

# Machine (or Reinforcement): Learning to assist vessel docking in extreme environments

Bachelor defense

June 18, 2020

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# Agenda



- ▶ Quick introduction to the problem
- ▶ Reinforcement Learning
- ▶ Simplified model
- ▶ Results & Discussion
- ▶ Conclusion & Future work

# Introductory

## Overview



### Overview of the problem

- ▶ Vessel stabilizer
- ▶ Why is a vessel stabilizer needed?
- ▶ What is Dacoma's current solution?
- ▶ The objective
- ▶ The approach

# Introductory

## Vessel stabilizer



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- ▶ **Vessel stabilizer**
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## Vessel stabilizer



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# Introductory

Current solution



## Overview of the problem

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# Introductory

## Objective



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### Overview of the problem

- ▶ Vessel stabilizer
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# Reinforcement Learning

## Overview



### Overview:

- ▶ Classic Reinforcement Learning & Terminology
- ▶ The Approach
- ▶ Issues and Shortcomings



## Terminology

- ▶ Agent
- ▶ Environment
- ▶ States, Statespace, Actions & Actionspace
- ▶ Reward and Reward function
- ▶ Policy

## Classic Reinforcement Learning (CRL)

- ▶ Markov Decision Process (MDP)
- ▶ Problem Review
- ▶ Why CCRL does not fit on this problem

# Reinforcement Learning

The approach



Concepts:

- ▶ Policy Gradient Methods
- ▶ Neural Networks
- ▶ Optimizer

Implementation specifics:

- ▶ Finite differences
- ▶ Reward & Reward Function

# Reinforcement Learning

The approach - Implementation specifics



Implementation specifics:

- ▶ **Finite differences**
- ▶ Reward & Reward Function

# Reinforcement Learning

The approach - Implementation specifics



Implementation specifics:

- ▶ Finite differences
- ▶ **Reward & Reward Function**

Matematiske og grafiske metoder til syntese af **lineære tidsinvariante systemer**:<sup>1</sup>

- ▶ **diskret og kontinuert tilstandsbeskrivelse**
- ▶ analyse i tid og frekvens
- ▶ stabilitet, reguleringshastighed, følsomhed og fejl
- ▶ digitale PI, PID, LEAD og LAG regulatorer (serieregulatorer)
- ▶ tilstandsregulering, pole-placement og tilstands-estimering (observer)
- ▶ optimal regulering (least squares) og optimal tilstands-estimation (Kalman-filter)

### Færdigheder:

Efter gennemførelse af kurset kan den succesfulde studerende:

- ▶ kunne analysere, dimensionere og implementere såvel kontinuert som tidsdiskret regulering af lineære tidsinvariante og stokastiske systemer

### Kompetencer:

Efter gennemførelse af kurset kan den succesfulde studerende:

- ▶ anvende og implementere klassiske og moderne regulerings teknikker for at kunne styre og regulere en robot hurtig og præcist

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<sup>1</sup> Based on [https://fagbesk.sam.sdu.dk/?fag\\_id=39673](https://fagbesk.sam.sdu.dk/?fag_id=39673)