Long-term Dynamical Predictions and Control for Autonomous Underwater Vehicles

HERIOT WATT UNIVERSITY

Nicolay Pierre, Ignacio Carlucho, Mykhaylo Marfeychuk, Michele Grimaldi & Yvan Petillot

About Me

- I’m a PhD student at Heriot-Watt & University of Edinburgh in the UK.
- My Research is focused on control for Autonomous Underwater Vehicles.
- I want to bridge the gap between “classic” control methods with “modern” machine learning.

Objective

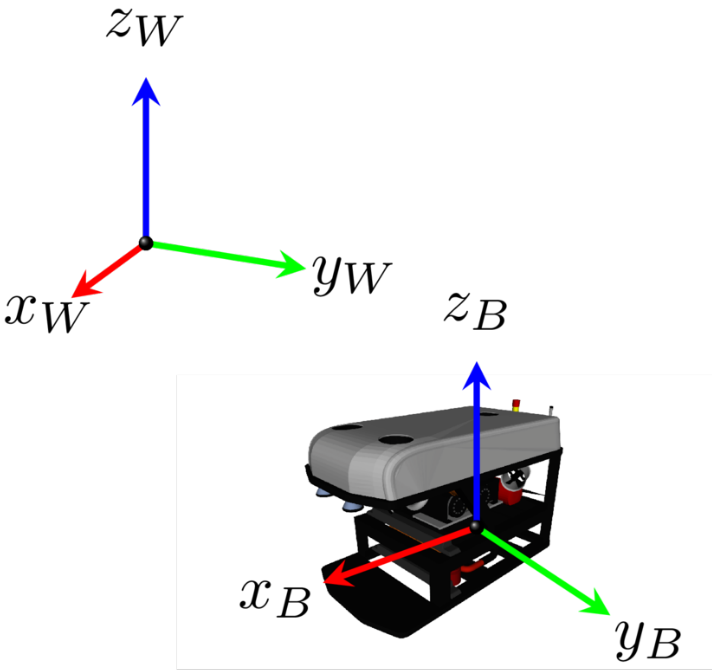
- As part of my PhD, the goal is to design new controllers for Autonomous Under Water Vehicles (AUVs).

Challenges

- Underwater environments exhibit complex non-linear & coupled dynamics.
- Communication is difficult. After a couple of meters there is only acoustic signal with low bandwidth.
- The environment is harsh for human operators.

