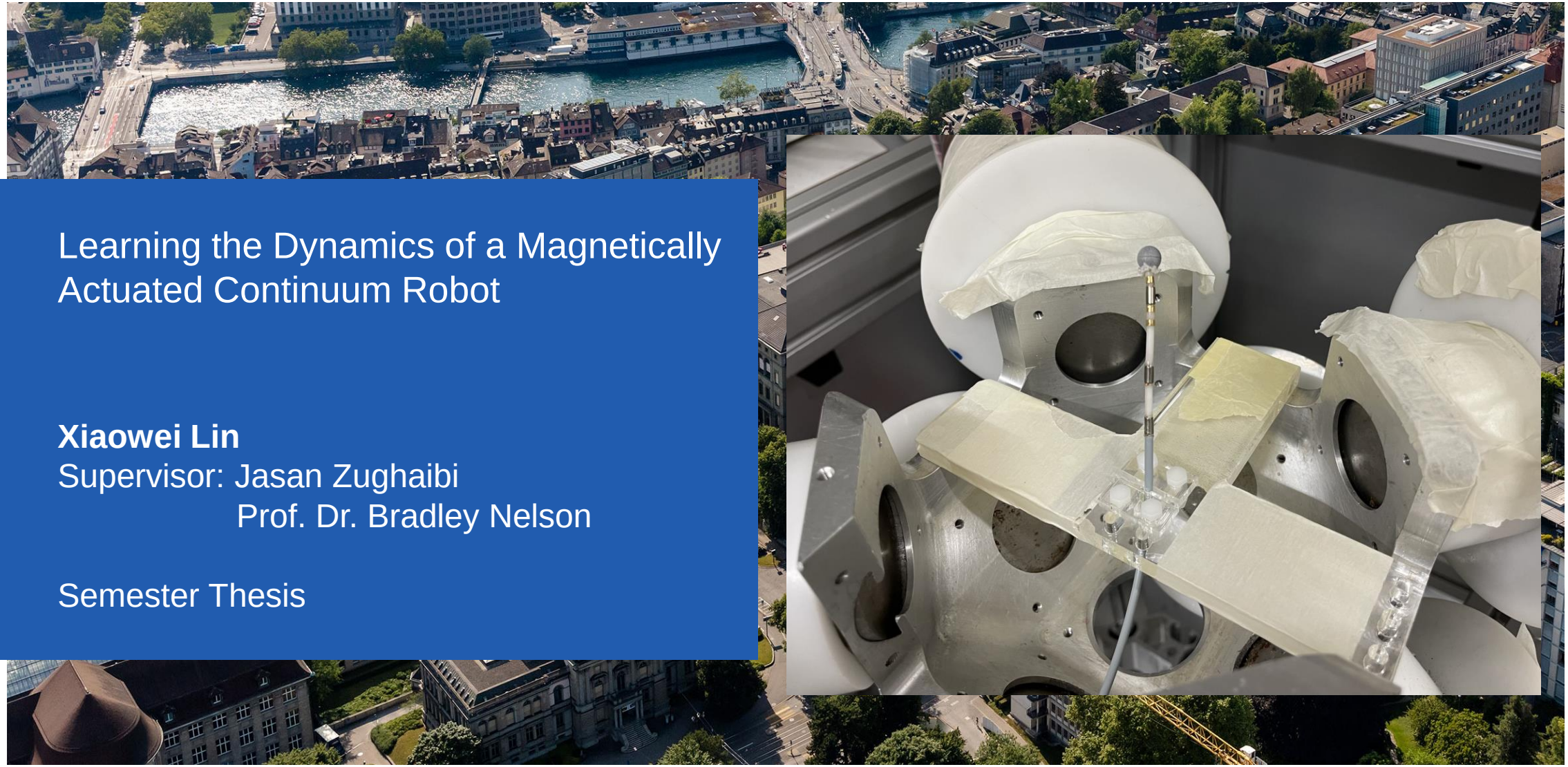
ETH zürich

MSRL
Multi-Scale Robotics Lab



Learning the Dynamics of a Magnetically Actuated Continuum Robot

Xiaowei Lin
Supervisor: Jasan Zughaibi
Prof. Dr. Bradley Nelson

Semester Thesis

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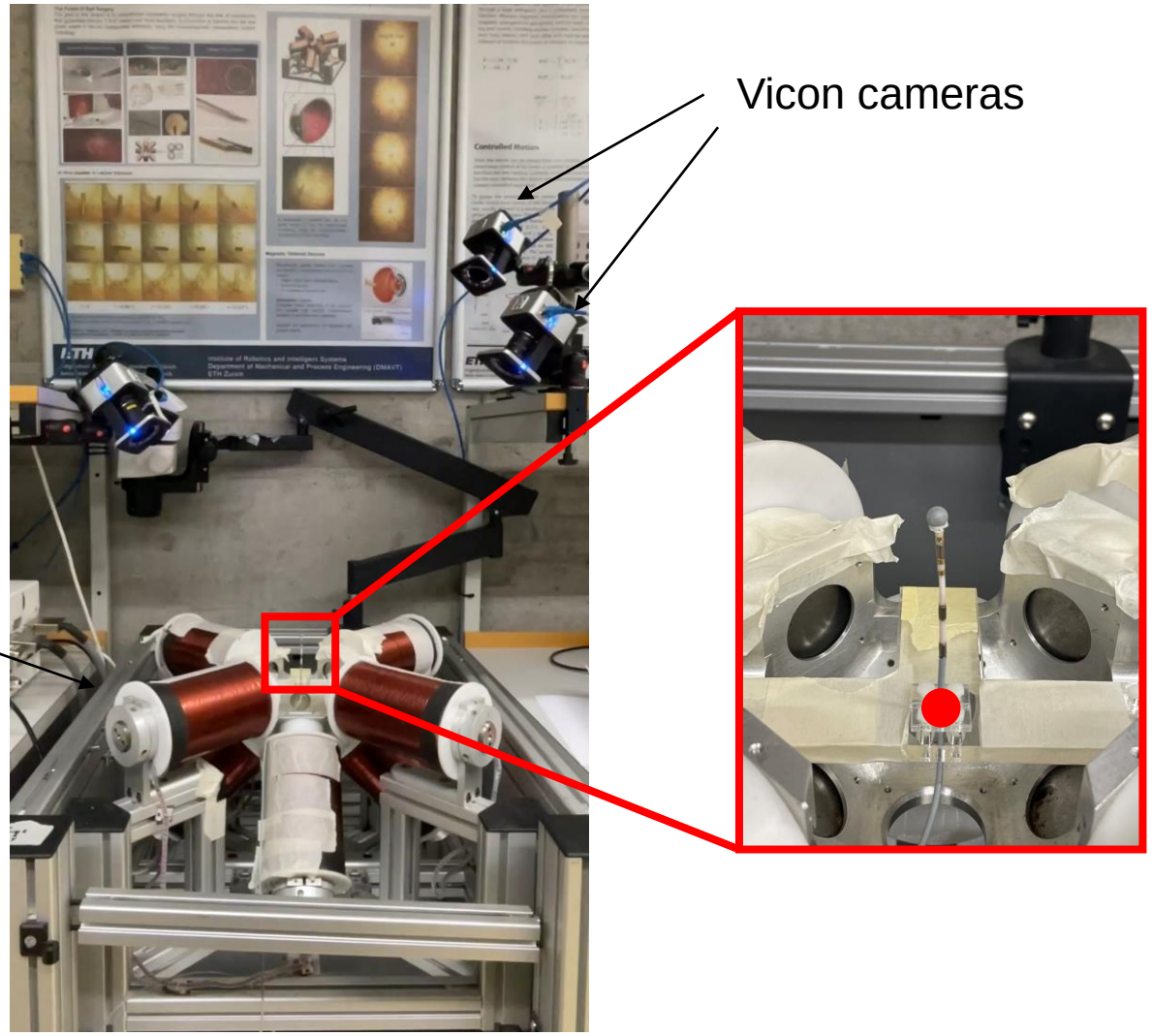
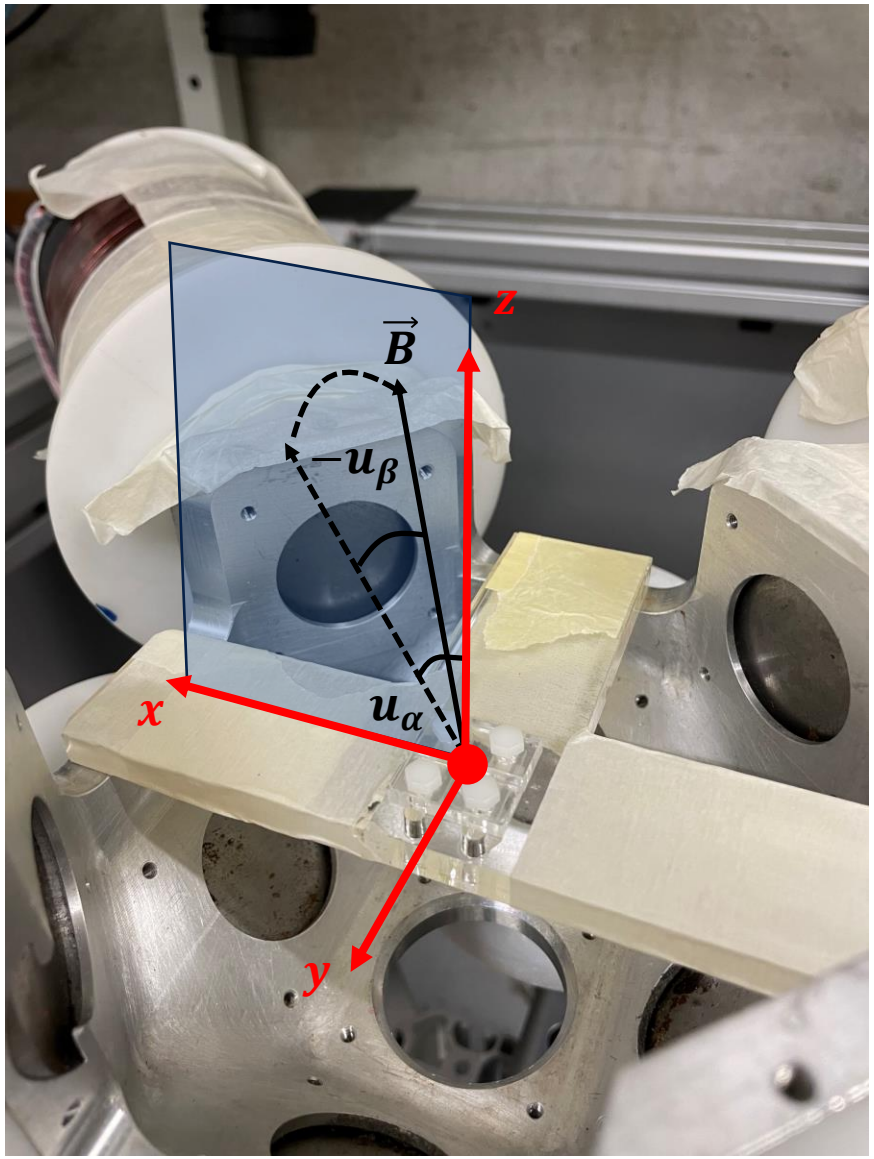
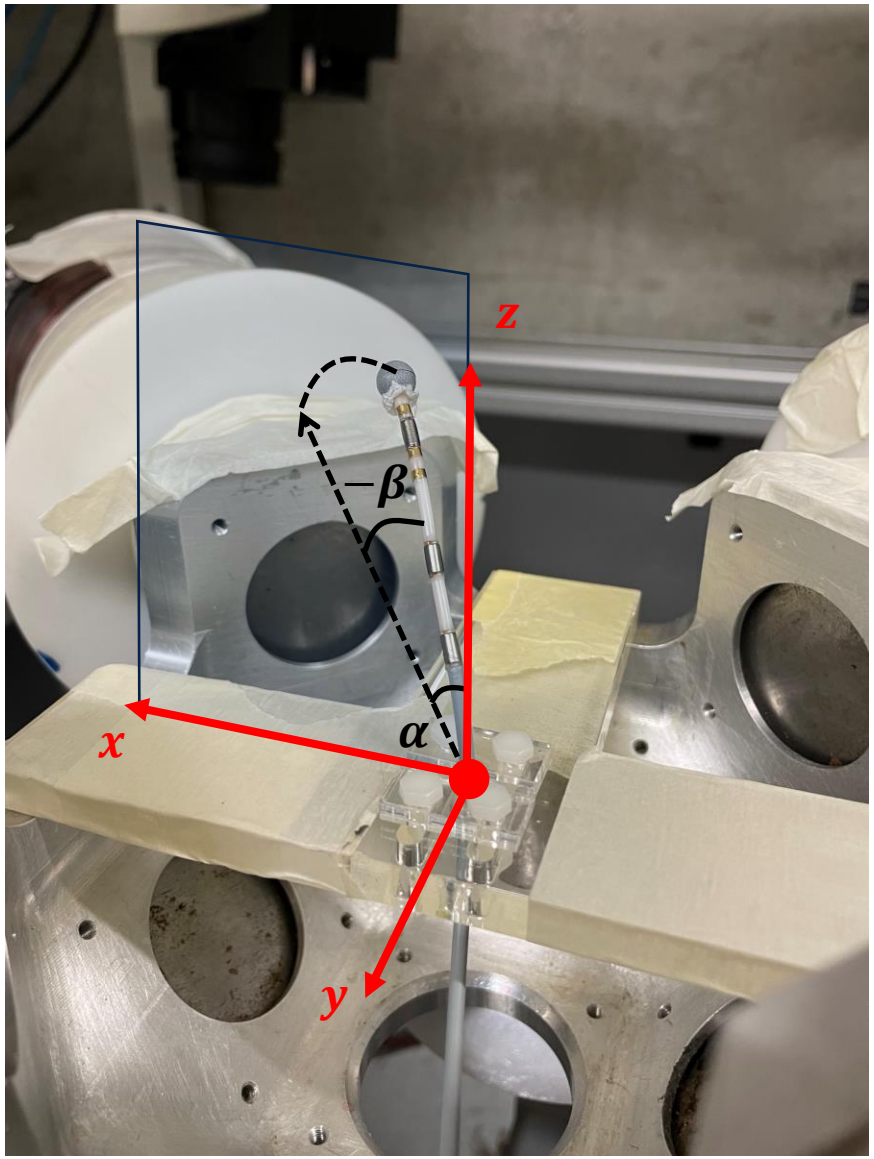
Experimental Setup

