Friedrich-Alexander-Universität
Technische Fakultät

Dynamic Motion State Estimation and Control via RNNs and Sim-to-Real Transfer

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Erlangen, 18.03.2025

Dynamic Motion Surrounds Us Everywhere

Introduction

— Agile motion plays a vital role in biological and technological domains.

Evolutionary adaptation of animals

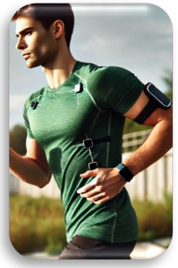
Everyday activities of humans

Capabilities and efficiency of robots

— Fundamentally, there are two tasks that involve dynamic motions: **motion state estimation and motion control.**

Dynamic, agile motion

estimate and track state information of a system in dynamic motion



Motion State Estimation

actuate system to achieve a desired motion

Motion Control

Applications

Introduction

— Motion state estimation and motion control are central for various applications.

Motion State Estimation

Motion Control

VR/AR

diagnostics cerebral palsy in infants

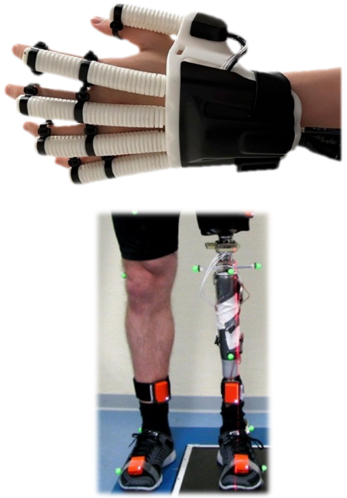
gait analysis and joint stabilisation

drop foot detection

FES control

paraplegic cycling

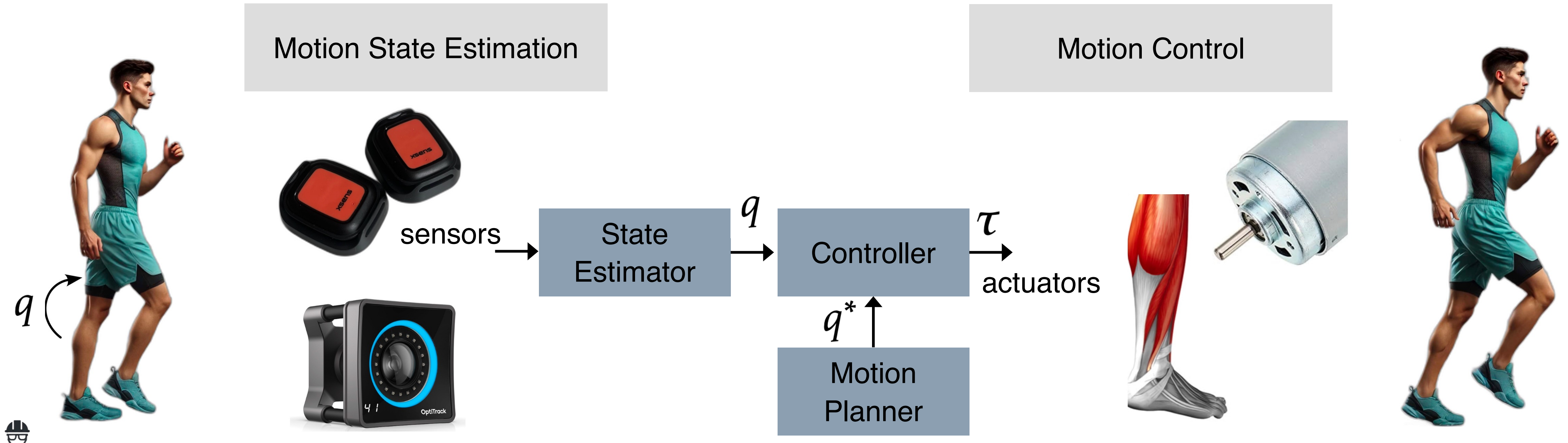
assistive devices



Sensors and Actuators

Introduction

- Motion state estimation and motion control are central for various applications.
- These applications require a suitable set of **sensors and actuators**.

