MARINE & MARITIME INTELLIGENT ROBOTICS

UNIVERSITY OF TOULON, NORWEGIAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

DYNAMIC POSITIONING OF A ROV USING REINFORCEMENT LEARNING

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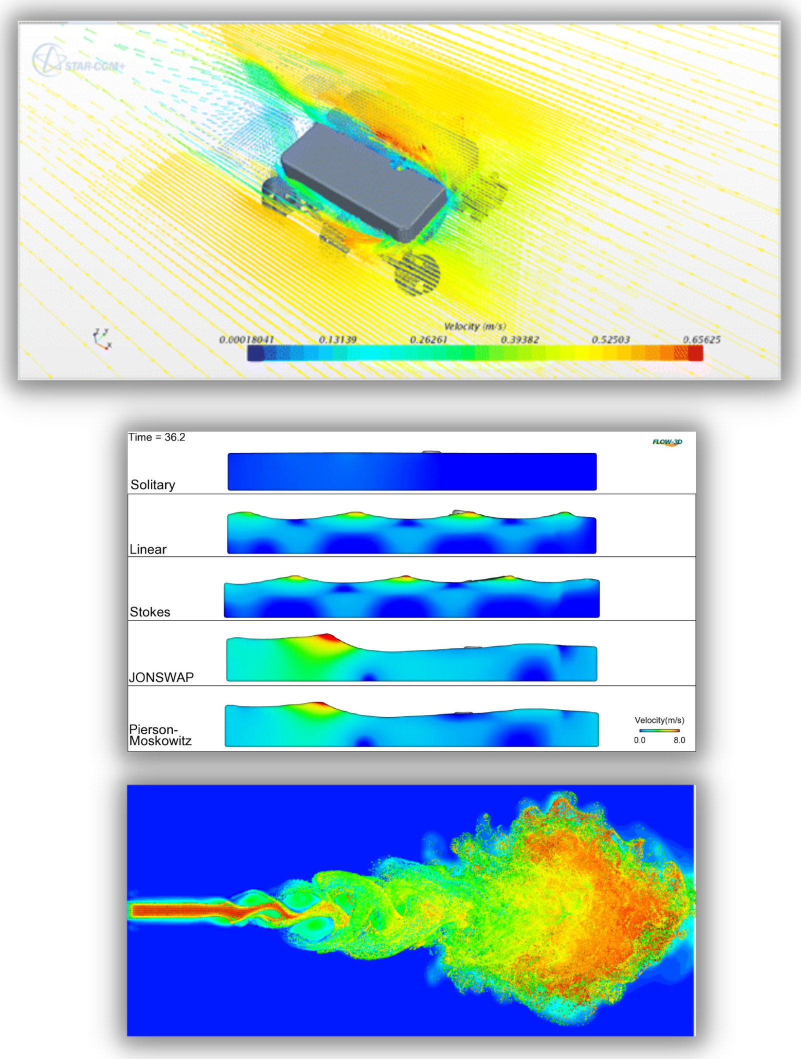
MOTIVATION

Classical control has successfully drive the ROV industry for several years, but as technology advances challenges advance as well. Models have nonlinearities, singularities and difficult to model phenomena such as waves and currents.

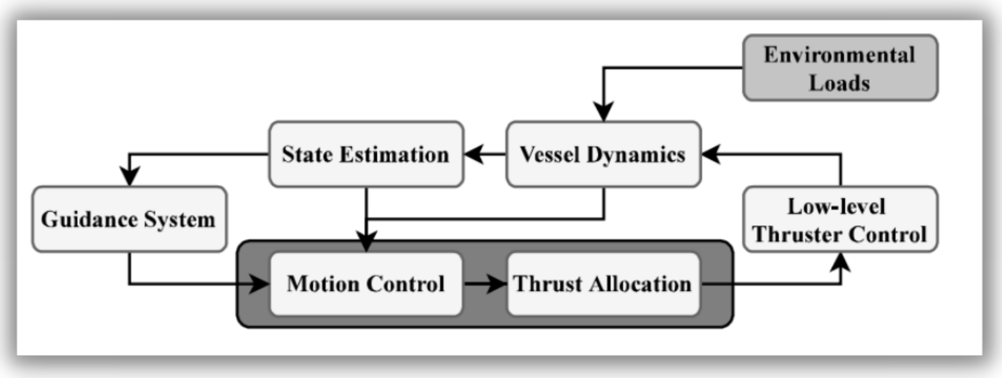
$$M(q)\dot{\vartheta}+C(q,\vartheta)\vartheta+D(q,\vartheta)\vartheta+g(q,\phi)=\tau_{wind}+\tau_{waves}+\tau_{thrs}$$

Objective:

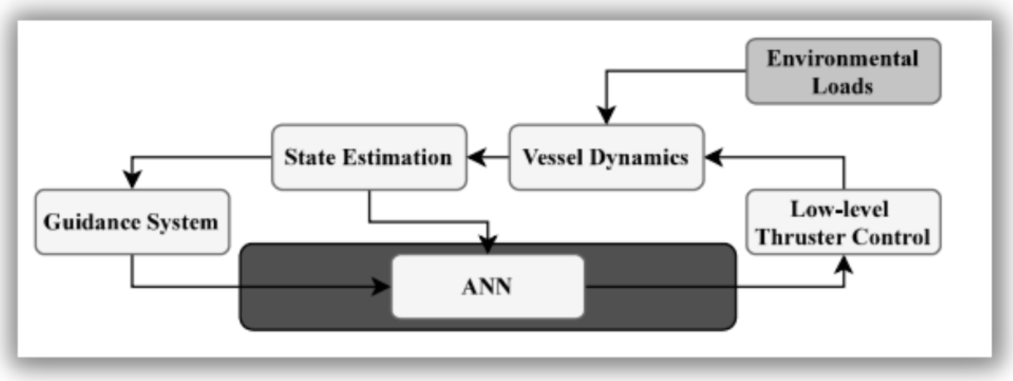
- *Find an alternative solution through* ***Reinforcement Learning RL.***
- *Let's make the ROV learn from experience and make its own decisions to unknowns!*



Currents, waves and turbulent flows are difficult to model



Classical control approach diagram[1]

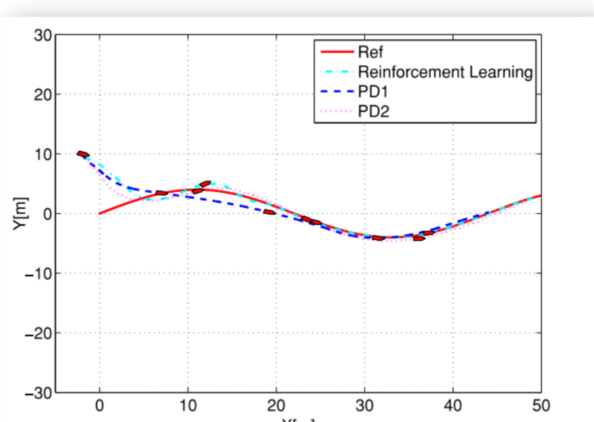


RL control approach diagram[1]

STATE OF THE ART

RL CUI ET AL.

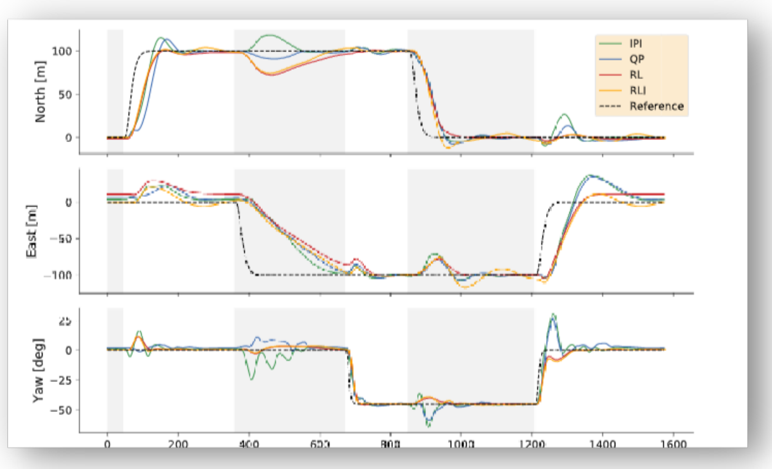
- **Actor-Critic NN.**
- **Robust** against unknown. model params, unknown. disturbances.



AUV Trajectory following, RL vs PD[2]

RL ØVERENG ET AL.

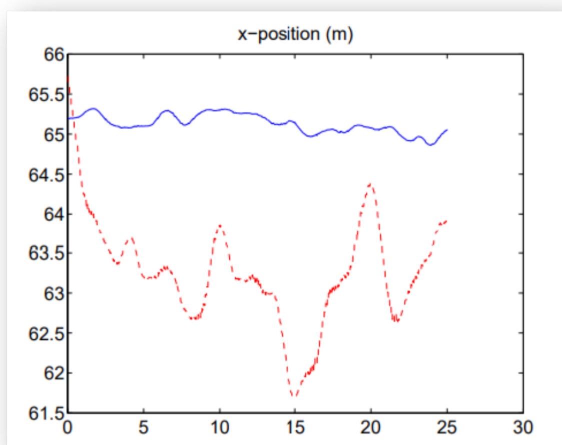
- **Actor-Critic NN.**
- Transfer learning to sea trial.