Objective

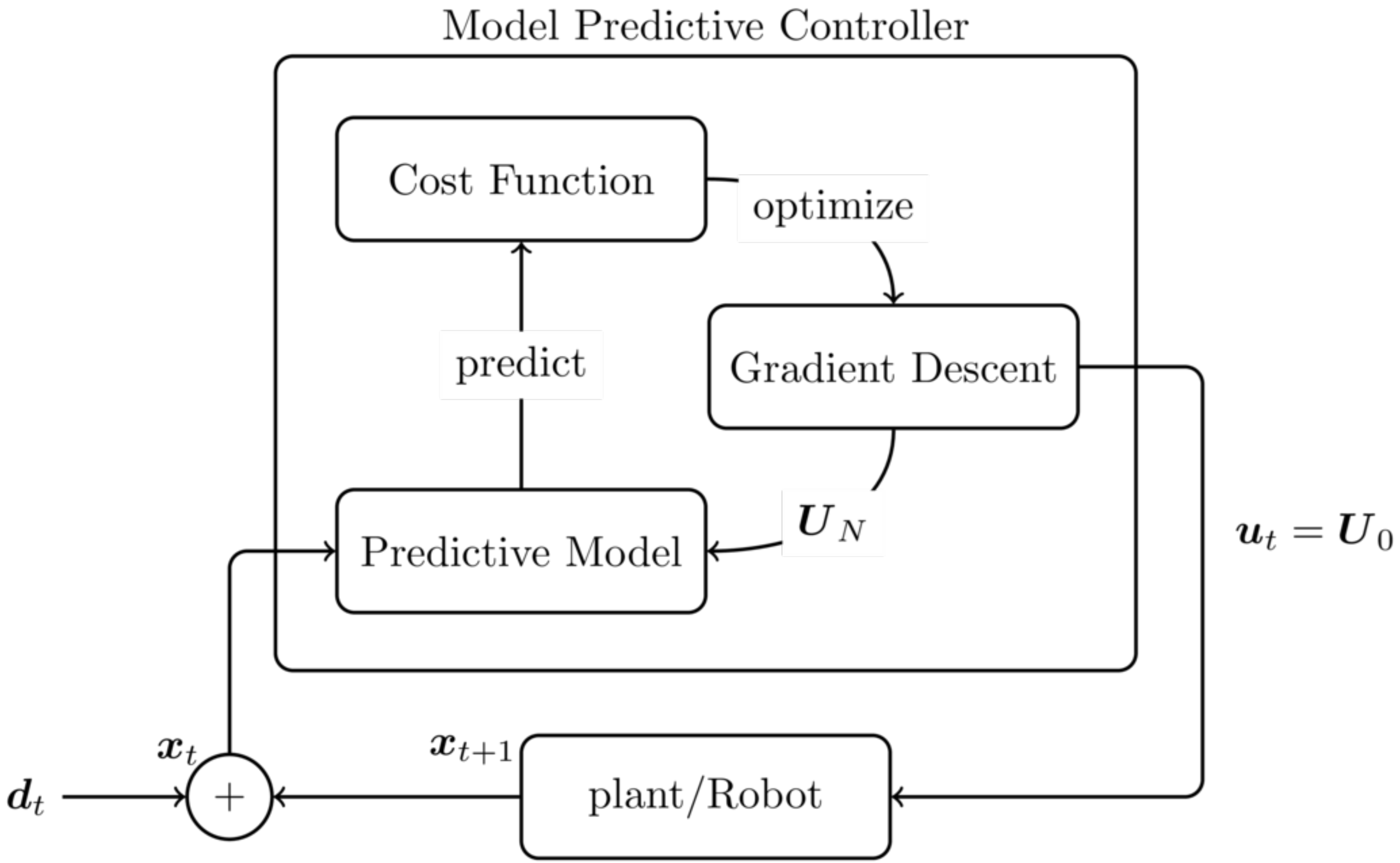
- Adaptive
- Reliable
- Robust
- Data Efficient



