Design of Passive Fault-Tolerant Augmented Neural Lyapunov Control Laws for Autonomous Maritime Vehicles

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UCL

National Oceanography Centre

1. Rationale – underwater vehicles

[NOC]

[Scripps]

1. A plethora of different vehicles.

2. Long term over-the-horizon missions.

1. Rationale – underwater vehicles

[UWA]

[NOC]

[WHOI]

[SOCCO]

Unstructured environment.

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Possible faults to the structure and protruding actuators.

1. Rationale – how is the challenge tackled

Fault-Tolerant Control

Active methods

1) Require constant monitoring of the status of the actuators;
2) Detecting and reacting (switching control gain, online adaptation …).

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1) Higher performance;
2) Higher design and manufacturing costs, power requirements, complexity.

Passive methods

1) No monitoring;
2) Unique set of control gain to cope with both nominal (faultless) and faulty modes.

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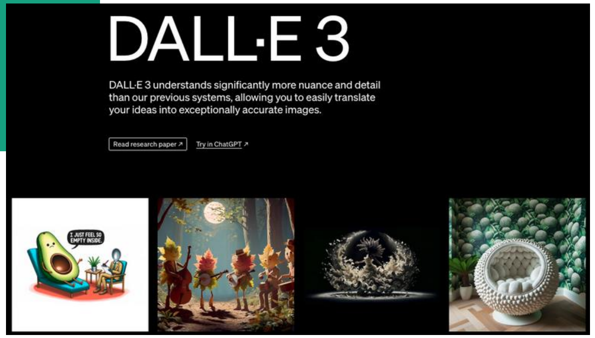
1) More conservative performance;
2) Based on Robust Control theory, with minor results available in the nonlinear case.

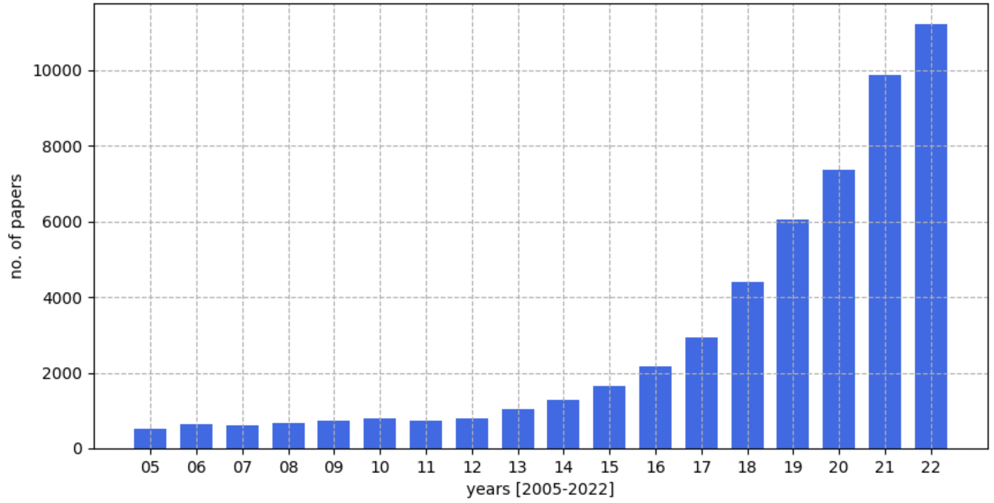
1. Rationale – AI trend

Industrial trend

2022-24: increasing large scale use of Machine Learning applications



Academic trend



The majority of works lack formal proof of stability!