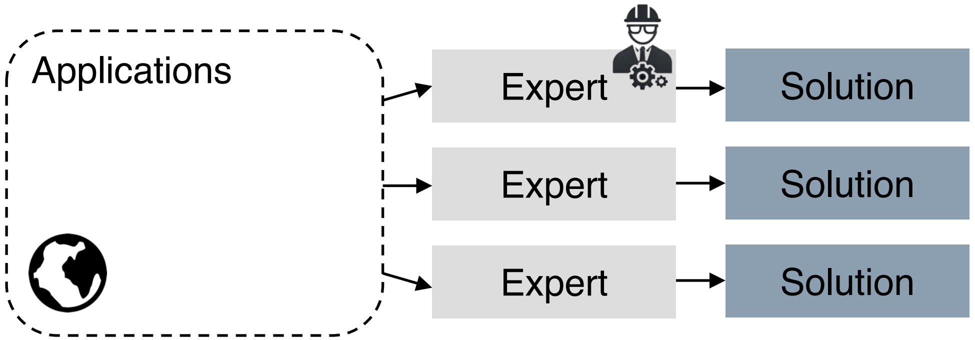


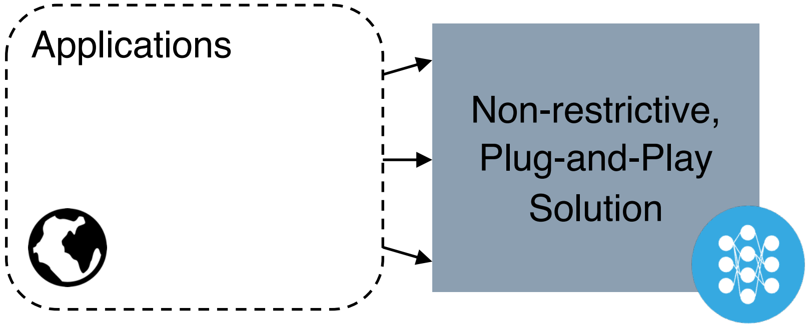
- **Experts are required** to identify the problem and select & calibrate the suitable methods.

Non-Restrictive, Plug-and-Play Solution

Introduction

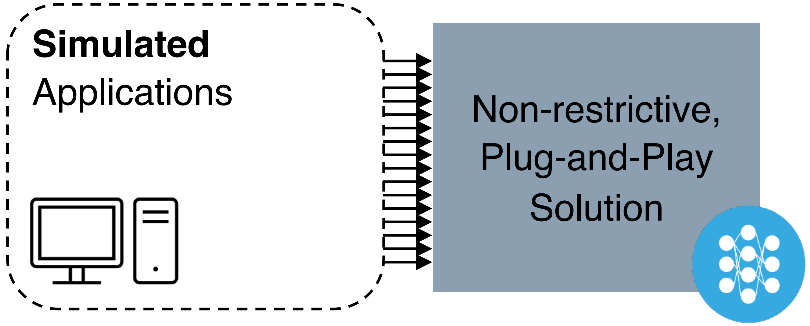
— Typically, each application requires a tailored solution; we want **plug-and-play, non-restrictive** methods.





— Model-based approaches do not scale and generalize → **RNNs that learn to identify the problem and calibrate.**

— Training the RNN in **simulation** allows for thousands (or millions) of training datapoints.



Core Research Question: How can the combination of RNNs and Sim-to-Real Transfer contribute to the development of non-restrictive, plug-and-play solutions for motion state estimation and solutions for motion control?

Outline

State Estimation with IMUs

IMUs and Inertial Motion Tracking

State Estimation with IMUs

— Inertial Measurement Units (IMUs, or inerital sensors) have become small and affordable.

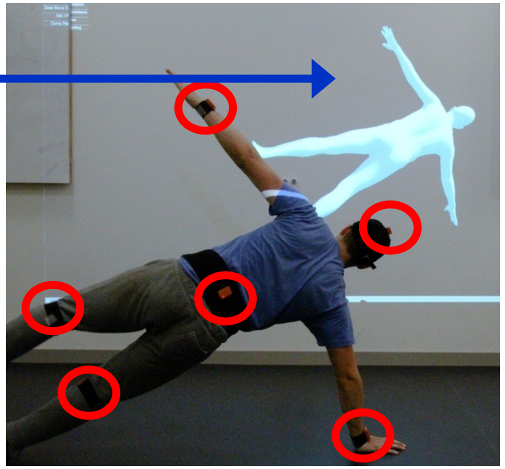
Apollo IMU (1969, ~0.5m)

MEMS IMU (2019, ~1cm)

- lightweight, wireless, and battery-powered
- 3D gyroscope (angular velocity)
- 3D accelerometer (gravity + change of velocity)
- 3D magnetometer (Earth’s magentic field + others)

— Inertial Motion Tracking (IMT) tracks human or robot motion using wearable IMUs. Typically, one IMU per segment.