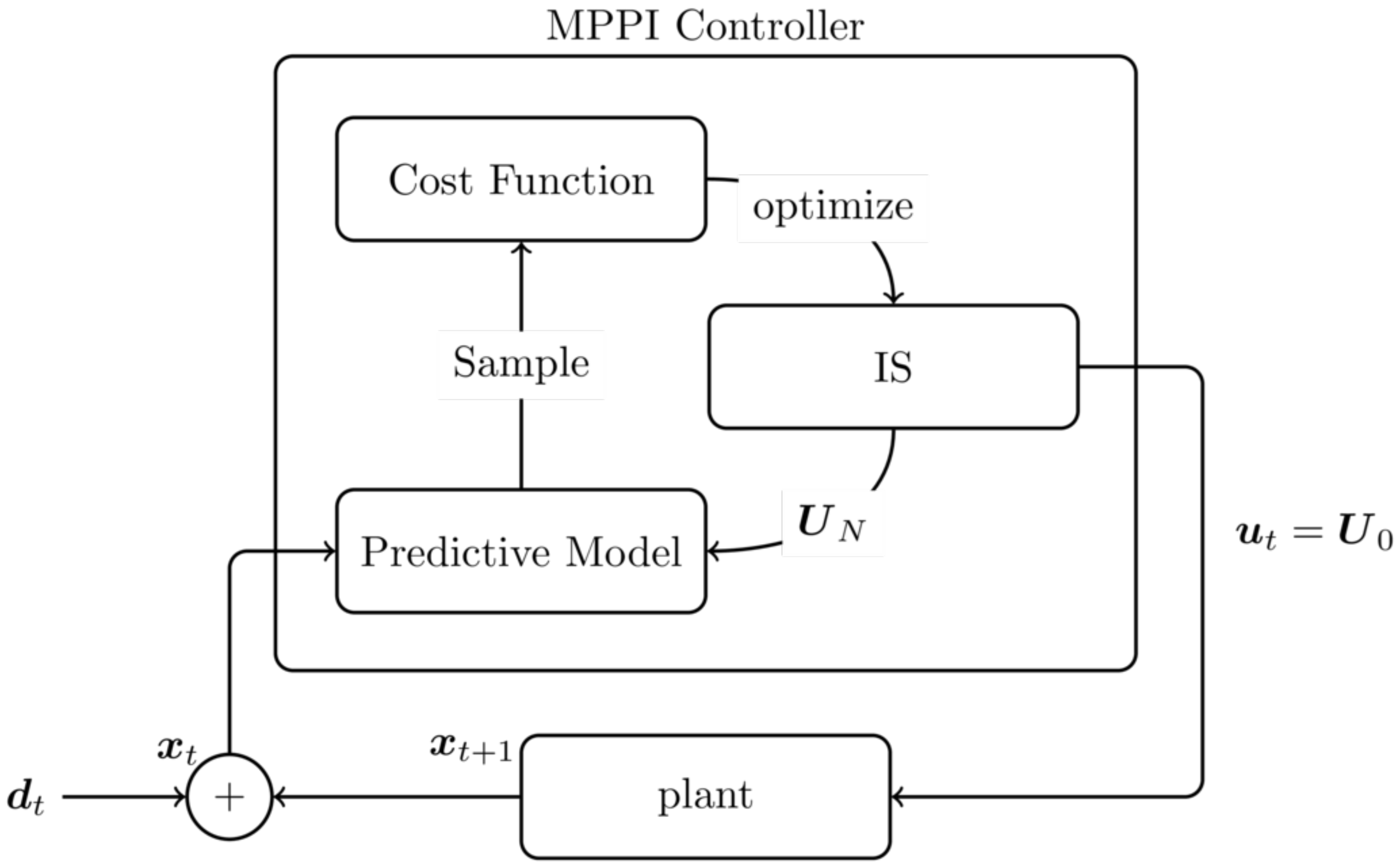
Controller Choice

- Model Based
- Task Agnostic & Optimal Control
- Theoretical Guarantees
- Designed For Non-Linear Systems
- MIMO controller

Model Predictive Control



Model Predictive Path Integral



MPC/MPPI Properties

- MPC
  - Model Based
  - Task Agnostic
  - Extensively studied
  - Theoretical Guarantees
  - Feed Forward (trajectory optimization + obstacle avoidance)

- MPPI
  - Gradient Free
  - Work naturally with None-Linear Systems
  - Robust to Noise (modelling & Environment)

Early Results: I

Early Results: II

Questions?

- Recap + 5 min of questions on MPPI

A Few Robotics Key Words

- Reference Frame: The Main frame in which all the robot are located. Usually a Local Inertial Frame.
- Robot Pose: Defines position and orientation of the robot in a Frame.

Problem

- We’re focused on learning a dynamical model for a Non-Linear Model Predictive Controller (MPPI) with applications to Autonomous Underwater Vehicles (AUVs).
- The requirements for the model are the following:
  - Model Accuracy, needs to be effectively representing the AUV.
  - Model Stability over many prediction steps.
  - Fast inference time to work with the controller.

Challenges

- There are multiple challenges to acquire this model:
  - Long term prediction is subject to compounding errors.
  - Underwater environment are highly coupled across degrees of freedom and highly non-linear.
  - System Identification is a long and fastidious task that require much time, effort & human Knowledge.
  - Learning rigid body motion is complex for Machine Learning algorithms.