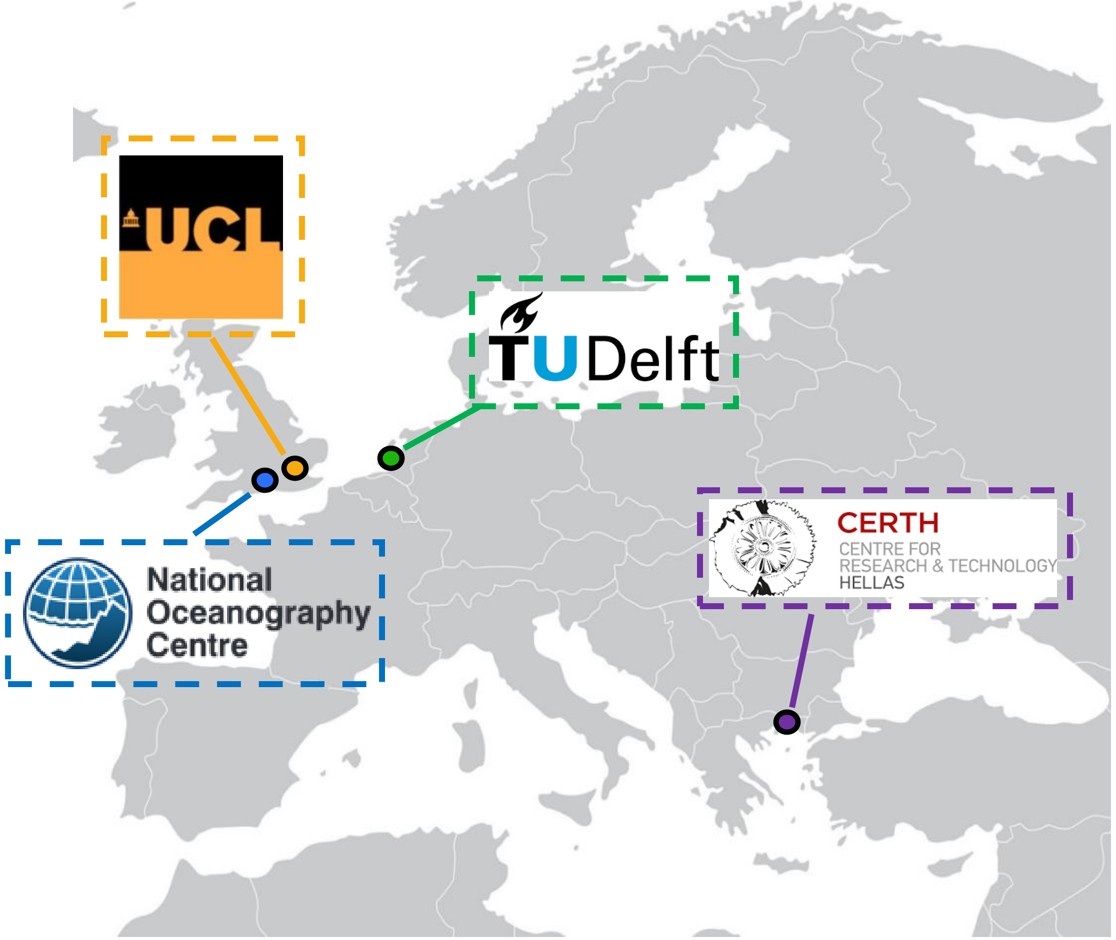
1. Rationale

Research Aims

Aim #1:
In presence of **sound mathematical theories**, how can one employ Machine Learning methods tailored to control applications?

Aim #2:
How can this class of methods be used to **streamline the design of Passive Fault-Tolerant Control** laws for marine vehicles?