IMUs → IMT algorithms → Orientations / Visualised Pose

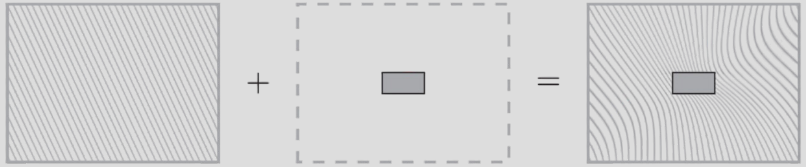


Four Major Challenges in IMT

State Estimation with IMUs

— In many real-world applications, IMT algorithms are faced with several challenges.

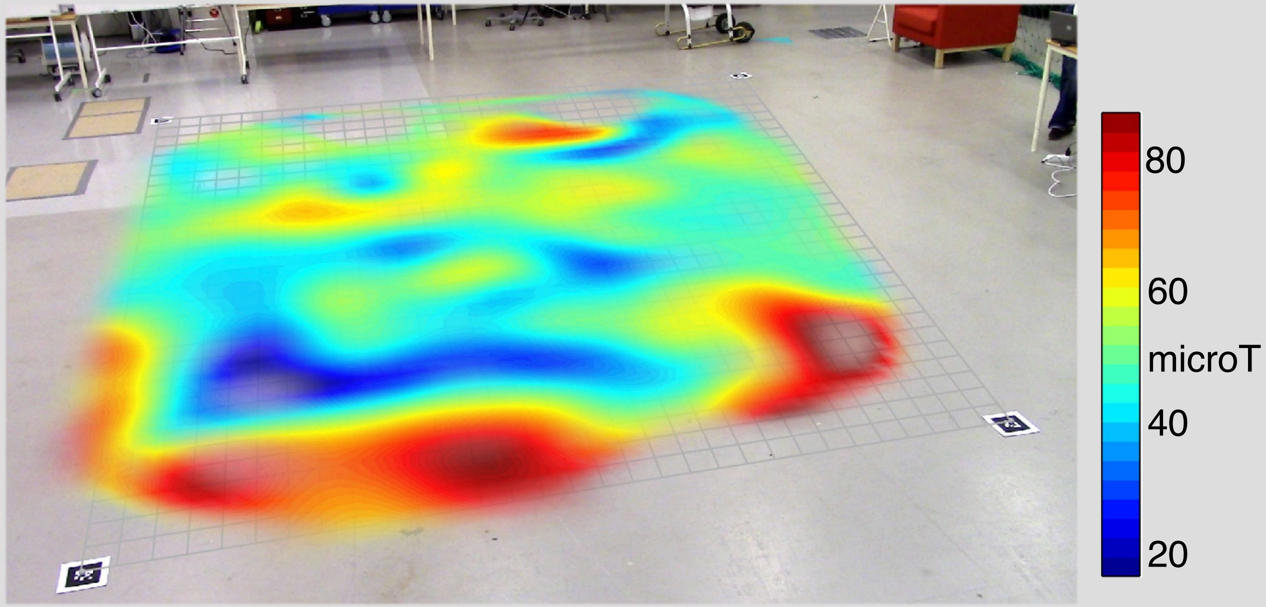
Magnetic Disturbances
(e.g. in indoor environments)



Earth field

Ferromagnetic Material

Disturbed Field



Adopted from [Solin et al. 2018]