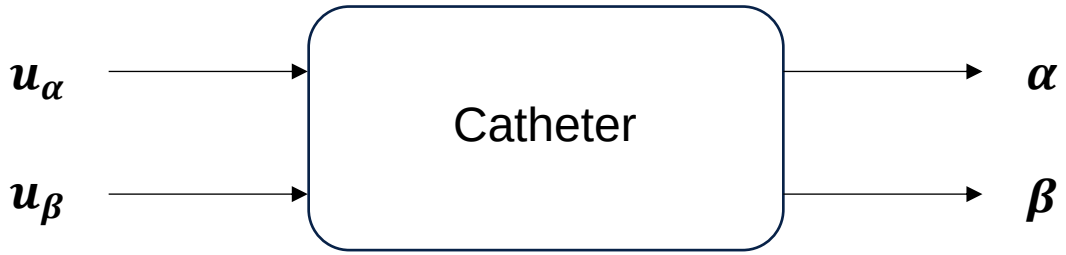


Input and Output





Input and Output



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Goal and Motivation

1. Non-Linearity
2. Coupling Effect
3. Simulation
4. Control

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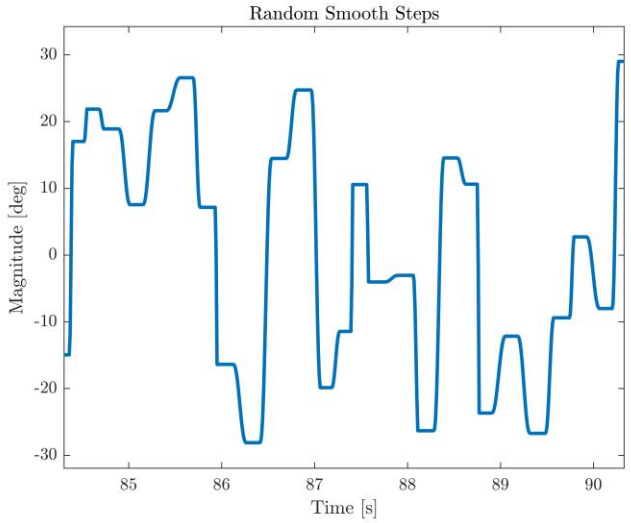
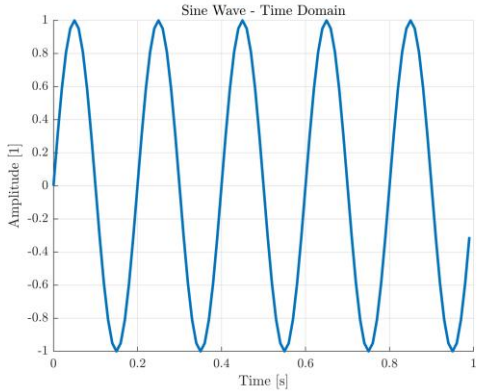
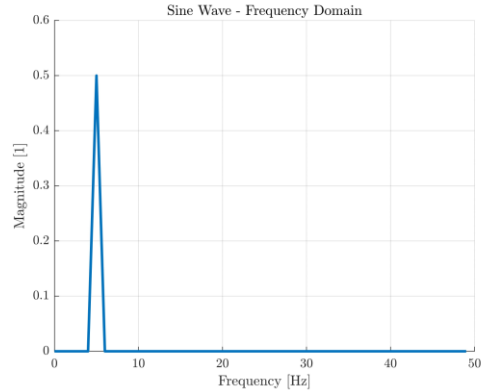
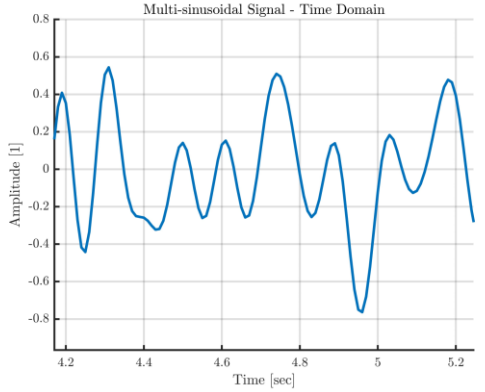
Excitation Signals

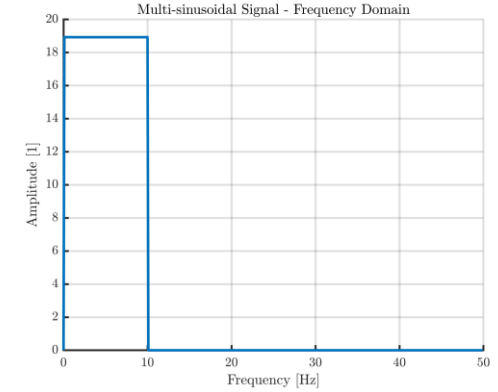
1. Sinusoidal Signals
2. Multisine Signals
3. PRBS(Pseudo Random Binary Sequence)
4. Random Smooth Steps

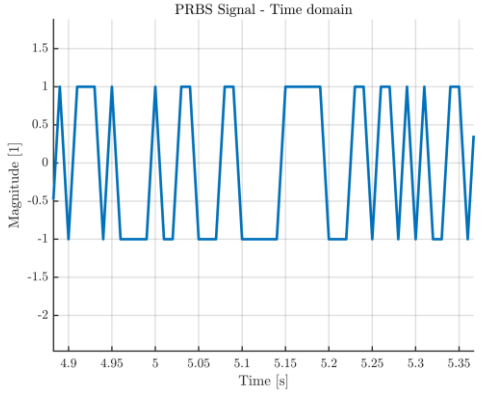


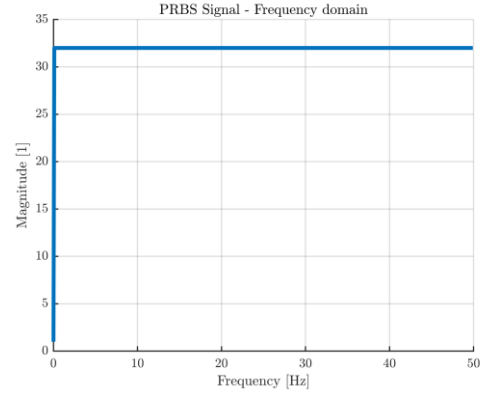












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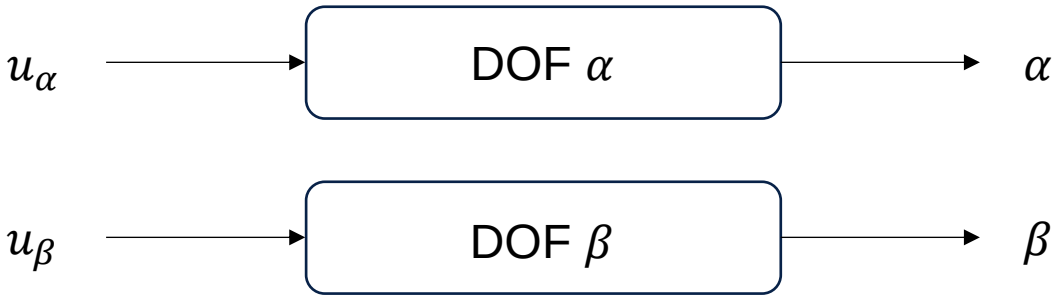
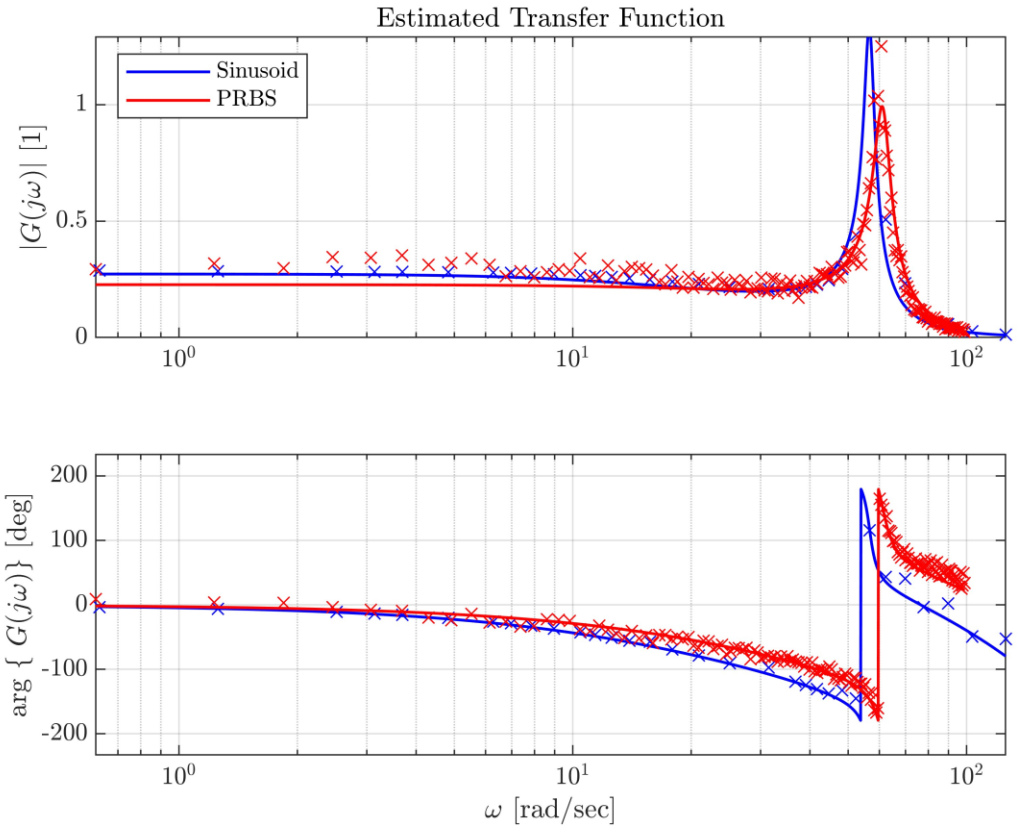
Linear System Identification



$$G_\alpha(s) = \frac{\alpha(s)}{u_\alpha(s)}$$



Identification using Sinusoidal: ~820s
Identification using PRBS: ~120s

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Learning-based System Identification