Fossen Model Introduction

$$(\boldsymbol{M}_{added} + \boldsymbol{M}_{rb})\dot{\nu} = (\boldsymbol{C}_{added} + \boldsymbol{C}_{rb})(\nu)\nu + \boldsymbol{D}(\nu)\nu + \boldsymbol{g}(\eta) + \boldsymbol{\tau}_{c+d}$$

- Added Mass and Inertial Mass (72 Parameters)
- Coriolis Forces (Computer from Mass Matrices)
- Damping Forces (72 Parameters, for simpler models)
- Restoring Forces (8 Parameters)
- Force Input.
- Total of 152 model parameters.

Approach

- We investigate a Neural Network approach solution.
- The model is aware of Rigid body motion before learning by using a Lie Group Math Library.
- Designed a new loss function based on Lie Groups.

Lie Groups

- What are Lie Groups?
  - Lie Groups are Groups but also smooth (differentiable) manifolds.
  - A Smooth manifold is a space that locally resembles a linear space.
  - A group is a set with composition operation that respect the following axioms: Closure, Identity, Inverse and Associativity.

$$
\begin{aligned}
&\forall \mathcal{X}, \mathcal{Y}, \mathcal{Z} \in \mathcal{M} \\
&\mathcal{X} \circ \mathcal{Y} = \mathcal{Z} \in \mathcal{M} \\
&\mathcal{E} \circ \mathcal{X} = \mathcal{X} \circ \mathcal{E} = \mathcal{X} \\
&\mathcal{X} \circ \mathcal{X}^{-1} = \mathcal{X}^{-1} \circ \mathcal{X} = \mathcal{E} \\
&(\mathcal{X} \circ \mathcal{Y}) \circ \mathcal{Z} = \mathcal{X} \circ (\mathcal{Y} \circ \mathcal{Z})
\end{aligned}
$$

Lie Group SE(3)

- The particular group of interest for us is SE(3).
- SE(3) can be used to define rigid body motion within a single mathematical object.
- In robotics, a SE(3) element is usually referred to as the pose of a robot.

Lie Group Tangent Space

- The Tangeant space of a Lie Group at its origin is called the Lie Algebra.
- The Lie Algebra corresponds to the world frame, wether a Tangeant space at a given element corresponds to the body frame.

$\mathfrak{se}(3)$

- In the context of SE(3) for Rigid Body motion, its Lie Algebra corresponds the velocity times time in world frame.
- The Tangent space at any point in a Lie Group is a vector space that is isomorphic to the Euclidean space → we can represent it into a Euclidean space that are suited for Neural

A Few Useful Operations

$$Exp({}^{\mathcal{E}}t) : \mathfrak{se}(3) \rightarrow SE(3)$$

$$Log(\mathcal{X}) : SE(3) \rightarrow \mathfrak{se}(3)$$

$$\mathcal{X} \oplus {}^{\mathcal{X}} v\delta t = \mathcal{Y} = \mathcal{X} \circ Exp({}^{\mathcal{X}} v\delta t)$$

$$\mathcal{X} \ominus \mathcal{Y} = Log(\mathcal{X}^{-1} \circ \mathcal{Y}) = {}^{\mathcal{X}} t \in \mathcal{T}_{\mathcal{X}} SE(3)$$

Gradients on Lie Groups

- Derivatives for the SE(3) Lie Group are clearly defined.
- The computed gradient are constrained to the Lie Group’s topology.
- For SO(3) elements, the Jacobian is a vector of size 3 even though the rotation matrix is a 3*3 matrix. If we compute the gradients without the SO(3) knowledge we would have a gradient of size 9 without SO(3) constraint.

Loss Function I

- We designed a loss functions that works on an entire trajectory.
- It is composed of 3 different quantities:
  - The pose Loss
  - The velocity Loss
  - The velocity delta Loss.