Four Major Challenges in IMT

State Estimation with IMUs

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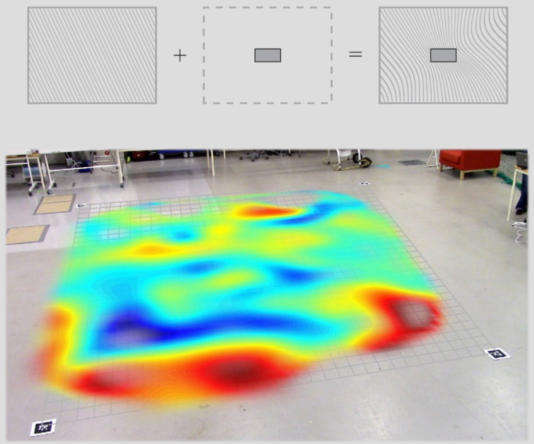
Magnetic Disturbances



Sparse Sensor Setups

Adopted from [Movella Inc. 2024]

Four Major Challenges in IMT

State Estimation with IMUs

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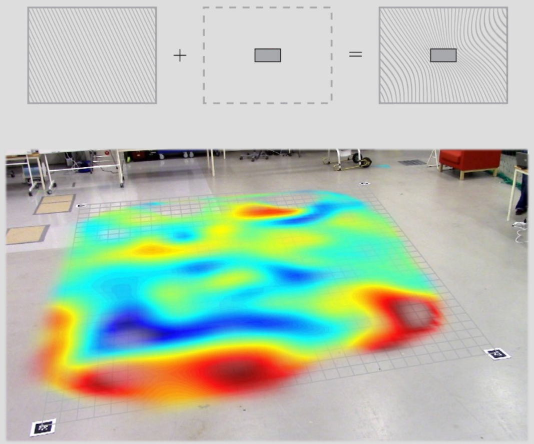
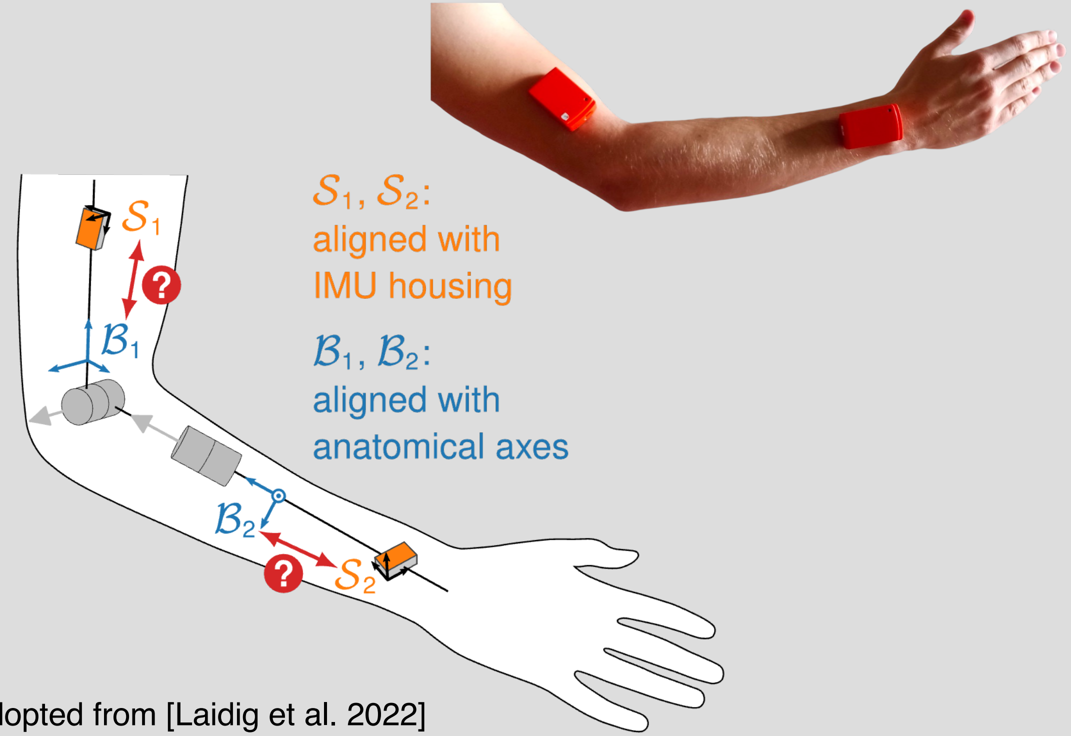
Magnetic Disturbances



Sparse Sensor Setups

Anatomical Calibration



Adopted from [Laidig et al. 2022]