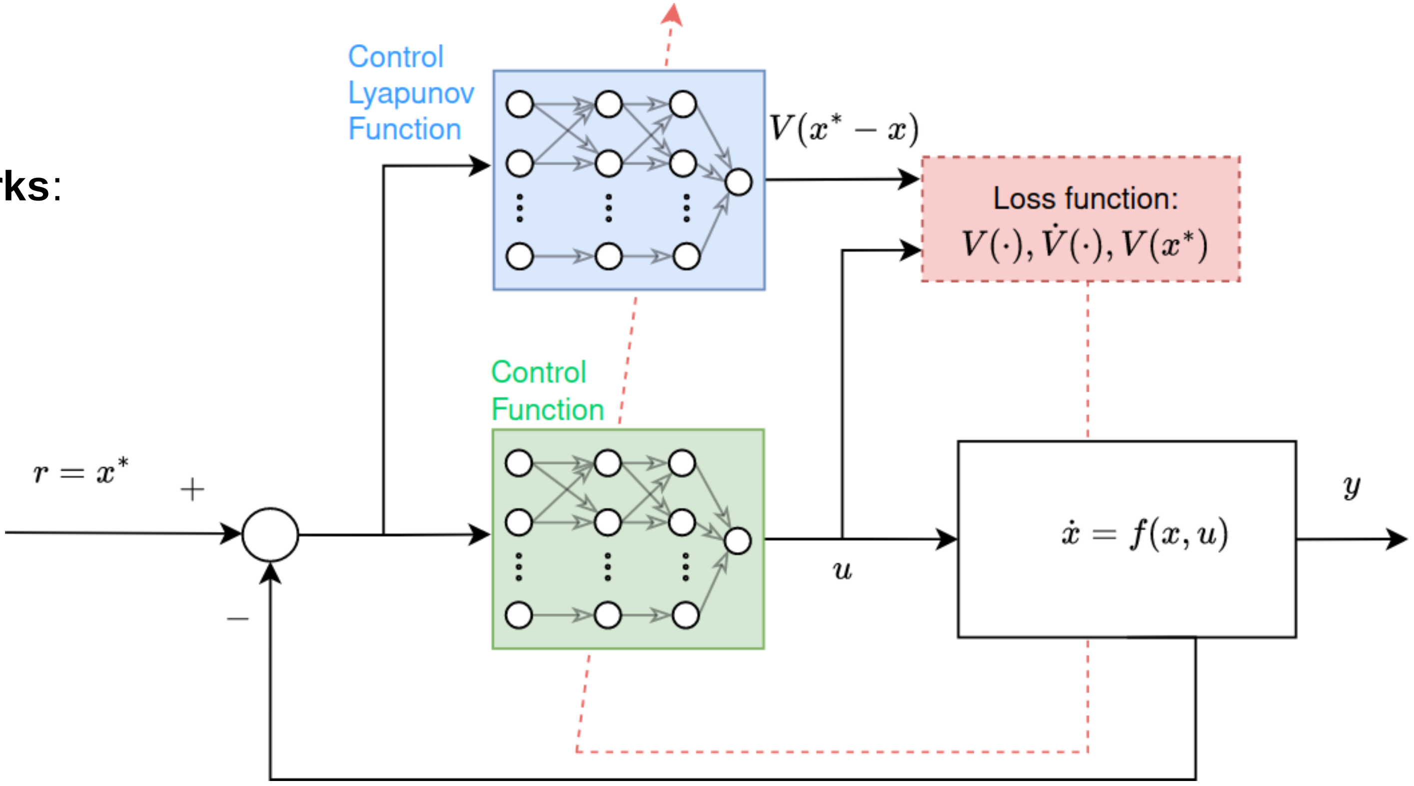
2. The project



3. Augmented Neural Lyapunov Control (ANLC)

Architecture

Comprises **two artificial neural networks**:
a) the **control law**;
b) the **Control Lyapunov Function**.



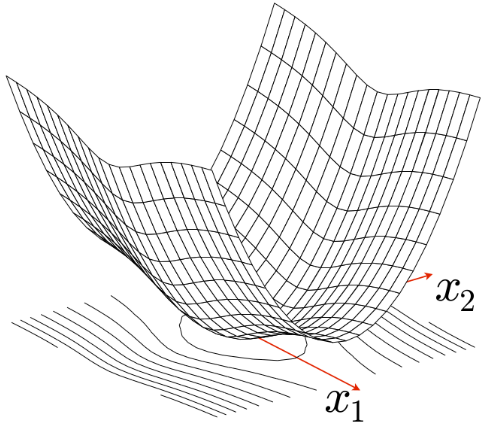
A (nonlinear) control law is used "in the loop" while a Control Lyapunov Function is used during the training to enforce closed-loop stability.

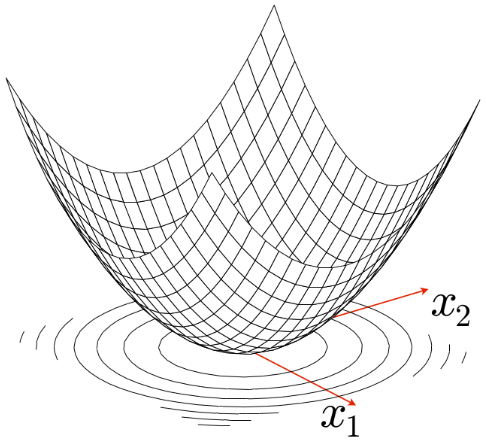
3. Augmented Neural Lyapunov Control

Control Lyapunov Function

Properties

1) Positive definite;
2) Lie derivative is negative definite;
3) Is 0 in 0.