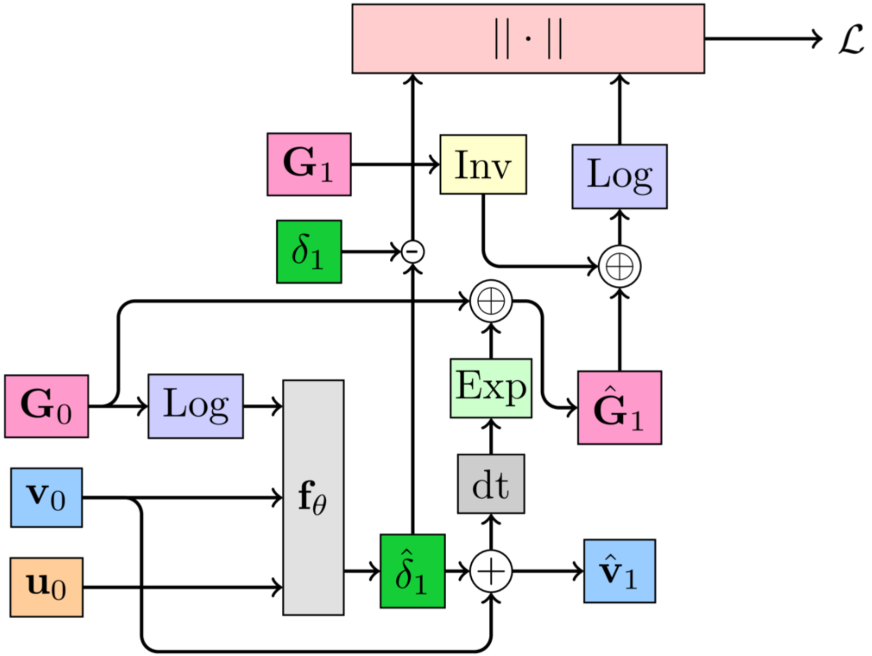
Loss Function II

$$\mathcal{L}(\boldsymbol{\mathcal{G}}, \hat{\boldsymbol{\mathcal{G}}}, \boldsymbol{v}, \hat{\boldsymbol{v}}, \boldsymbol{\delta v}, \widehat{\boldsymbol{\delta v}}) = \alpha \mathcal{L}_{geo}(\boldsymbol{\mathcal{G}}, \hat{\boldsymbol{\mathcal{G}}}) + \beta \mathcal{L}_2(v_1, v_2) + \gamma \mathcal{L}_2(\Delta v_1, \Delta v_2)$$