Four Major Challenges in IMT

State Estimation with IMUs

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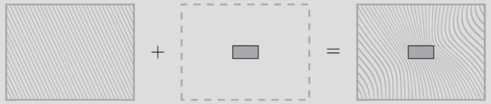
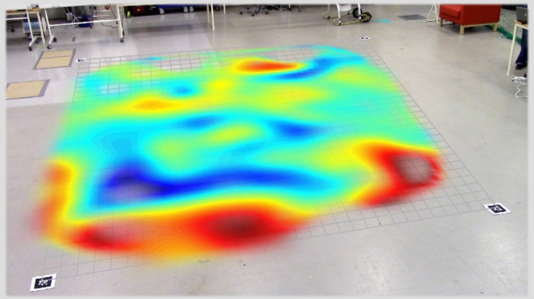
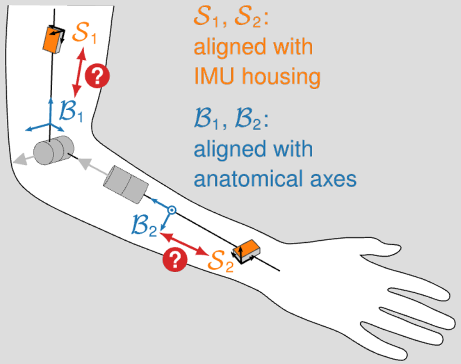
Magnetic Disturbances





Sparse Sensor Setups

Anatomical Calibration



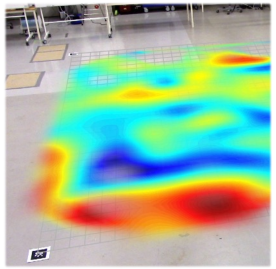
Nonrigid IMU Attachment

Addressing All Four Challenges

State Estimation with IMUs

— We want a non-restrictive method that can tackle all four **challenges**.

✅ mag.-free

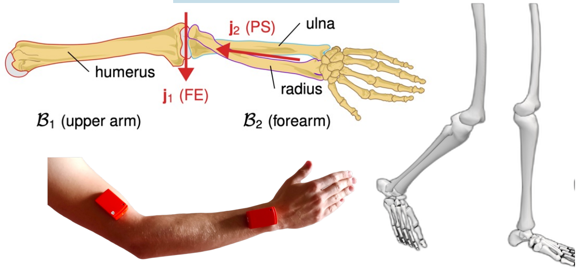


reliable outdoors and indoors

✅ sparse

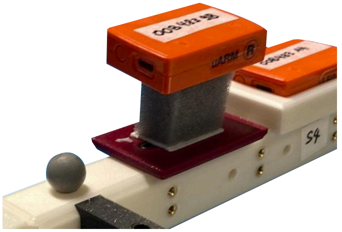
allows for sparse sensor setups

✅ calib.