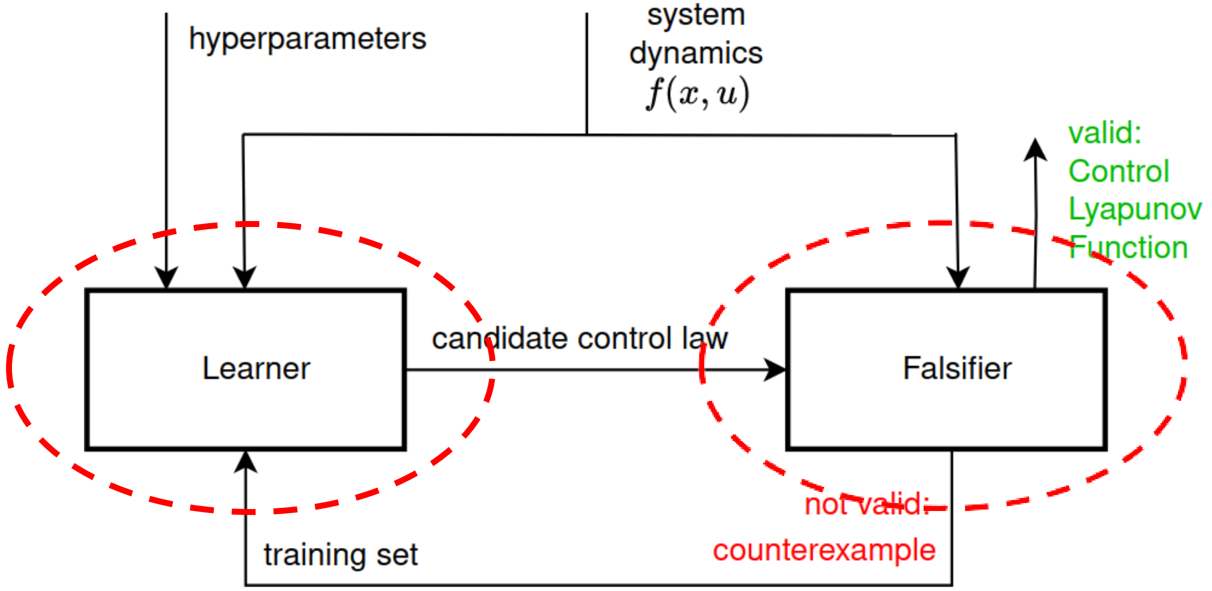


1) Control Lyapunov Functions are system-specific.
2) No closed-form solution is available to compute such functions.

3. Augmented Neural Lyapunov Control

Learning paradigm

Training controller



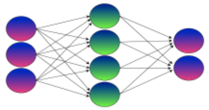
Formally verifying controller

Counter Example Guided Inductive Synthesis.

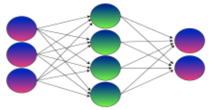
3. Augmented Neural Lyapunov Control

Falsifier

candidate Control Lyapunov Function



candidate control law



Translator

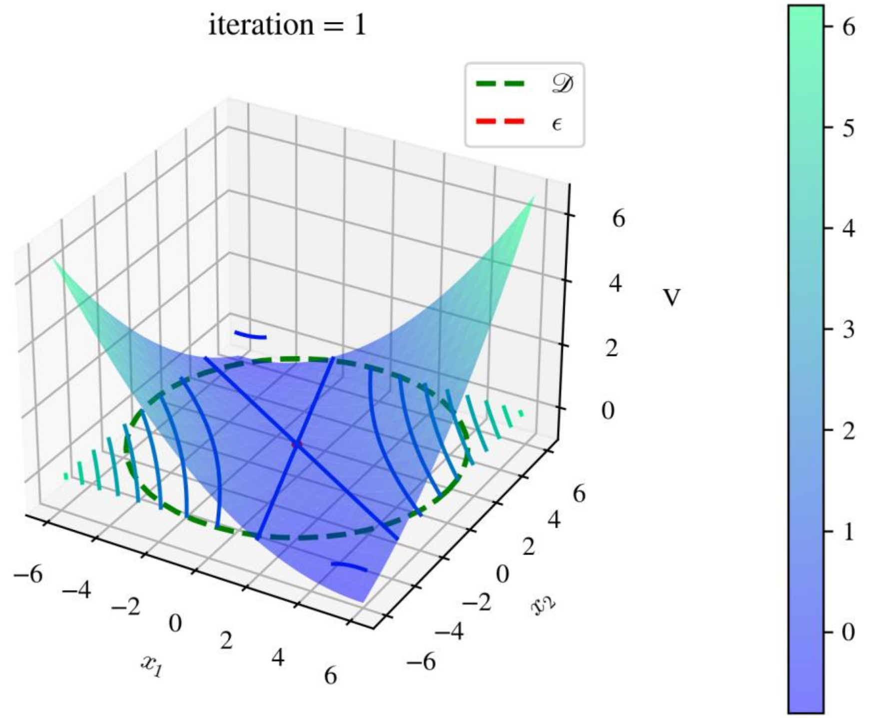
Example:

$$\boldsymbol{V_c}=(0.27(x_1x_2)+0.52x_1^2+0.29x_2^2)$$

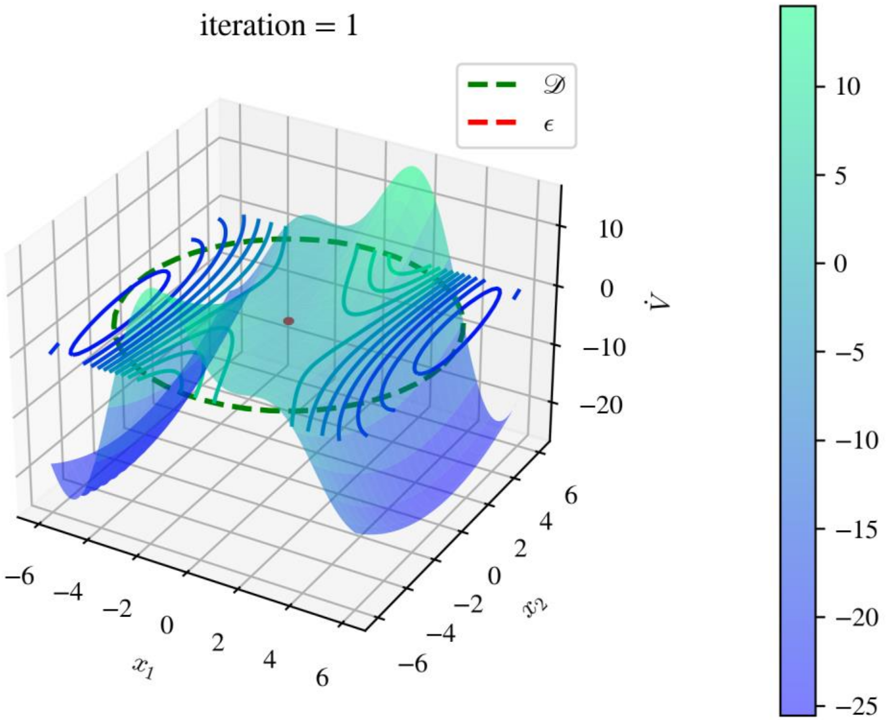
$$\begin{aligned}\boldsymbol{\dot{V}_c}=(&0.02x_1+0.05x_2+0.33(x_1x_2)+0.66(x_1x_2\tanh((-0.136-5.34x_1-12.72x_2)))+0.25(x_1x_2^2))+0.52(x_1x_2^2\tanh((-0.13-5.33x_1-12.72x_2)))+\\&0.05(x_1\tanh((-0.13+-5.33x_1-12.72x_2)))+44.52(x_1\tanh((0.02-6.57x_1+4.91x_2)))+0.55x_1^2x_2)+1.13x_1^2x_2\tanh((-0.13-5.33x_1-12.72x_2)))+\\&0.31x_1^2\tanh((-0.13-5.33x_1-12.72x_2)))+0.52x_1^3\tanh((-0.13-5.33x_1-12.72x_2)))+0.10(x_2\tanh((-0.13-5.33x_1-12.72x_2)))-\\&34.71(x_2\tanh((0.02-6.57x_1+4.91x_2)))-0.04x_2^2\tanh((-0.13-5.33x_1-12.72x_2)))+1.13x_2^3)\tanh((-0.13-5.33x_1-12.72x_2)))+0.15x_1^2+0.25x_1^3-\\&0.02x_2^2+0.55x_2^3))\end{aligned}$$

3. Augmented Neural Lyapunov Control

Learning process (initial learning iteration)