1. Problem Description
2. Learning Routine
3. Data Collection and Post-Processing
4. Training
5. Results

Learning-based System Identification

1. Problem Description
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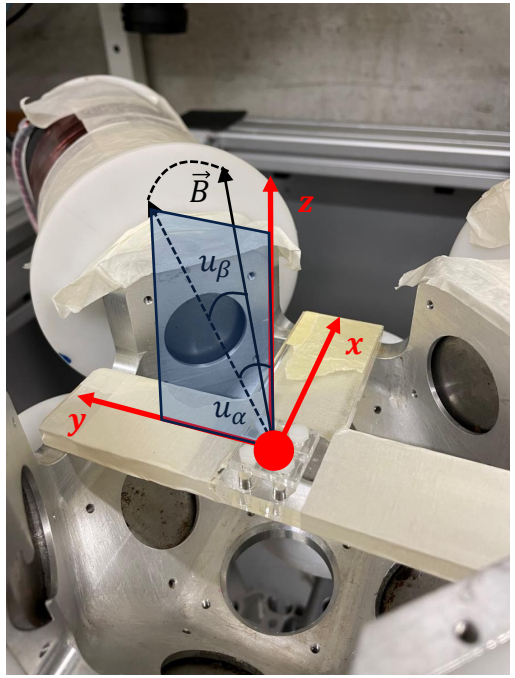
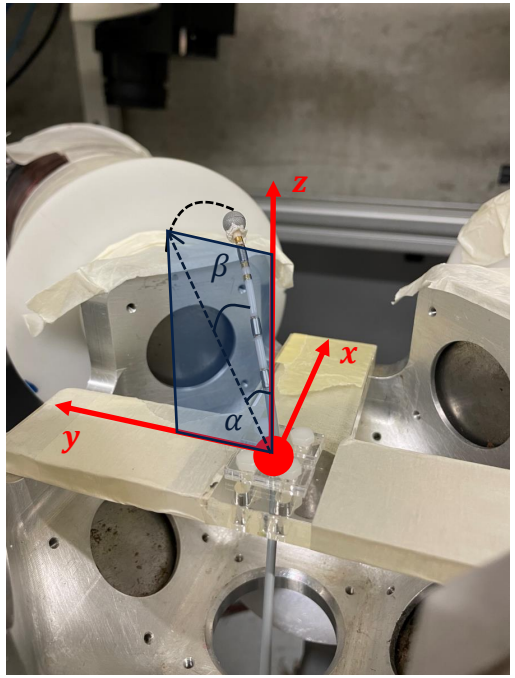
5. Results

Problem Description





$$\left(\ddot{\alpha}, \ddot{\beta}\right) = f\left(\alpha, \dot{\alpha}, \beta, \dot{\beta}, u_\alpha, u_\beta\right)$$
$$x = \left(\alpha, \dot{\alpha}, \beta, \dot{\beta}\right), u = \left(u_\alpha, u_\beta\right)$$

Non-linearity
complicated coupling

$$\left(\ddot{\alpha}, \ddot{\beta}\right) = NN\left(\alpha, \dot{\alpha}, \beta, \dot{\beta}, u_\alpha, u_\beta\right)$$

Learning-based System Identification

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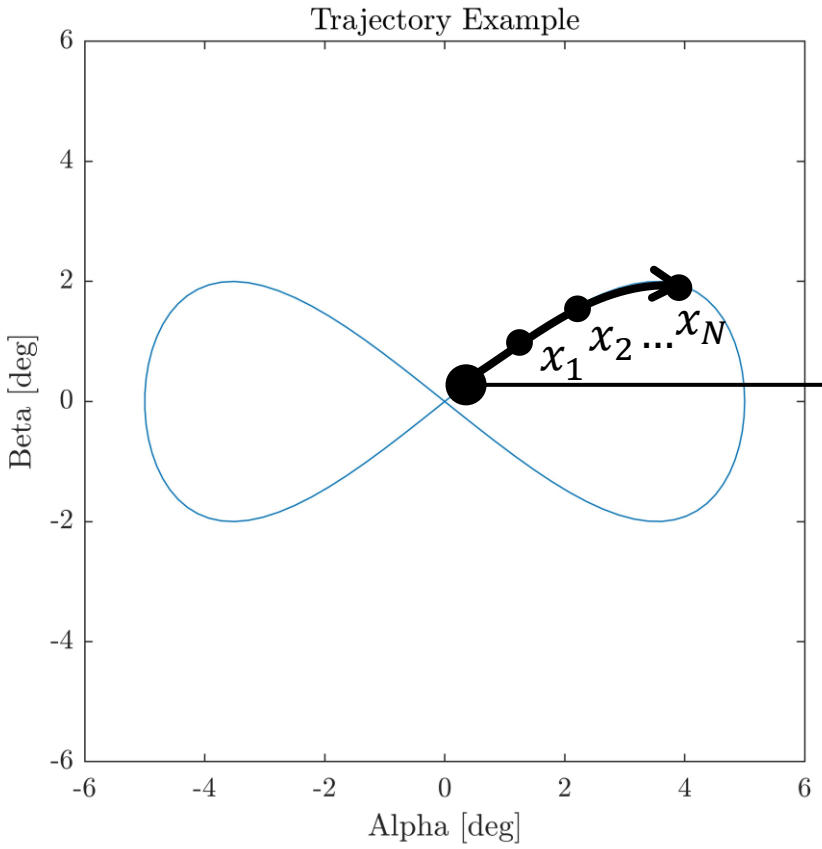
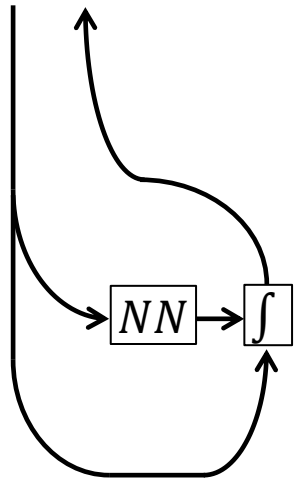
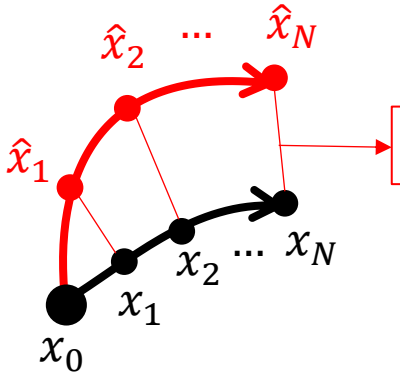
4. Training
5. Results

Learning Routine



x_0 $\hat{x}_1$ $\hat{x}_2$ ... $\hat{x}_N$





$\mathcal{L} = MSE(\hat{x}, x)$

$$(\ddot{\alpha}, \ddot{\beta}) = NN(\alpha, \dot{\alpha}, \beta, \dot{\beta}, u_\alpha, u_\beta)$$

Plot inspired by Legaard, Christian, et al.

Learning-based System Identification

1. Problem Description
2. Learning Routine
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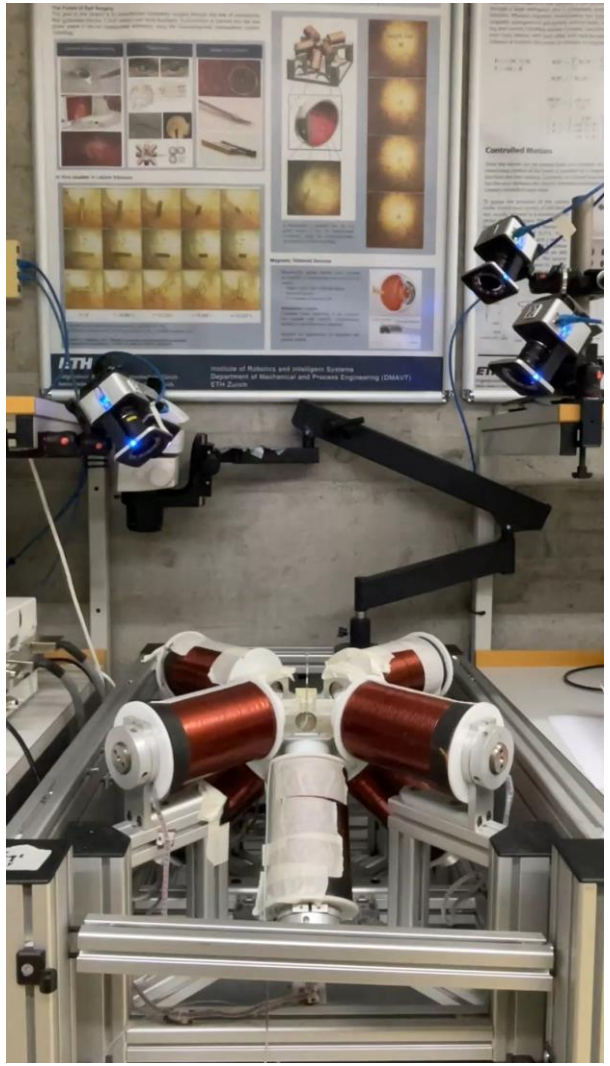
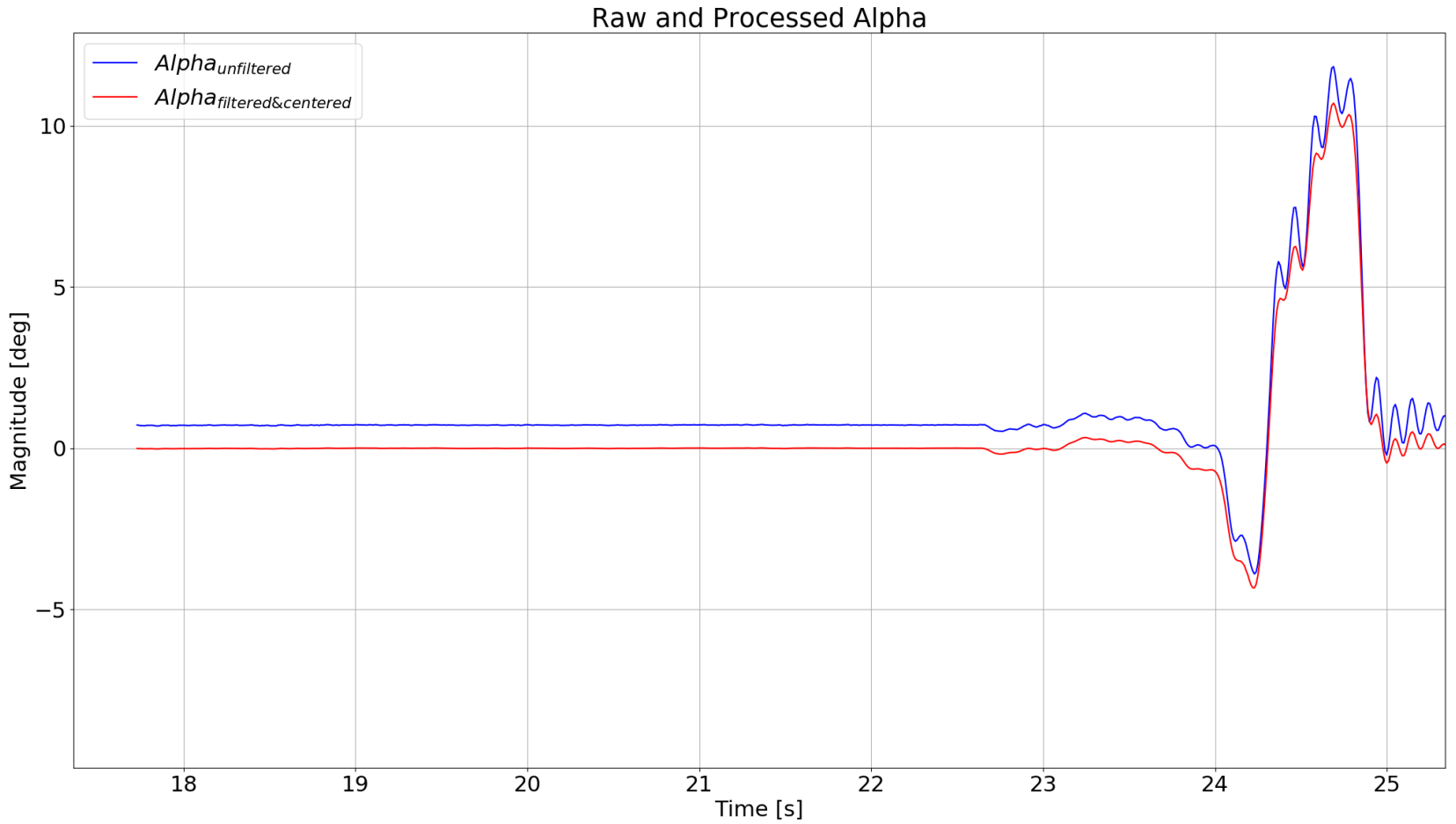
5. Results

