality [8].

A major advantage of DRL is that it can be used as an agnostic tool for control and optimization tasks, both in continuous and discrete contexts. Its only requirement is a well-defined interface from the environment, which can consist of a numerical simulation or a real-life experiment [3].

Among the several AI technologies, Reinforcement Learning proved to be effective in learning a control strategy by trial-and-error via stochastic agent-environment interactions [8]. In particular, Proximal Policy Optimization (PPO) has been used successfully to develop RL controllers for fluid flows [5], and has been chosen in previous studies among other policy-based methods due to its relative simplicity in implementation, better sample efficiency, and ease of hyperparameter tuning [6].

This scenario will be the starting point of the proposed project, aiming for improved control algorithms via deep reinforcement learning.

3 Approaches: Methods and Tools for Design, Analysis and Evaluation

The proposed methodology to complete this project will consist of several steps as follows:

- Research and design
- Aerodynamic solver discovery
- Systems coupling
- Reinforcement learning development
- Integrated systems training and testing
- Integrated systems evaluation
- Results presentation

3.1 Research and design

An initial research and development phase will be necessary for an in-depth analysis of the literature and to consolidate the planning of subsequent activities. In this phase, it will be possible to make a more accurate estimate of workload management and, above all, to try to intercept possible risks and problems in advance for prompt resolution.

3.2 Aerodynamic solver discovery

This phase will be an actual discovery of the aerodynamic solver. The key part will be to evaluate the software and, if it does not fit the requirements, to find another one that is compatible. Therefore, the objective of this phase will be to obtain a stable aerodynamic solver, the functionality of which has been proven by a software test phase. In this case, having assessed the feasibility at an early stage, the occurrence of an incompatibility finding during the ongoing project is avoided.

A first proposal, for the purpose of this project, is the open-source software turleFSI (`https://github.com/KVSlab/turtleFSI`) [1]. This software is based on the concept of fluid-structure interaction (FSI) which couples computational fluid mechanics (CFD) and computational structural mechanics (CSM). This will be the effectual backbone on which the analysis of artificial intelligence algorithms will be based for subsequent control.

Generally, CFD and CSM are individually well numerically resolved. FSI introduces a layer of complexity tracking of the interface separating the fluid and solid domains. Both mechanics are treated with separate governing equations of the individual fluid and structure problem, together with unique auxiliary kinematic, dynamic, and material relations [7].

Another possible candidate as aerodynamic solver can be the open-source CFD software OpenFoam (https://openfoam.org/).

Phase output: A working and tested aerodynamic solver with the geometry of interest, ready for subsequent integration with the control logic

3.3 Systems coupling

Once the aerodynamic representation of the environment is developed and tested, it will be possible to integrate it with the deep reinforcement learning control logic framework to get a single system.

A descriptive diagram of this coupling is shown in figure 2 with the control part on the left and the aerodynamic model part on the right.

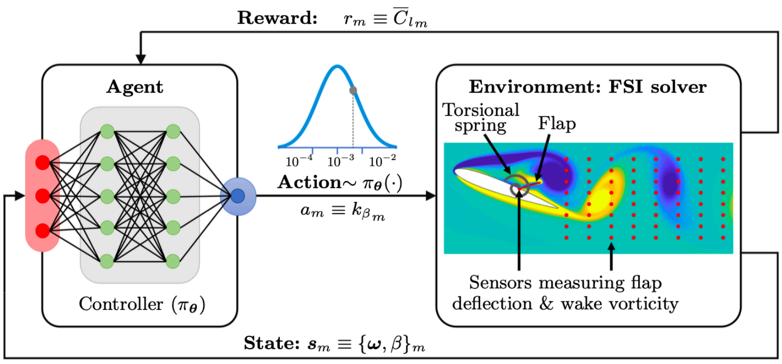

Figure 2: Coupled systems [4]

Operationally, this task could be achieved by employing Gymnasium (cf. https://pypi.org/project/gymnasium/), a tool that provides an API to communicate between learning algorithms and environments.

Phase output: A functional framework consisting of the coupling of control logic via deep reinforcement learning and the aerodynamic solver

3.4 Reinforcement learning development

This will be the core phase of the project, the one that will aim to contribute the most innovation.

This step consists of three distinct but interconnected moments: a research and in-depth reinforcement learning phase aimed at identifying one or more possible algorithms useful for control logic, an algorithm development phase and an algorithm testing phase.

At this stage, a thorough study of the available literature will be important in order to know the state of the art and thus identify the most viable possibilities for innovation. The literature on reinforcement learning is rich, providing a wide choice of algorithms.