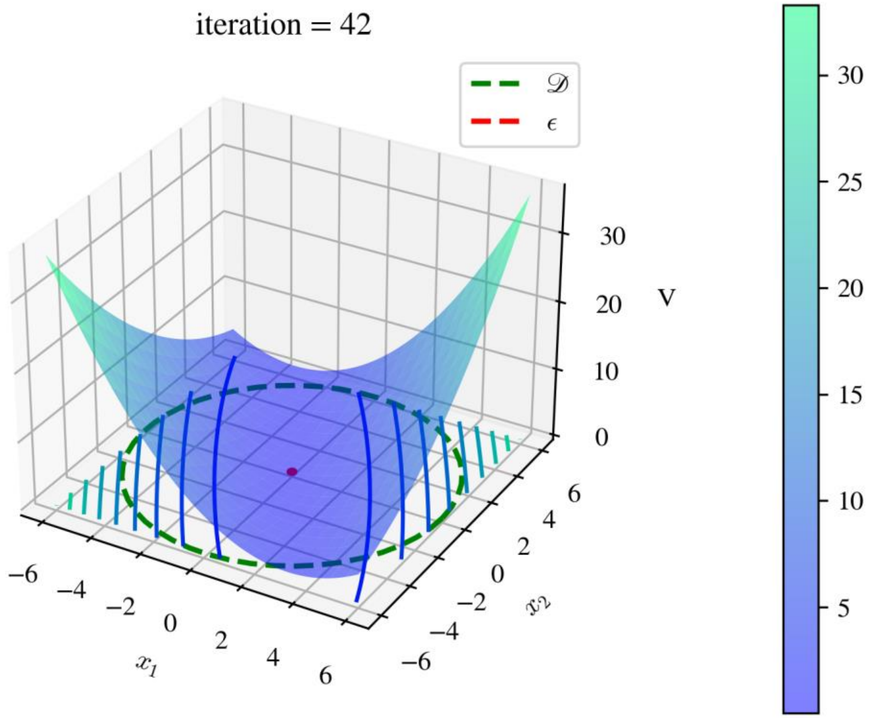
Control Lyapunov Function.



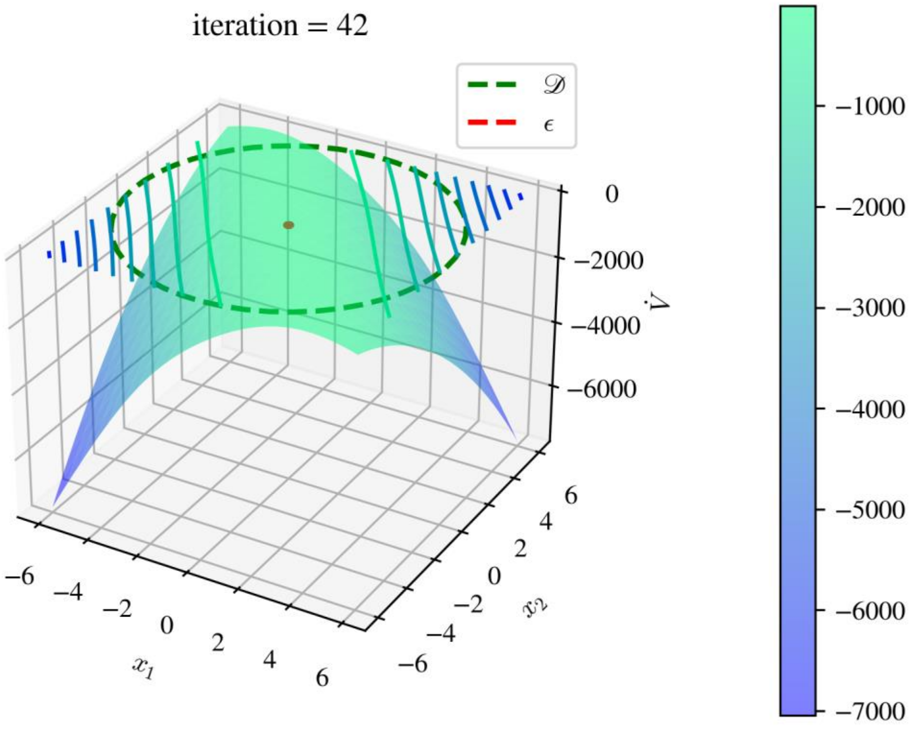
Lie derivative.

3. Augmented Neural Lyapunov Control

Learning process (final learning iteration)



Control Lyapunov Function.