Data Collection



Data Post-Processing

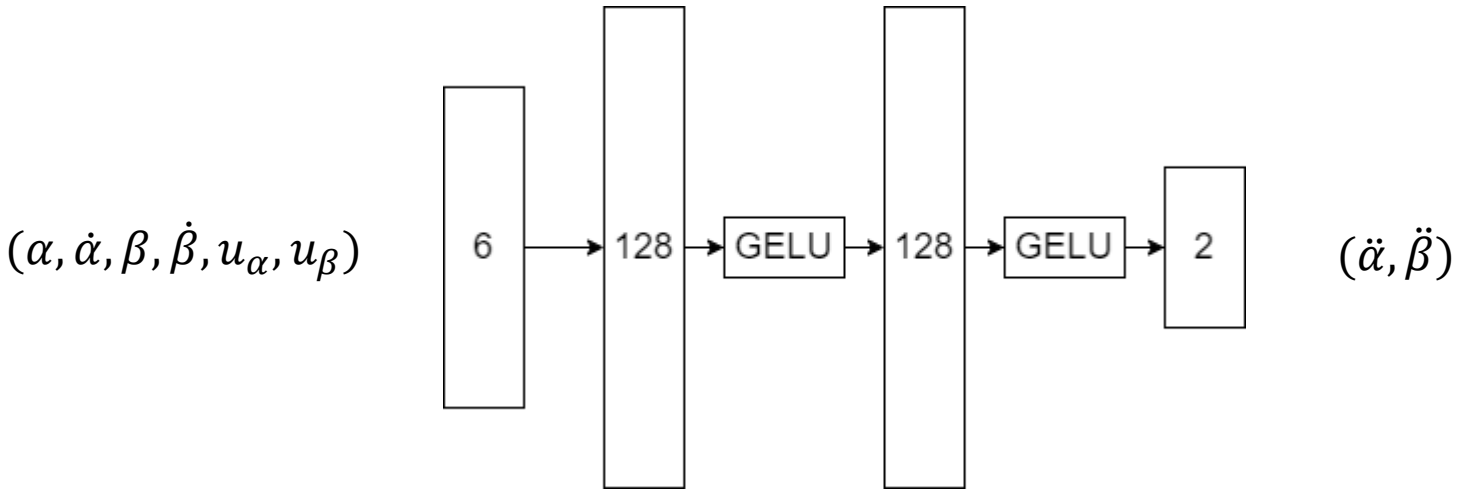


Learning-based System Identification

1. Problem Description
2. Learning Routine
3. Data Collection and Post-Processing
4. Training
5. Results

Training

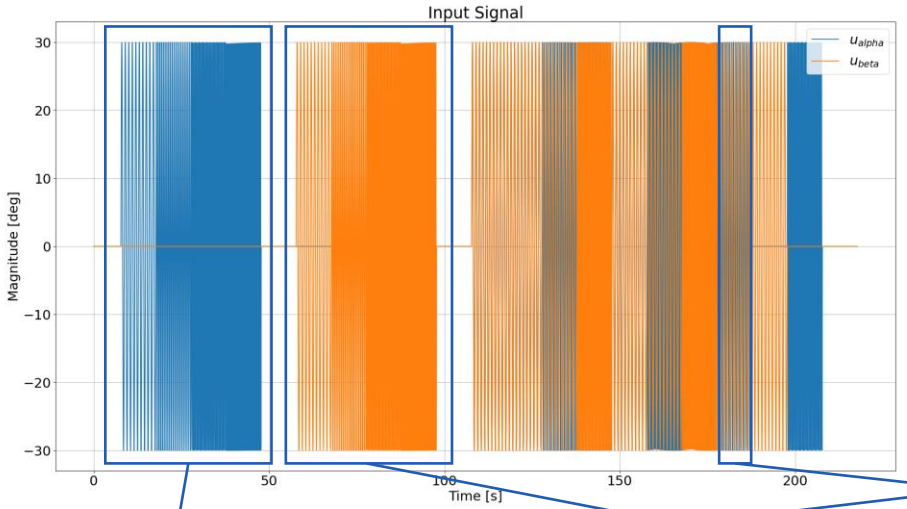
1. ~50 mins of data is used
2. Network Structure
3. Training (~8 hours)

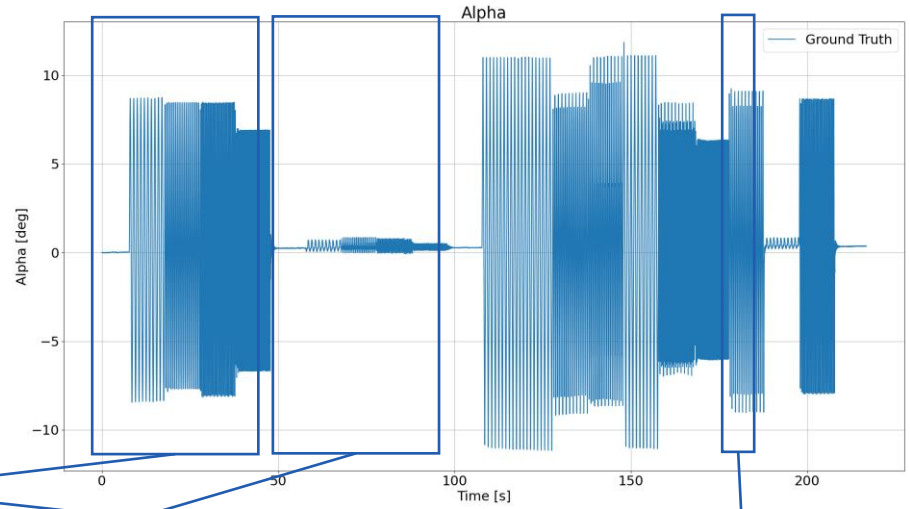


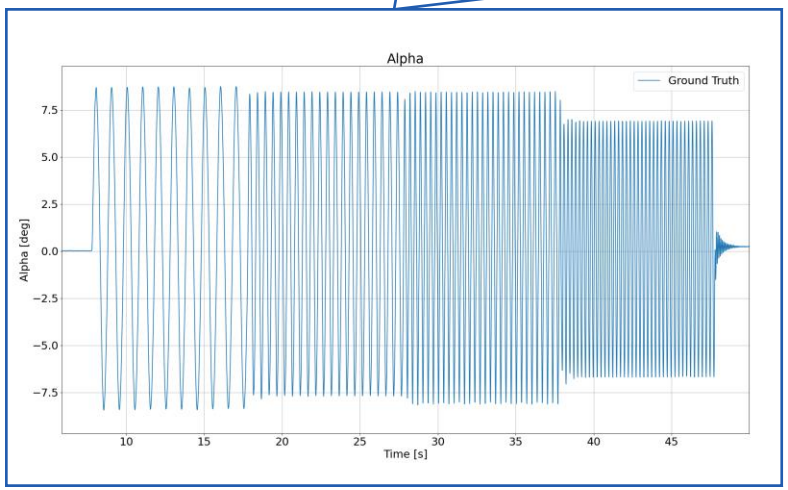
Learning-based System Identification

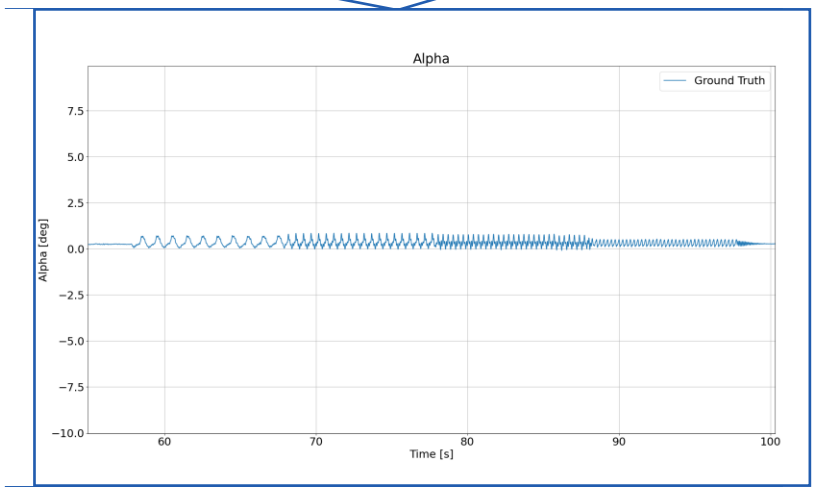
1. Problem Description
2. Learning Routine
3. Data Collection and Post-Processing
4. Training
5. Testing

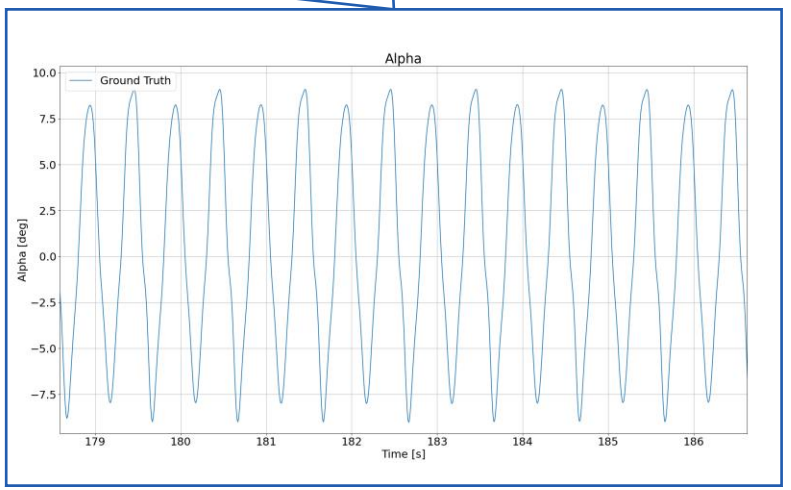
Testing – Sinesweep with random sine combination ($-30°\sim30°, 0\sim4Hz$)