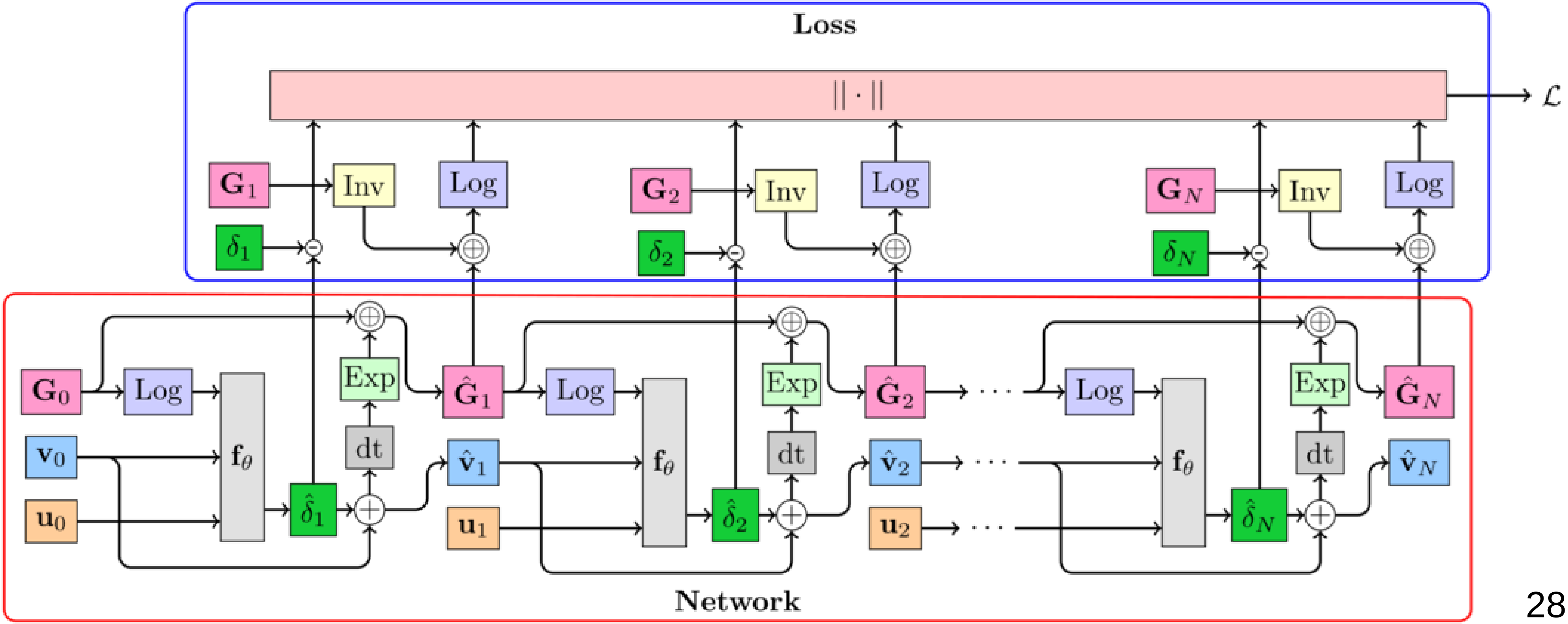
$$\mathcal{L}_{geo}(\boldsymbol{\mathcal{G}}, \hat{\boldsymbol{\mathcal{G}}}) = \sum_{i=1}^{\mathcal{T}} \mathcal{G}_i \ominus \hat{\mathcal{G}}_i$$

$$s.t: \quad \mathcal{G}_i \in SE(3); v_{i,j} \in \mathcal{T}_{\mathcal{G}_i} SE(3); \Delta v \in \mathcal{T}_{\mathcal{G}_i} SE(3)$$