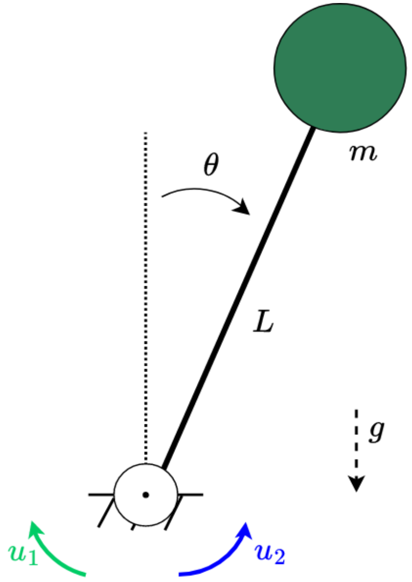
Lie derivative.

Animation available at: https://github.com/grande-dev/Augmented-Neural-Lyapunov-Control

4. Fault-Tolerant ANLC

Preliminary case study

An inverted pendulum with actuator redundancy is employed.



Problem

Compute a unique control function that can simultaneously stabilise:

1) the "Nominal (faultless) mode";
2) the "Fault on first actuator";
3) the "Fault on second actuator".

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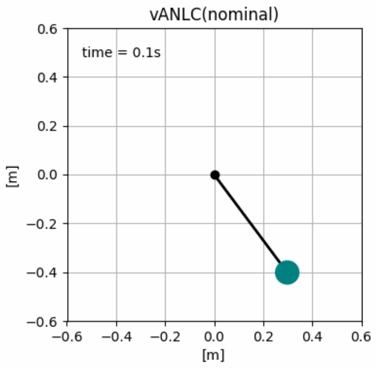
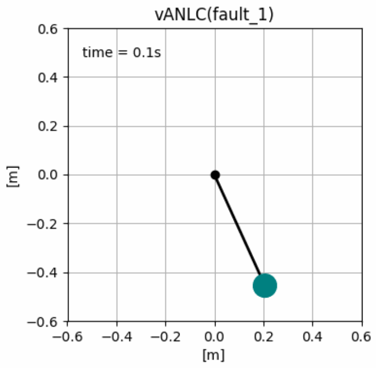
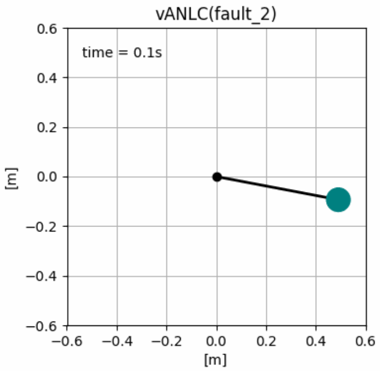
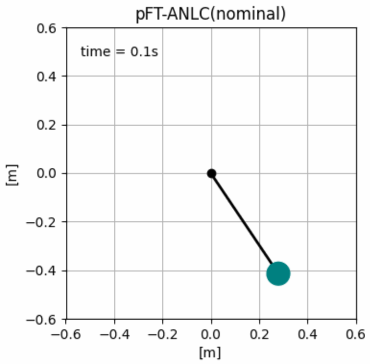
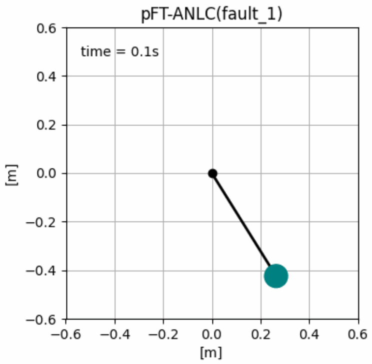
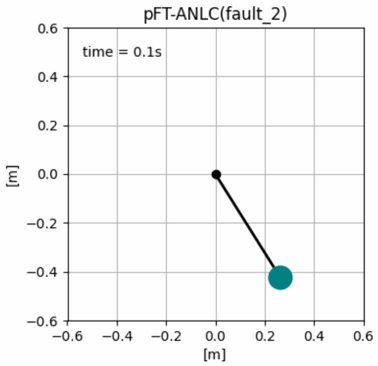
Results

a. 10/10 tests converged;
b. overall campaign run time: 8' (unassuming office laptop, no GPU).