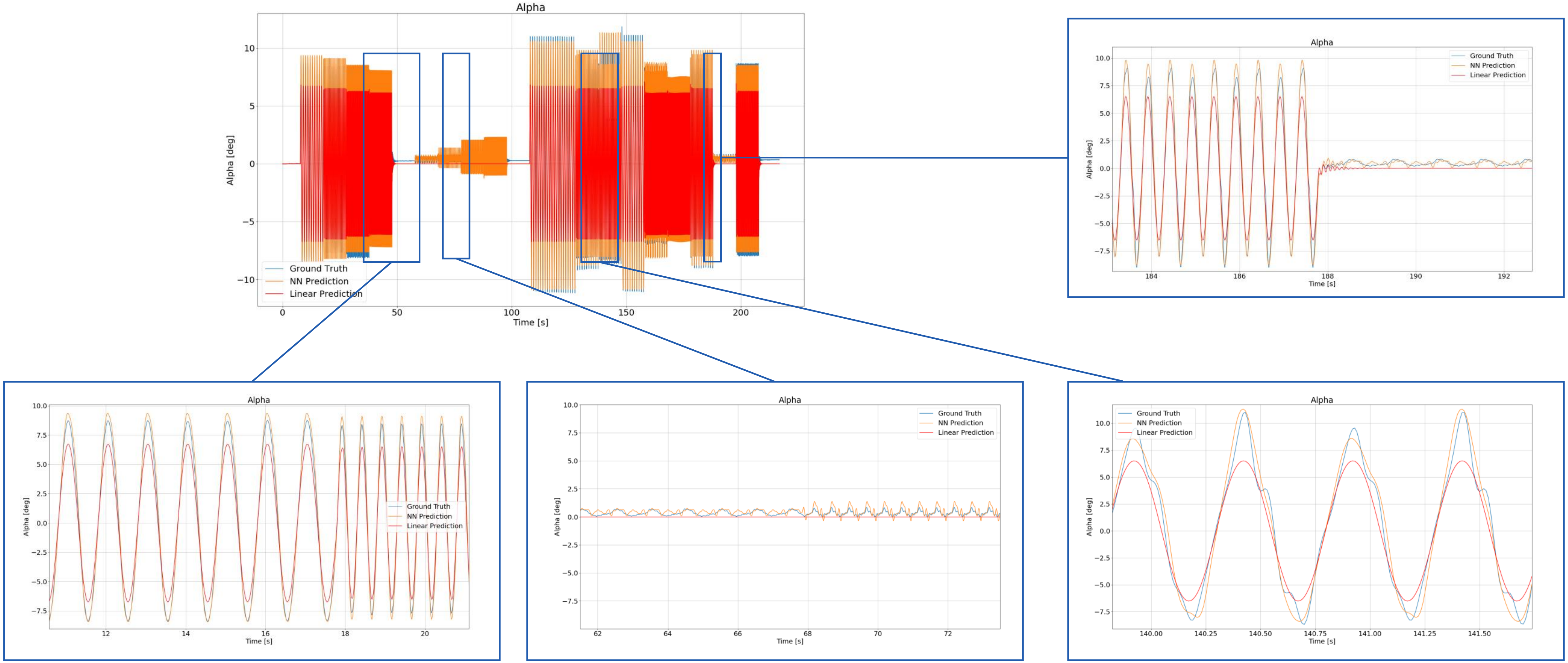






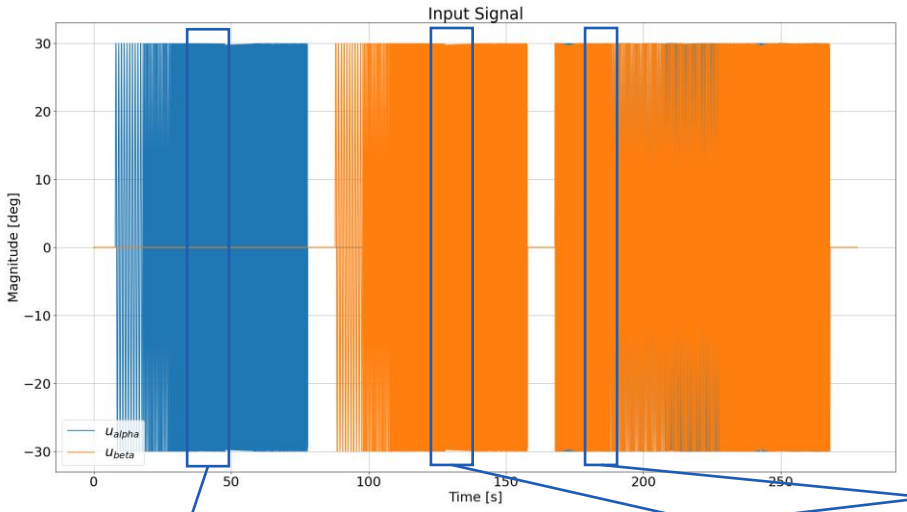


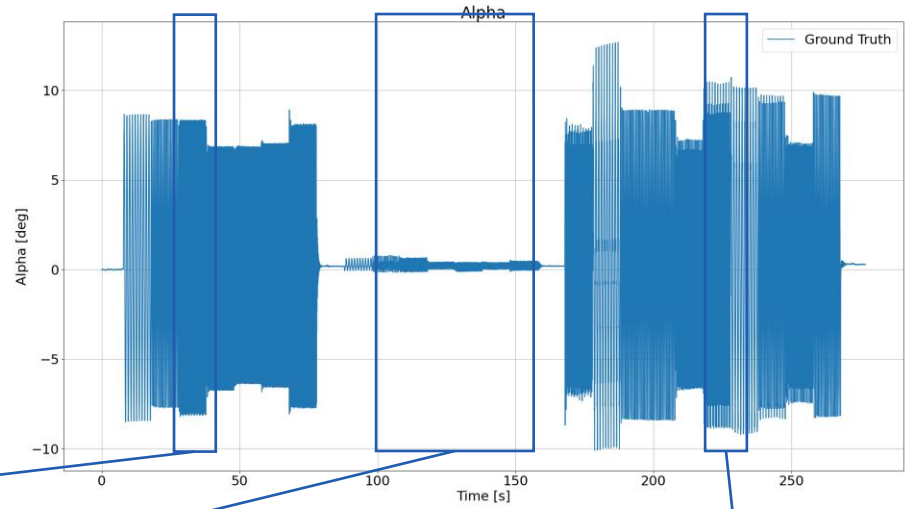
Comparison

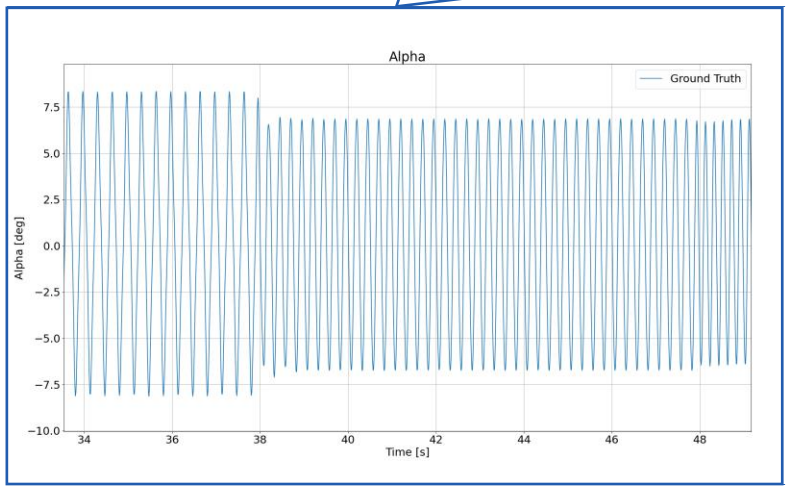


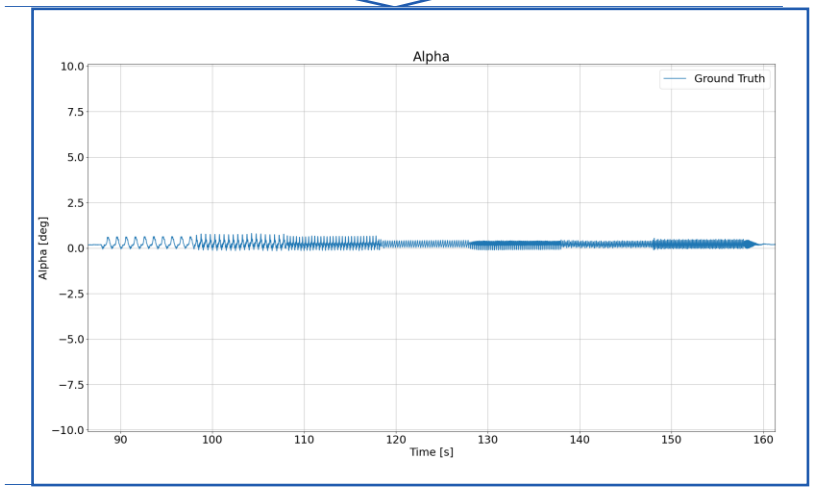
Alpha
Alpha [deg]
Time [s]
Ground Truth
NN Prediction
Linear Prediction

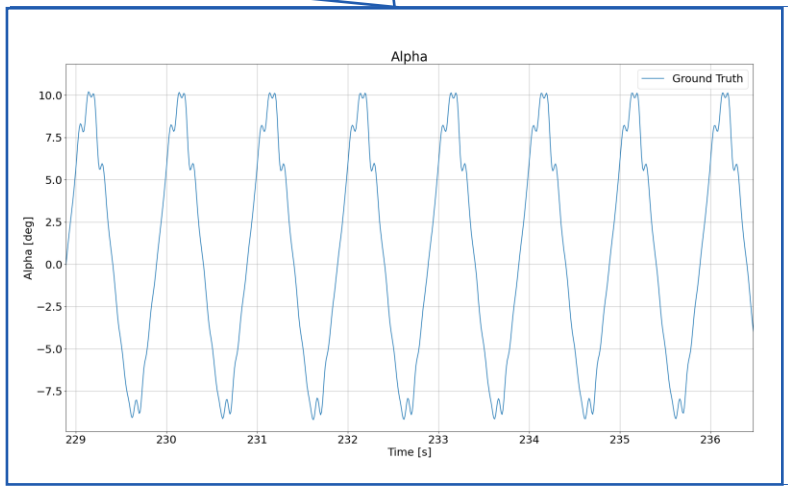
Testing – Sinesweep with random sine combination ($-30°\sim30°, 0\sim7Hz$)