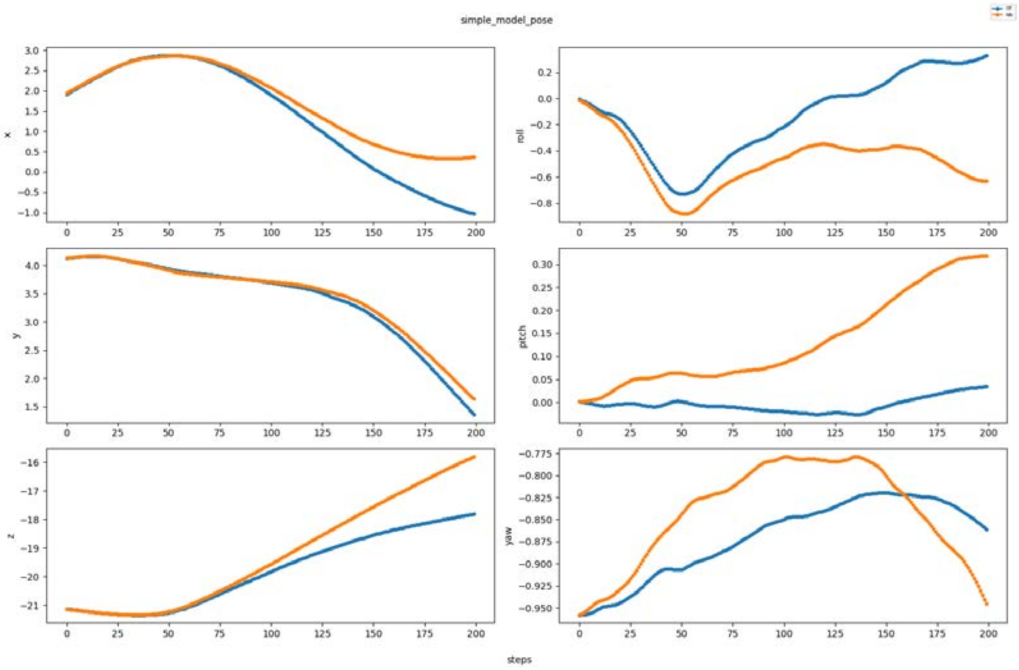
Step Model

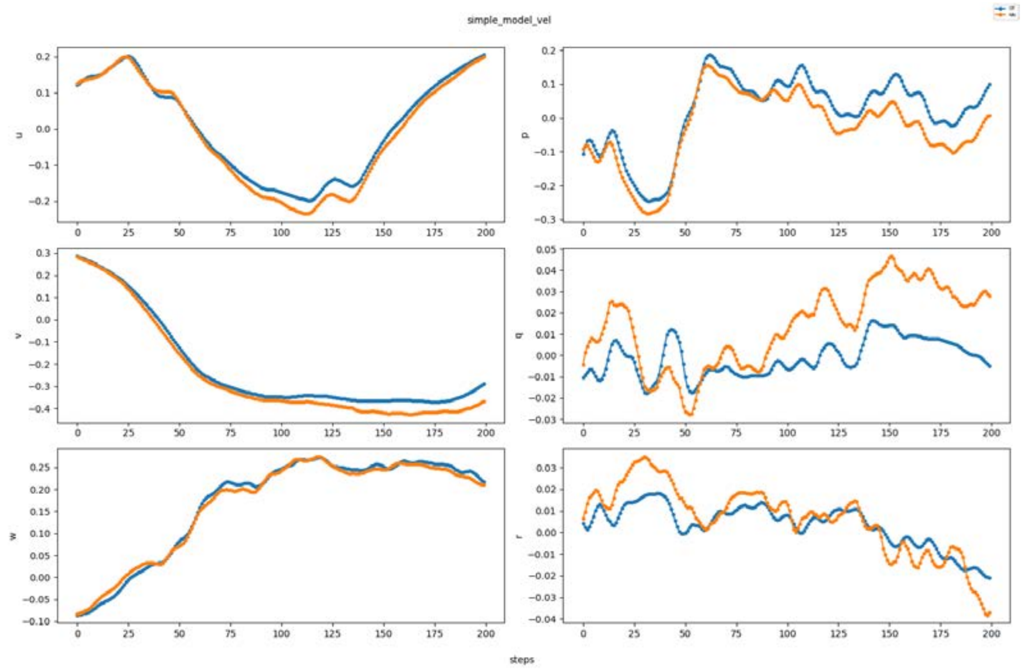

$||\cdot||$
$\mathcal{L}$
$\mathbf{G}_1$
Inv
Log
δ_1
$\oplus$
$\mathbf{G}_0$
Log
$\mathbf{f}_\theta$
Exp
$\hat{\mathbf{G}}_1$
$\mathbf{v}_0$
dt
$\mathbf{u}_0$
$\hat{\delta}_1$
$\hat{\mathbf{v}}_1$