With regard to flow control, the main algorithms implemented, also in different scenarios, are deep Q-learning (DQN), asynchronous DQN, trust region policy optimisation (TRPO), asynchronous actor-critic methods (A3C) and PPO [3].

At this stage, the use of a new algorithm for these topics or the enhancement of an already used algorithm application will be evaluated.

Phase output: At least one deep reinforcement learning algorithm developed and running, ready for subsequent training and testing with the coupled aerodynamic solver

3.5 Integrated systems training and testing

Once the framework is functional, the actual training phase of the deep reinforcement learning algorithm in the scenario coupled with the aerodynamic solver begins. It is only at this stage that the performance of the system will actually become clear and the feasibility of the required learning algorithm can be assessed. The training phase is followed by a testing phase of the resulting system. It is then at this stage that it will be possible to begin an evaluation, mostly numerical, of the results obtained.

However, it should be noted that the training and testing phases will be part of a larger cyclic process in which several configurations will be tried in order to achieve the best possible design of the control logic. This phase will cover an extended period of time in order to reduce the causes of any problems not considered in the risk assessment.

Phase output: A trained and tested control law via deep reinforcement learning which allows aerodynamic improvements

3.6 Integrated systems evaluation

Once the numerical development phase of the solution has been completed, a physical interpretation phase of the results can be developed. This may allow a deeper explanation of the results, analysing the aerodynamic motivations behind the performance improvement enabled by the control law.

It is important to note that this phase is temporally at the end of the code testing phase, but it is possible that at certain times it may take place in parallel. In fact, anticipating the aerodynamic understanding may help to more correctly evaluate the results produced, if not in numerical terms, at least in physical terms.

Operationally, this step will be carried out by analysing the temporal and spatial trends of the calculated aerodynamic quantities (such as vorticity, circulation or lift coefficient) of the aerodynamic solver.

3.7 Results presentation

This final part will consist of the collection of all the material developed over previous months. It should be noted that the collection will take place in parallel with all the stages described above. However, it is only in this final phase that, once the numerical and experimental part has been completed, it will be possible to proceed with the organisation of what has been developed. The final output will be the report ready for final submission.

4 Work Plan

Figure 3 shows the work plan with the steps required to complete the work.

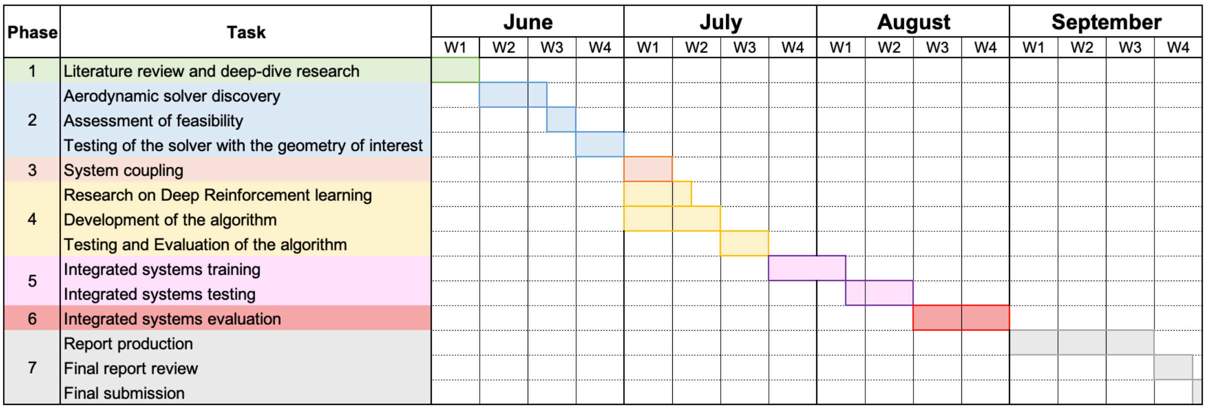

Figure 3: Work plan

5 Risks

The risk register in table 1 documents risks, their likelihood and severity, and procedures that will be put in place to mitigate them and recover in case of occurrence.