reduces expert knowledge and calibration & modelling efforts

✅ nonrigid

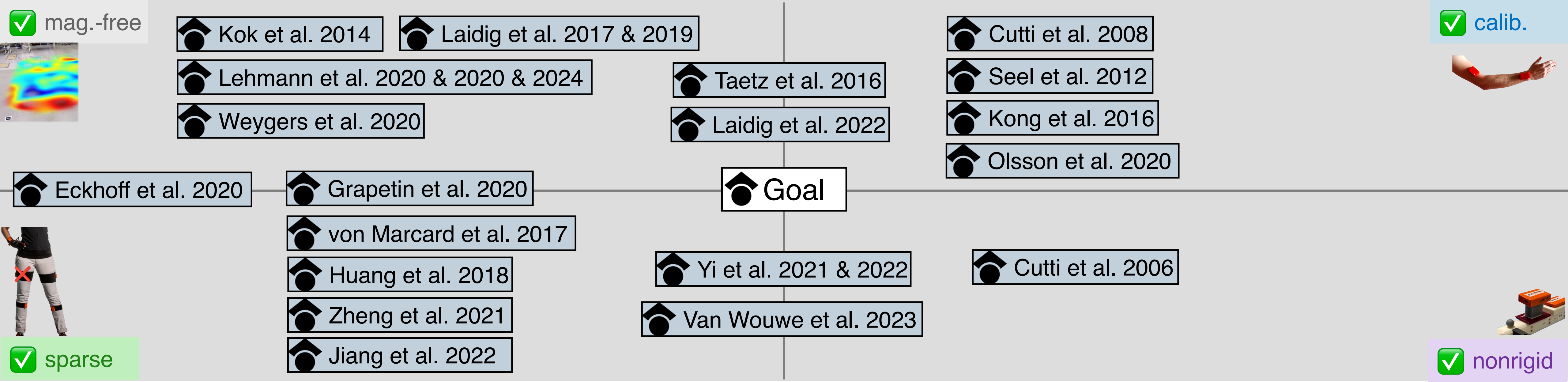


robust to nonrigid attachment and reduces motion artifacts

State of the Art

State Estimation with IMUs

— The current state of the art addresses at most two challenges simultaneously.



— **Goal**: Non-restrictive, plug-and-play solution for IMT that tackles **all four challenges**.

✅ mag.-free ✅ sparse ✅ calib. ✅ nonrigid

Methods

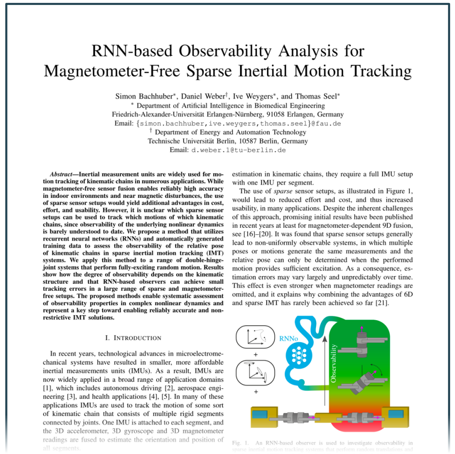
- **First**, train one RNN for each IMT problem, demonstrating observability of individual IMT problems in-silico.

- **Second**, develop domain randomisations to overcome the sim-to-real gap.

- **Third**, unify the individual solutions by training a single RNN on all observable IMTPs.

FUSION (2022)

S. Bachhuber, D. Weber, I. Weygers, and T. Seel, "RNN-based Observability Analysis for Magnetometer-Free Sparse Inertial Motion Tracking," 2022 International Conference on Information Fusion



RNN-based Observability Analysis for Magnetometer-Free Sparse Inertial Motion Tracking

Sensors L. (2023)

S. Bachhuber, D. Lehmann, E. Dorschky, A. D. Koelewijn, T. Seel, and I. Weygers, "Plug-and-Play Sparse Inertial Motion Tracking With Sim-to-Real Transfer," IEEE Sensors Letters

Plug-and-Play Sparse Inertial Motion Tracking With Sim-to-Real Transfer

TMLR (2024)

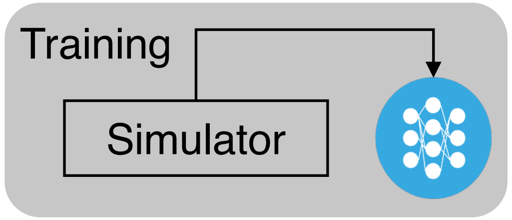
S. Bachhuber, I. Weygers, D. Lehmann, M. Dombrowski, and T. Seel, "Recurrent Inertial Graph-Based Estimator (RING): A Single Pluripotent Inertial Motion Tracking Solution," Transactions on Machine Learning Research

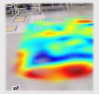
Recurrent Inertial Graph-Based Estimator (RING): A Single Pluripotent Inertial Motion Tracking Solution