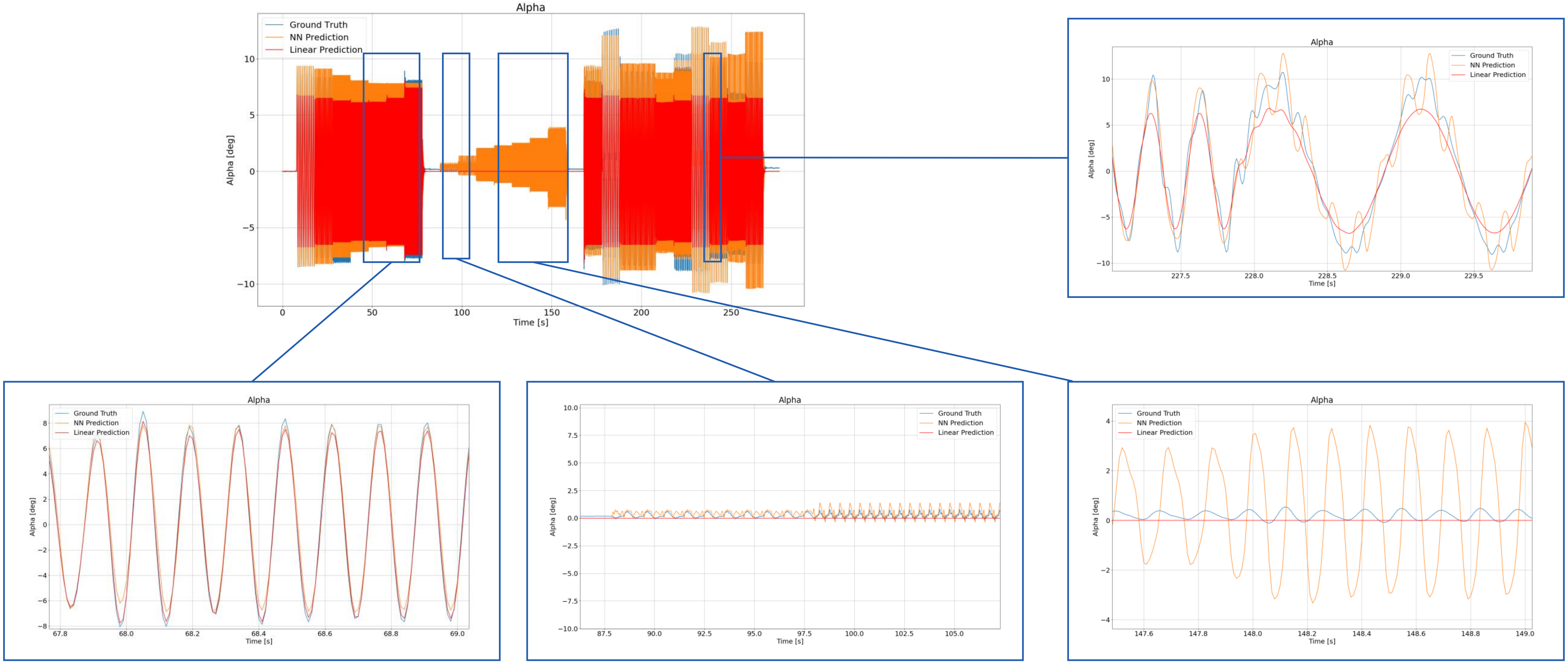




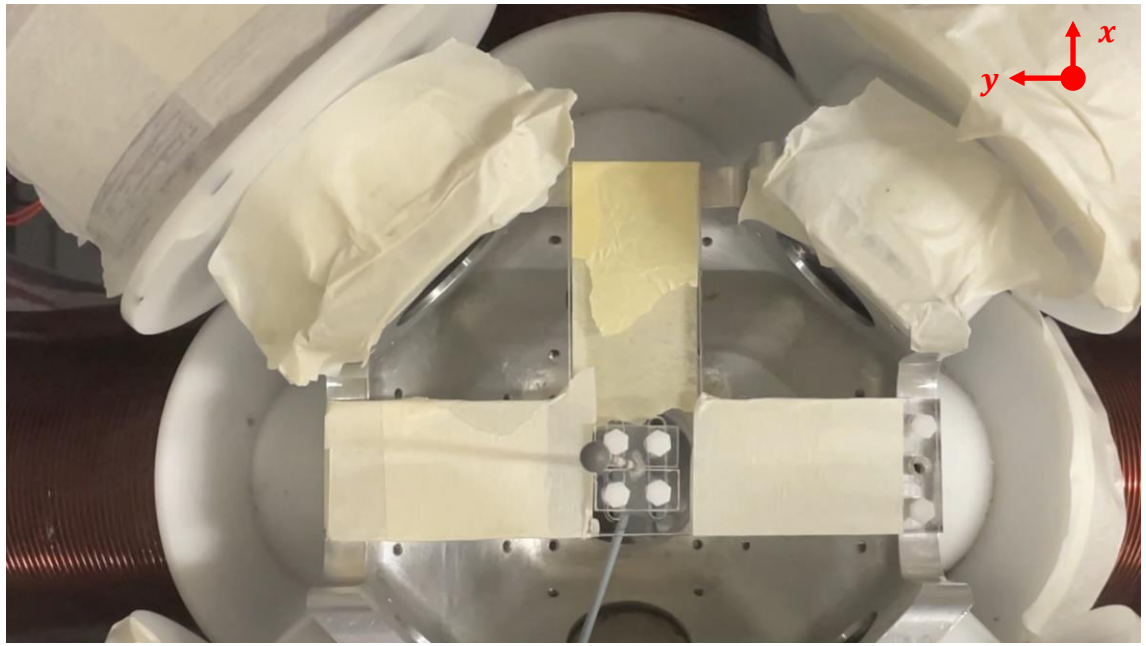


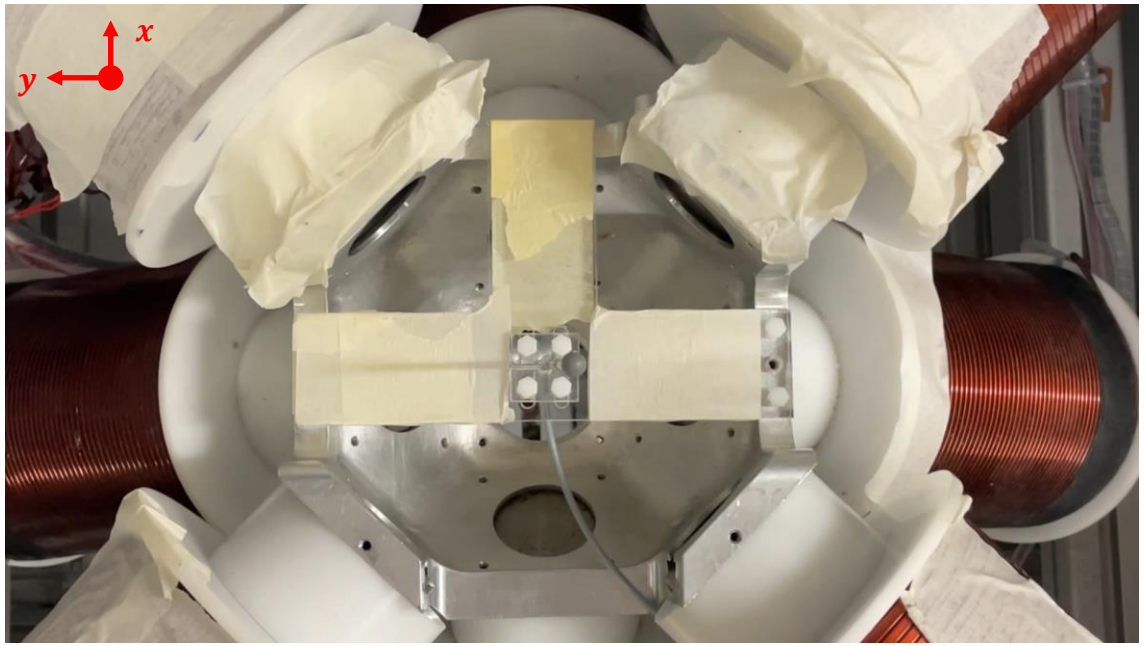


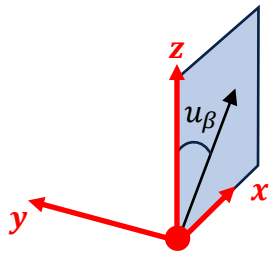
Comparison


Alpha
Ground Truth
NN Prediction
Linear Prediction
Alpha [deg]
Time [s]

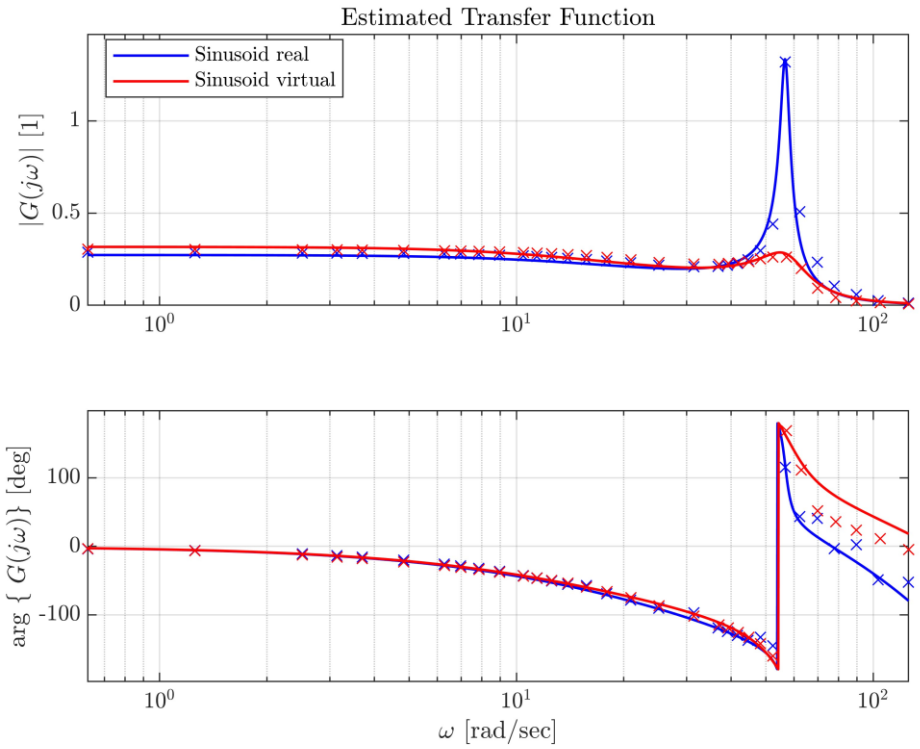
Discussion – Initial-condition-dependent coupling effect

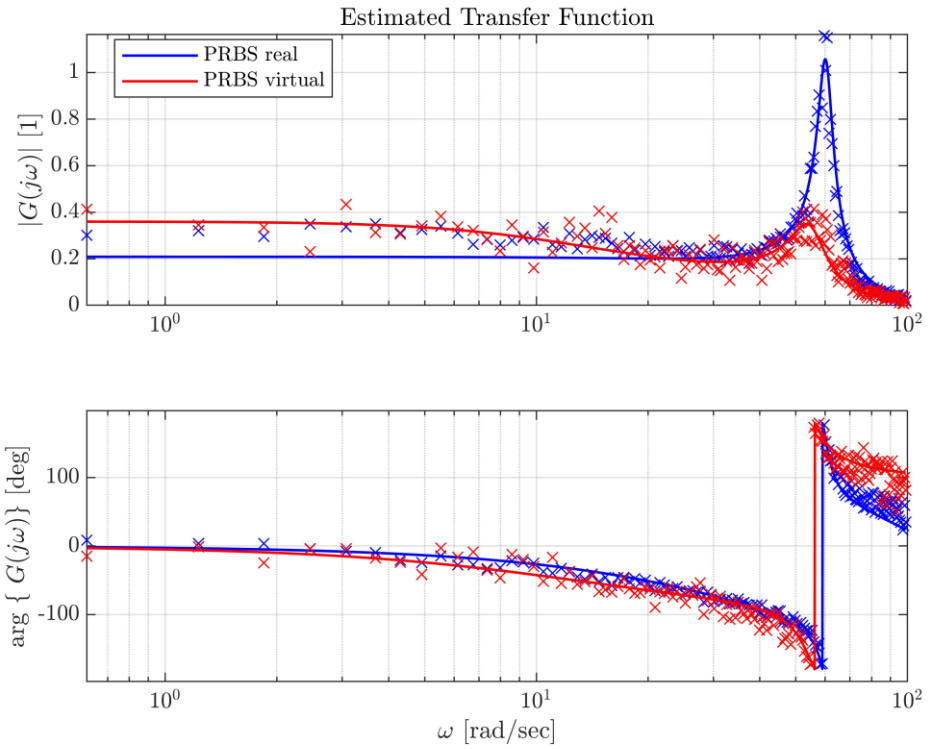






Simulated Linear System Identification





"Real" Identification: ~820s
"Virtual" Identification: ~80s

"Real" Identification: ~120s
"Virtual" Identification: ~10s

Outlook – Spectral bias of neural networks

- Rahaman, Nasim, et al.: „By using tools from Fourier analysis, we highlight a learning bias of deep networks towards low frequency functions, which manifests itself as a frequency-dependent learning speed. “
- Extend to Fourier Features

Outlook – Learning Control

$$(\ddot{\alpha}, \ddot{\beta}) = NN(x, u)$$

Linearize the NN

$$(\ddot{\alpha}, \ddot{\beta}) = A\,x + Bu$$

$$A = \frac{\partial NN}{\partial x}(x, u), B = \frac{\partial NN}{\partial u}(x, u)(Varying\ Parameters\ Linear\ Model)$$

$$State - space\ control\ techniques, such\ as\ time - varying\ LQR, time - varying\ MPC, become\ applicable.$$