Risk description	Likelihood (1-3)	Severity (1-3)	Risk (LxS)	Mitigation actions
The aerodynamic solver is too complex to be implemented	1	3	3	Identify and test the suitability of another open-source aerodynamic solver
The aerodynamic solver is not suitable for the problem	2	3	6	Identify and test the suitability of another open-source aerodynamic solver
There is a problem with the mesh of the airfoil	3	2	6	Implement another mesh or, in the worst case, change the airfoil
The RL algorithm doesn't perform as expected	2	1	2	Try another algorithm following verification of compatibility
The RL algorithm is found to be not suitable	2	2	4	Try another algorithm following verification of compatibility
The integrated system doesn't train properly	2	1	2	Perform an in-depth analysis on the system parameters to assess what can be changed
The trained system produces unexpected results	1	2	2	Invest some time in understanding the physical meaning behind and evaluating the correctness
The HPC cluster doesn't work	1	3	3	Use another computing facility

Table 1: Risk register

6 Research Ethics Review Form: BSc, MSc and MA Projects

Computer Science Research Ethics Committee (CSREC)

http://www.city.ac.uk/department-computer-science/research-ethics

Undergraduate and postgraduate students undertaking their final project in the Department of Computer Science are required to consider the ethics of their project work and to ensure that it complies with research ethics guidelines. In some cases, a project will need approval from an ethics committee before it can proceed. Usually, but not always, this will be because the student is involving other people ("participants") in the project.

In order to ensure that appropriate consideration is given to ethical issues, all students must complete this form and attach it to their project proposal document. There are two parts:

PART A: Ethics Checklist. All students must complete this part.
The checklist identifies whether the project requires ethical approval and, if so, where to apply for approval.

PART B: Ethics Proportionate Review Form*.* Students who have answered "no" to all questions in A1, A2 and A3 and "yes" to question 4 in A4 in the ethics checklist must complete this part. The project supervisor has delegated authority to provide approval in such cases that are considered to involve MINIMAL risk.
The approval may be ***provisional*** – *identifying the planned research as* likely to involve MINIMAL RISK.
In such cases you must additionally seek ***full approval*** from the supervisor as the project progresses and details are established. ***Full approval*** must be acquired in writing, before beginning the planned research.

A.1 If you answer YES to any of the questions in this block, you must apply to an appropriate external ethics committee for approval and log this approval as an External Application through Research Ethics Online - https://ethics.city.ac.uk/		
1.1	Does your research require approval from the National Research Ethics Service (NRES)?	**NO**
1.2	Will you recruit participants who fall under the auspices of the Mental Capacity Act?	**NO**
1.3	Will you recruit any participants who are currently under the auspices of the Criminal Justice System, for example, but not limited to, people on remand, prisoners and those on probation?	**NO**
A.2 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee, you must apply for approval from the Senate Research Ethics Committee (SREC) through Research Ethics Online - https://ethics.city.ac.uk/		
2.1	Does your research involve participants who are unable to give informed consent?	**NO**
2.2	Is there a risk that your research might lead to disclosures from participants concerning their involvement in illegal activities?	**NO**
2.3	Is there a risk that obscene and or illegal material may need to be accessed for your research study (including online content and other material)?	**NO**
2.4	Does your project involve participants disclosing information about special category or sensitive subjects?	**NO**
2.5	Does your research involve you travelling to another country outside of the UK, where the Foreign & Commonwealth Office has issued a travel warning that affects the area in which you will study?	**NO**

2.6	Does your research involve invasive or intrusive procedures?	**NO**
2.7	Does your research involve animals?	**NO**
2.8	Does your research involve the administration of drugs, placebos or other substances to study participants?	**NO**
A.3 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee or the SREC, you must apply for approval from the Computer Science Research Ethics Committee (CSREC) through Research Ethics Online - https://ethics.city.ac.uk/ **Depending on the level of risk associated with your application, it may be referred to the Senate Research Ethics Committee.**		
3.1	Does your research involve participants who are under the age of 18?	**NO**
3.2	Does your research involve adults who are vulnerable because of their social, psychological or medical circumstances (vulnerable adults)?	**NO**
3.3	Are participants recruited because they are staff or students of City, University of London?	**NO**
3.4	Does your research involve intentional deception of participants?	**NO**
3.5	Does your research involve participants taking part without their informed consent?	**NO**
3.5	Is the risk posed to participants greater than that in normal working life?	**NO**
3.7	Is the risk posed to you, the researcher(s), greater than that in normal working life?	**NO**
A.4 If you answer YES to the following question and your answers to all other questions in sections A1, A2 and A3 are NO, then your project is deemed to be of MINIMAL RISK. **If this is the case, then you can apply for approval through your supervisor under PROPORTIONATE REVIEW. You do so by completing PART B of this form.** **If you have answered NO to all questions on this form, then your project does not require ethical approval. You should submit and retain this form as evidence of this.**		
4	Does your project involve human participants or their identifiable personal data?	**NO**

References

[1] A. W. Bergersen, A. Slyngstad, S. Gjertsen, A. Souche, and K. Valen-Sendstad. turtlefsi: A robust and monolithic fenics-based fluid-structure interaction solver. *Journal of Open Source Software*, 5(50):2089, 2020.

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