Domain Randomizations

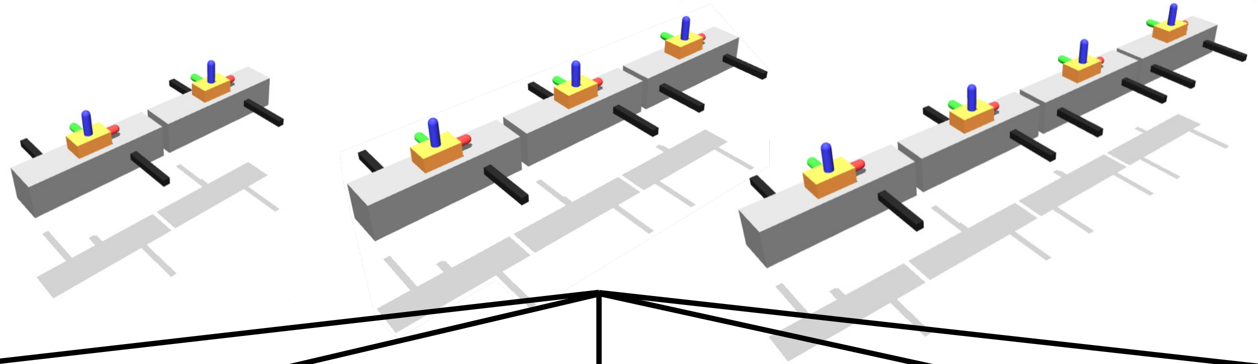
State Estimation with IMUs / Methods

— During training of RNN, extensive domain randomisations are applied.

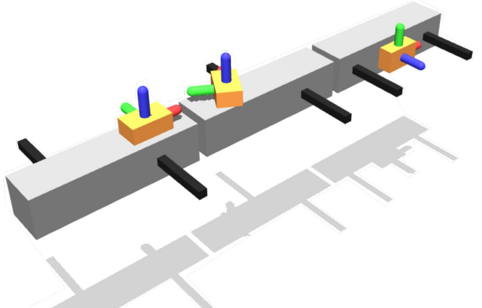



mag.-free

Kinematic Chains with different lengths



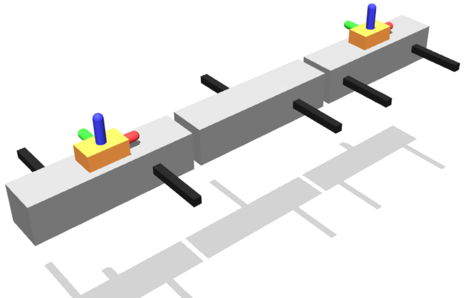
Randomized Sensor Placement



RNN learns to self-calibrate

calibr.

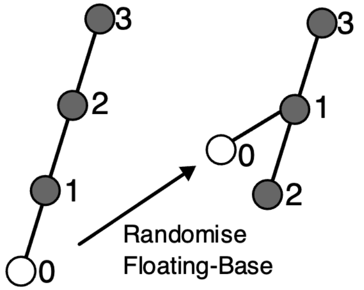
Sparse Sensor Setup



RNN learns sparse sensing

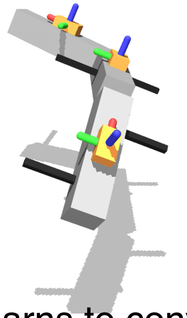
sparse

Randomized Graph



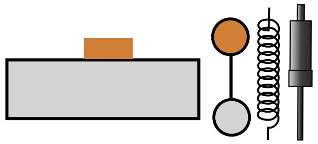
RNN learns to not exploit a fixed center of rotation