Trajectory Model

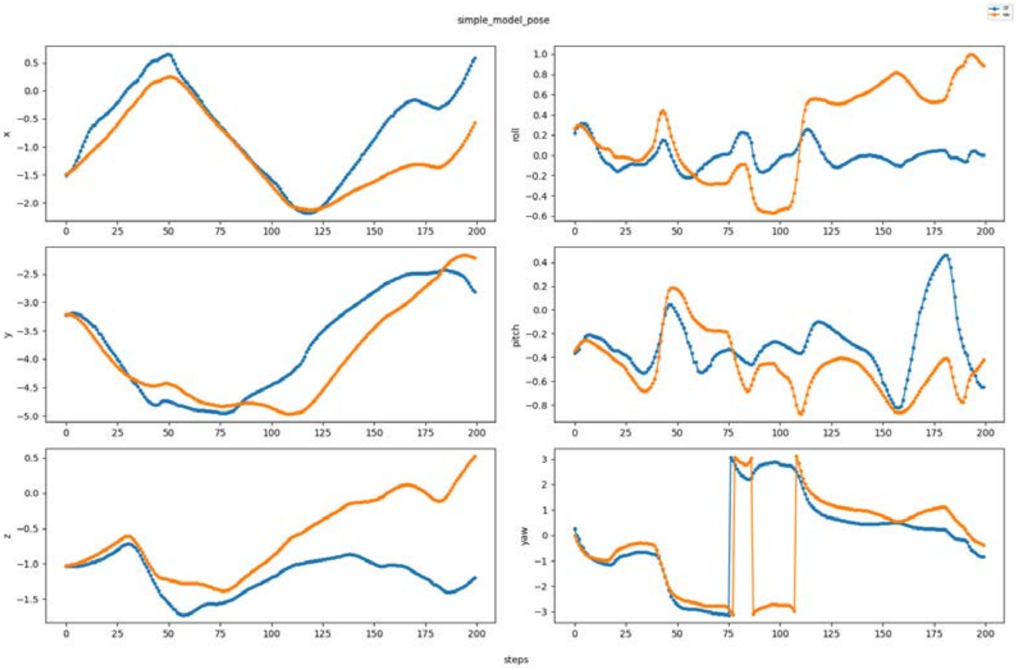


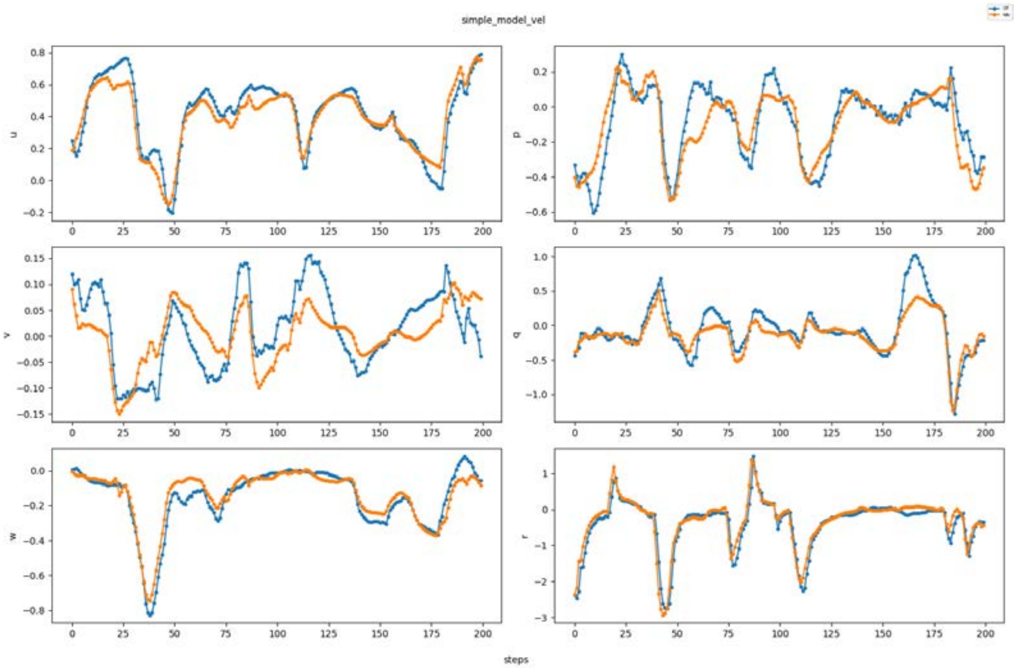
Results I: Simulation Data





Results II: Real Data





Stonefish Simulator

- New underwater simulator.
- Huge set of sensors
- Accurate modelisation of underwater physics through CAD
- Currently working on photo-realistic images

Live Demo + Discussion