Conclusion & Acknowledgement

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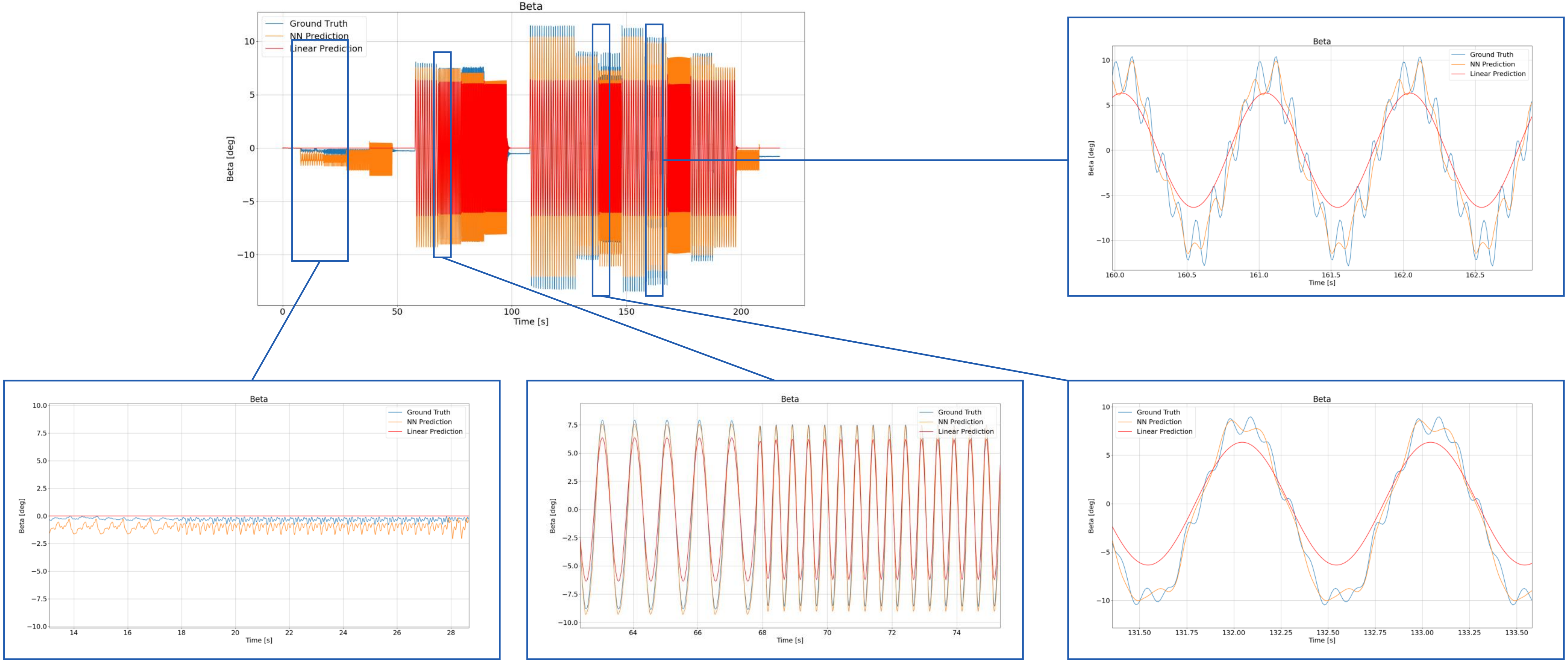
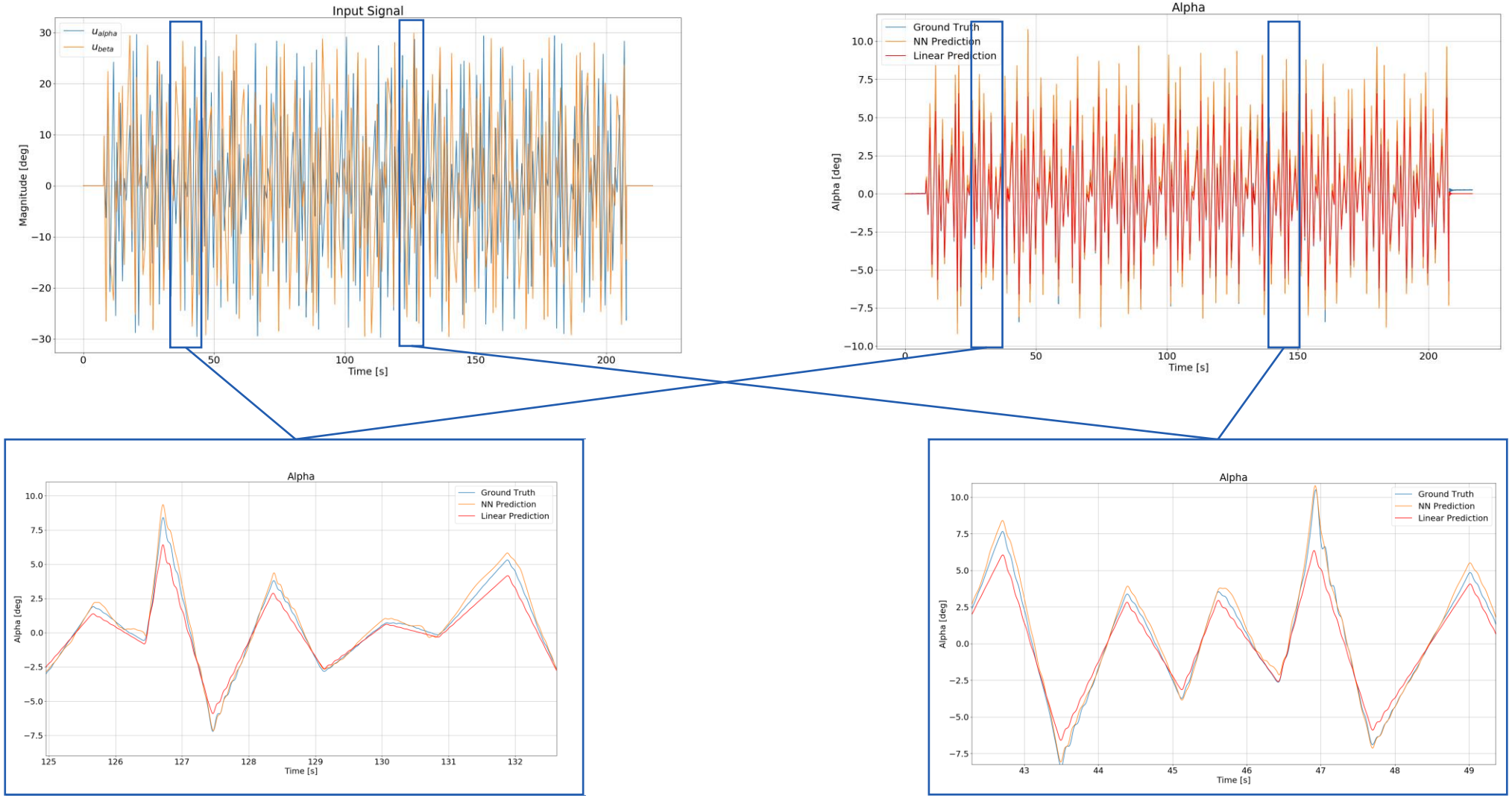
Testing – Sinesweep with random sine combination $(-30°\sim30°, 0\sim4Hz)$