Surface vehicle, error comparison.[1]

RL ANDREW ET AL.

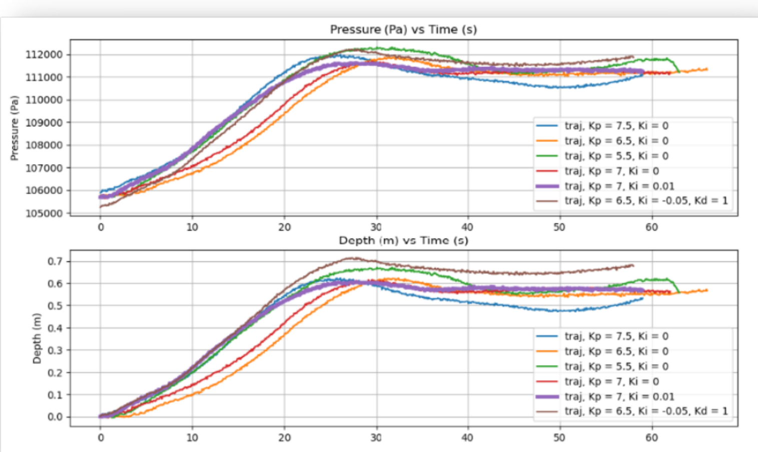
- Helicopter flight.
- **Pegasus Algorithm.**
- Model fitting.



Hovering X position, RL (blue) vs Human (red) [3]

PID

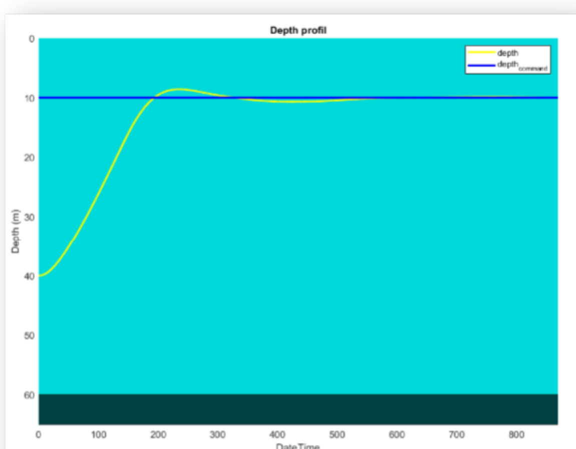
- Easy to implement.
- Low resource usage.
- Needs tunning.



PID depth control on BlueRov

LQR

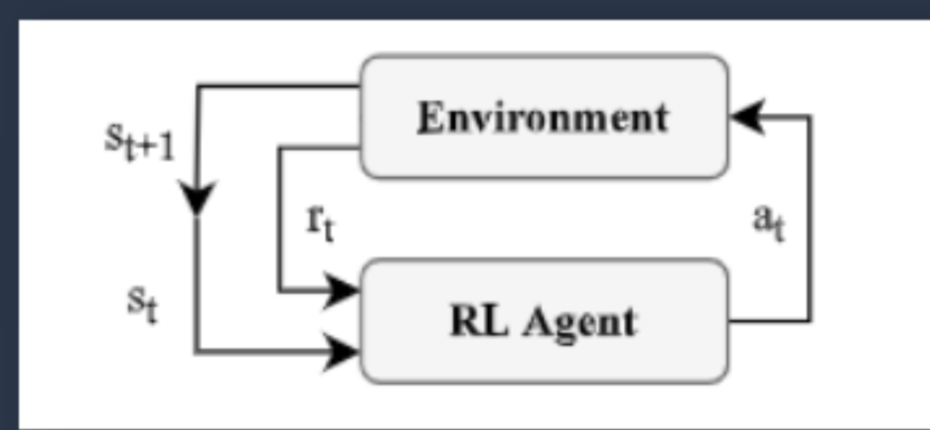
- Optimal control
- Optimizes output w.r.t a criterium.
- Ricatti Equation can be hard to approximate.



LQR depth control on SPARUS AUV

OBJECTIVE CONTRIBUTIONS

- *Design, implement and test a* ***RL algorithm*** *for* ***ROV DP*** *(Rotation and Depth)*
- *Virtual Training of the RL algorithm*
- ***Transfer learning*** *to real scenario*
- ***Compare*** *to most used methods i.e., PID.*



Basic Diagram of RL[1]

THESIS OVERVIEW

- Define and discretize RL Environment and States.
- Define and discretize Agent Actions.
- Reward Shaping.
- Create simulation.
- Train Agent
- Transfer training to BlueROV
- Fine train on BlueROV

BlueROV

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2.Cui, R., Yang, C., Li, Y., & Sharma, S. (2017). Adaptive neural network control of AUVS with control input nonlinearities using reinforcement learning. IEEE Transactions on Systems, Man, and Cybernetics: Systems, .
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