4. Fault-Tolerant ANLC

Preliminary case study

<table>
<tr><th></th><th>No fault</th><th>Fault on actuator 1</th><th>Fault on actuator 2</th></tr>
<tr><td>ANLC</td><td></td><td></td><td></td></tr>
<tr><td>Fault-Tolerant ANLC</td><td></td><td></td><td></td></tr>
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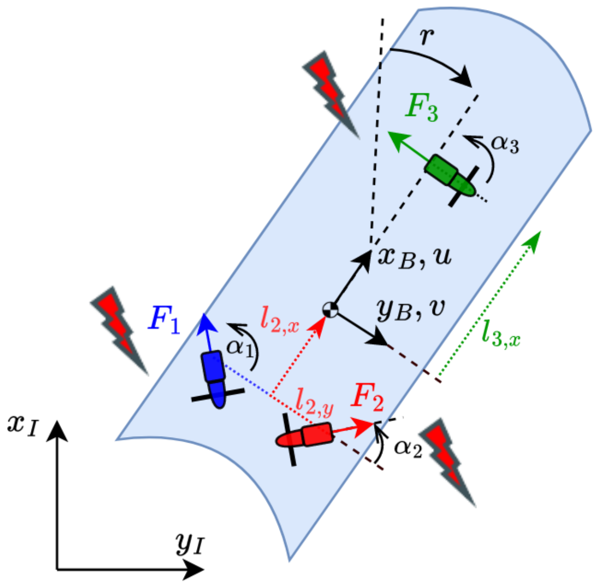
Animations available at: https://github.com/grande-dev/pFT-ANLC-preview

4. Fault-Tolerant ANLC

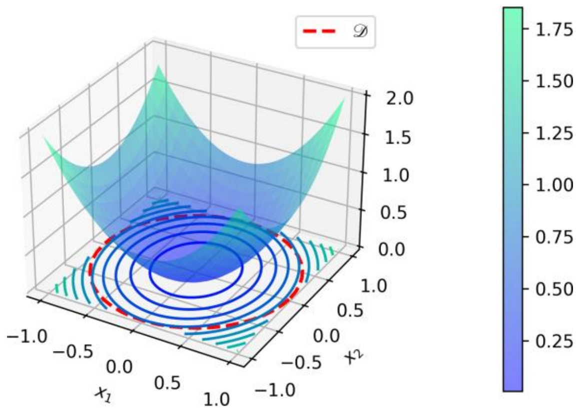
Maritime control case study

System dynamics



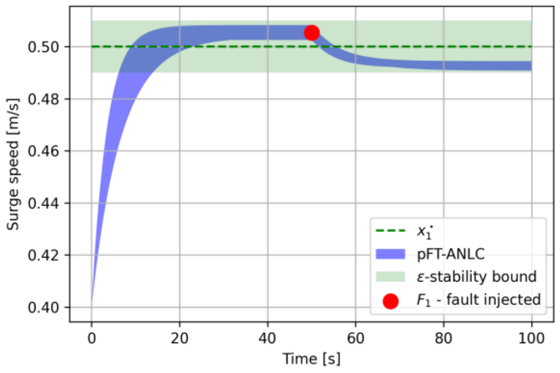
Test campaign

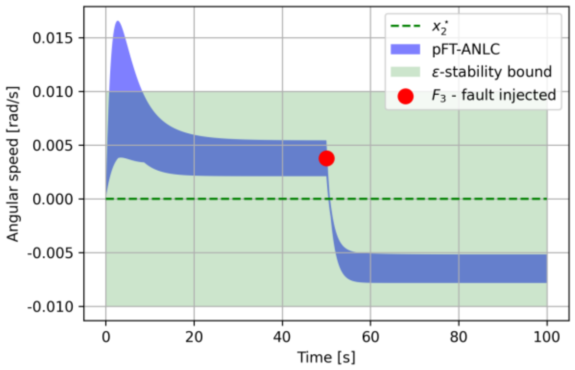
1. Nonlinear control laws;
2. Average test runtime: 10 ± 10 [s];
3. Success rate: 90%.



Control Lyapunov Function.

Closed-loop results





5. Conclusion and open questions

Novelty and contribution

a) First Machine Learning-based Passive Fault-Tolerant Control method with formal proof of correctness;
b) Open-source software tools.

All codes available at: https://github.com/grande-dev/

Theoretical open questions

1) Is there any theoretical result to prove the **existence of a unique control solution**?
2) Is there any theoretical result on the **scalability limit** related to high dimensional systems?

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