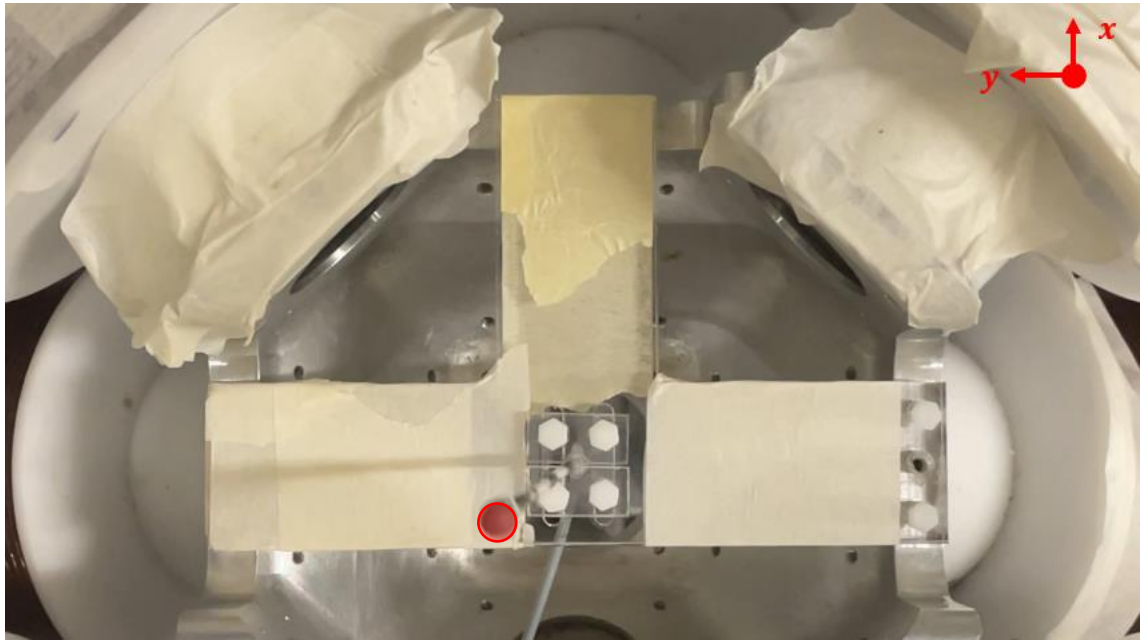


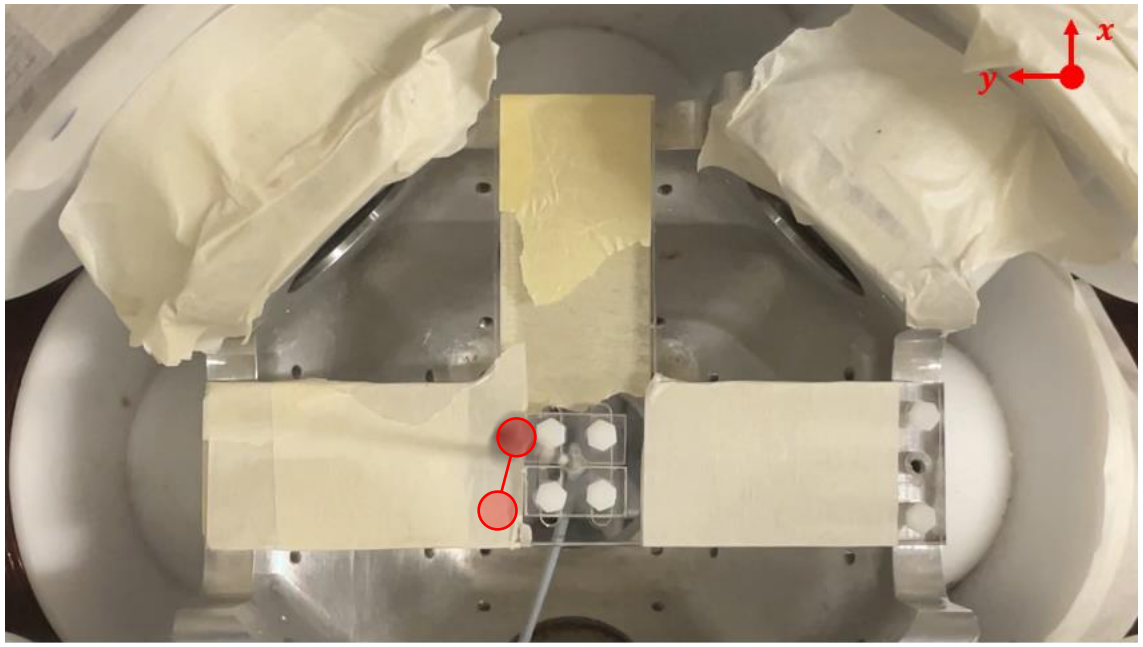
Test sets – Ramp

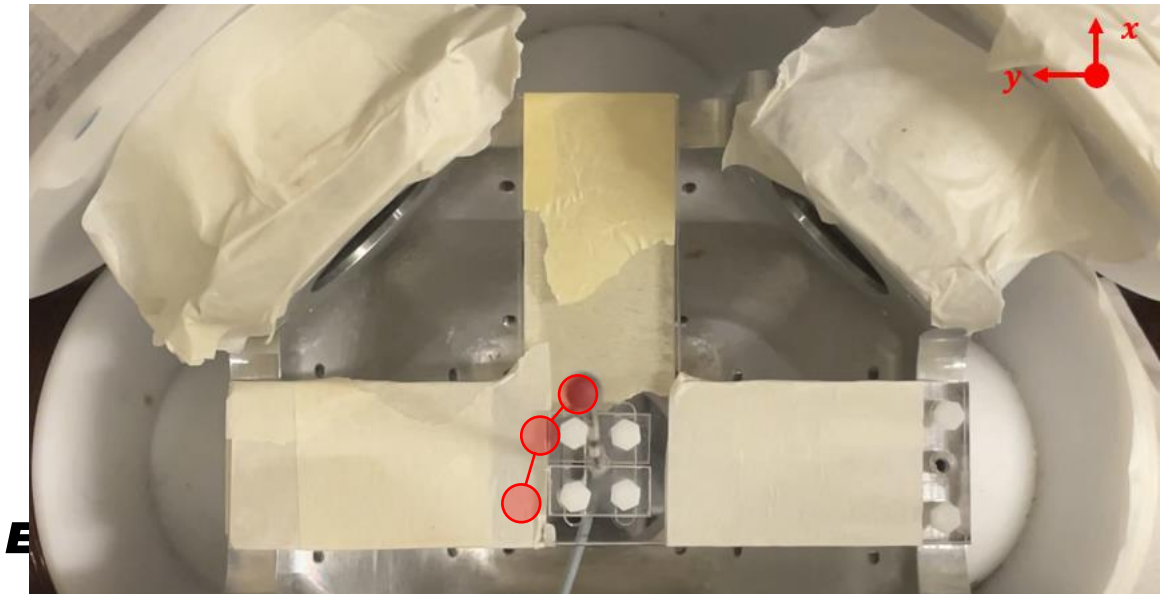


Linear System Identification

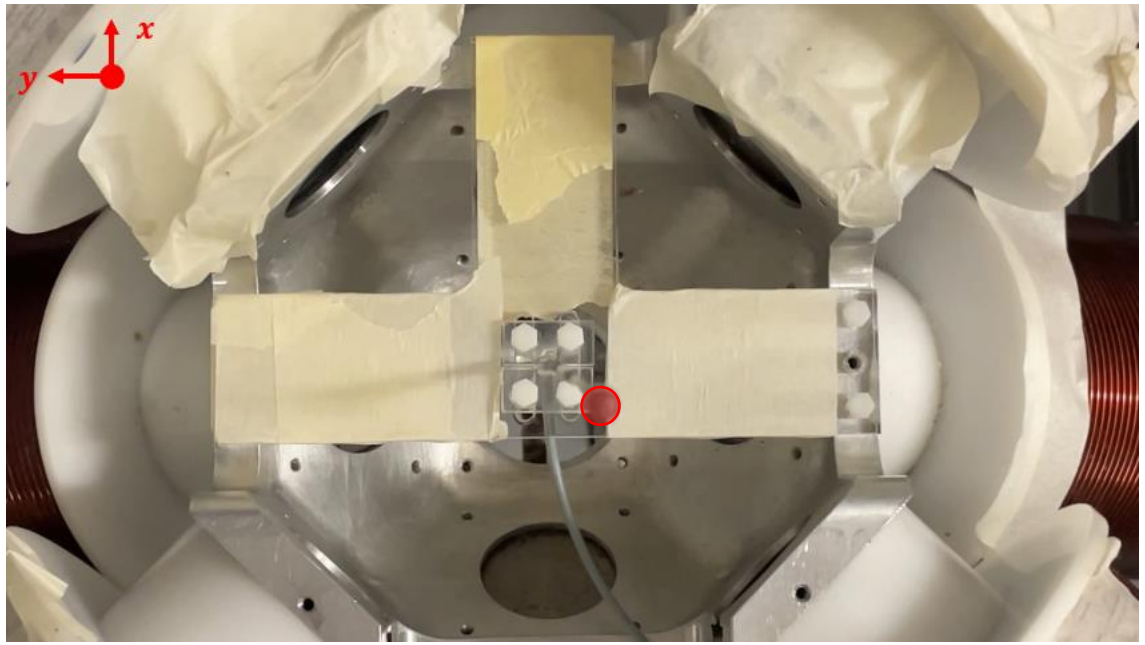
Discussion – Initial-condition-dependent coupling effect

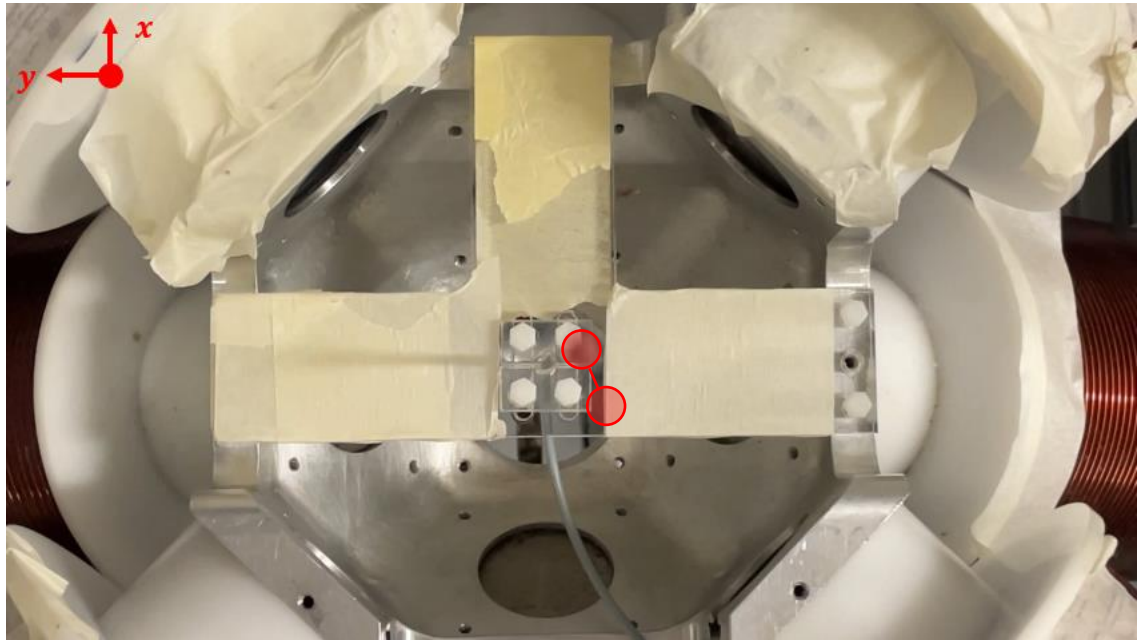


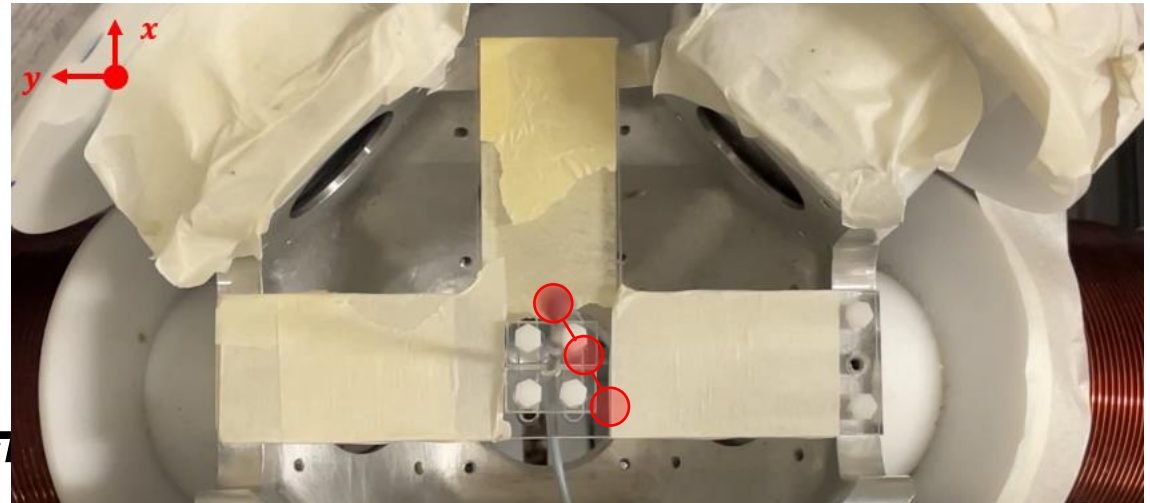




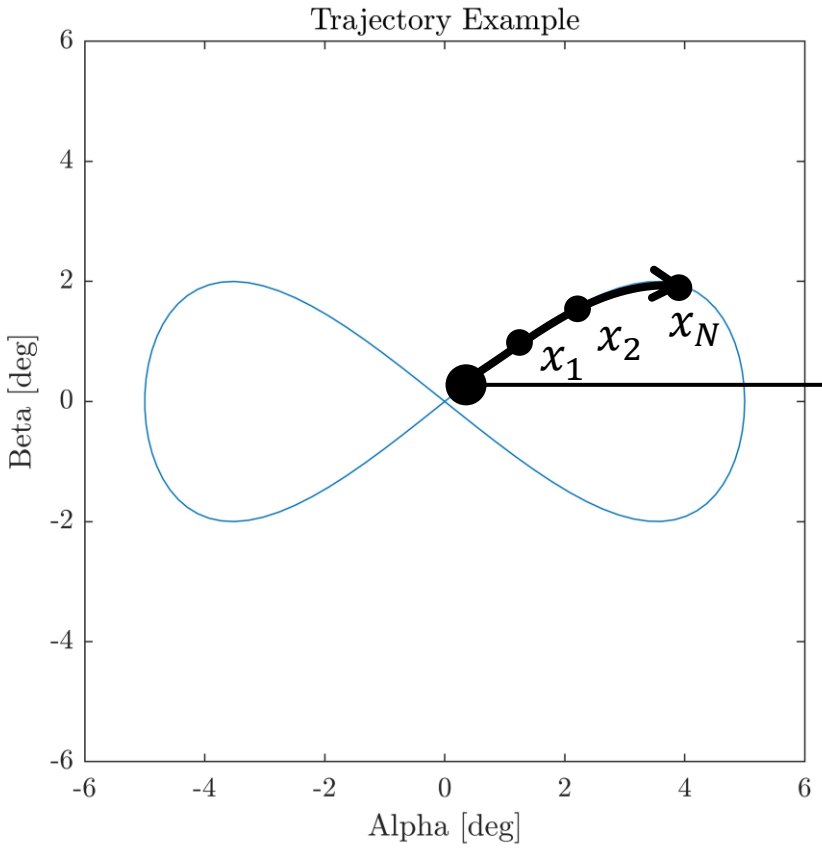
Discussion – Initial-condition-dependent coupling effect



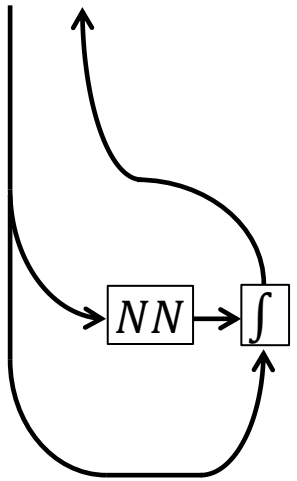


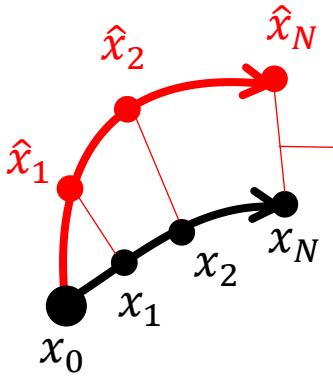


Learning Routine



x_0 $\hat{x}_1$ $\hat{x}_2$ ... $\hat{x}_N$





$\mathcal{L} = MSE(\hat{x}, x)$

$$(\ddot{\alpha}, \ddot{\beta}) = NN(\alpha, \dot{\alpha}, \beta, \dot{\beta}, u_\alpha, u_\beta)$$

Plot inspired by Legaard, Christian, et al.