Randomized Initial Pose



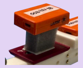
RNN learns to converge

Randomized Spring-Damper



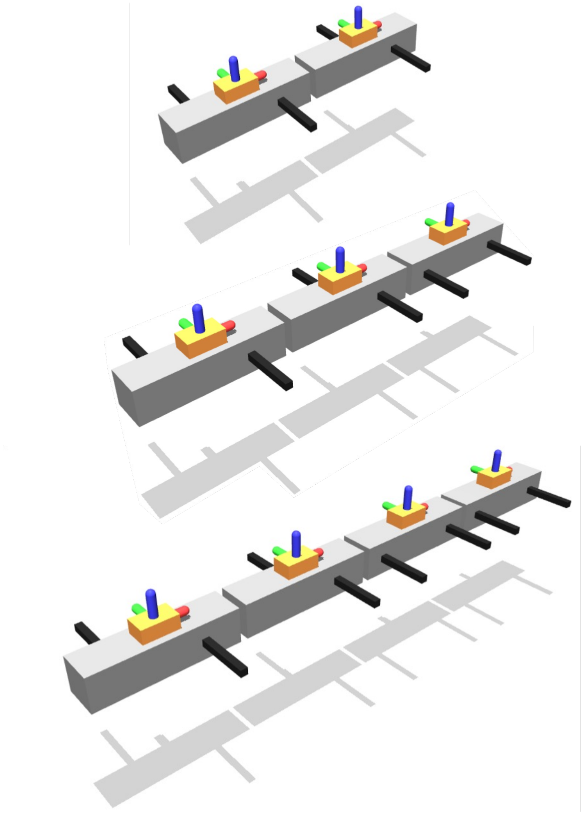
RNN learns motion artifact compensation

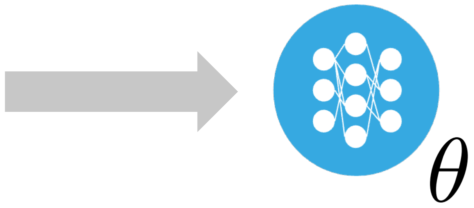
nonrigid



Generalising to Multiple IMT Problems

— How can we train a single NN with a fixed set of parameters despite different input/output shapes?





Method Overview Inertial Motion Tracking

State Estimation with IMUs / Methods

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FUSION (2022)

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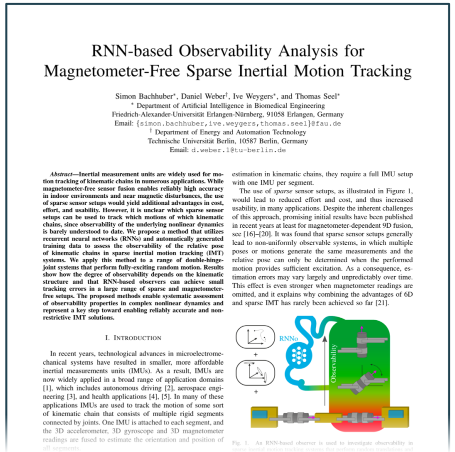
RNN-based Observability Analysis for Magnetometer-Free Sparse Inertial Motion Tracking

Simon Bachhuber, Daniel Weber, Ive Weygers, and Thomas Seel

— **Second**, develop domain randomisations to overcome the sim-to-real gap.

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Sensor signal processing

Plug-and-Play Sparse Inertial Motion Tracking With Sim-to-Real Transfer

Simon Bachhuber, Dustin Lehmann, Eva Dorschky, Anne D. Koelewijn, Thomas Seel, and Ive Weygers

— **Third**, unify the individual solutions by training a single RNN on all observable IMTPs.

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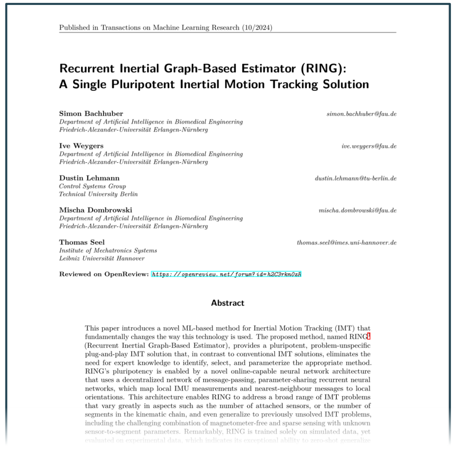
S. Bachhuber, I. Weygers, D. Lehmann, M. Dombrowski, and T. Seel, "Recurrent Inertial Graph-Based Estimator (RING): A Single Pluripotent Inertial Motion Tracking Solution," Transactions on Machine Learning Research


Published in Transactions on Machine Learning Research (10/2024)

Recurrent Inertial Graph-Based Estimator (RING): A Single Pluripotent Inertial Motion Tracking Solution

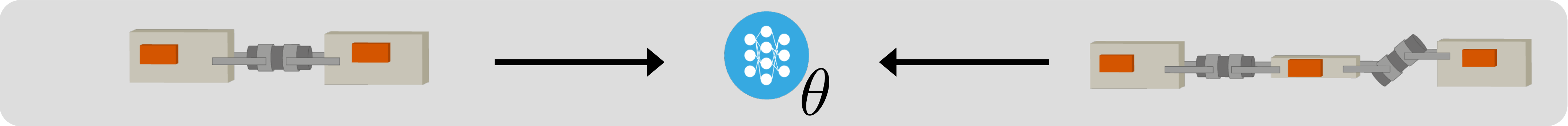
Simon Bachhuber, Ive Weygers, Dustin Lehmann, Mischa Dombrowski, Thomas Seel

Abstract

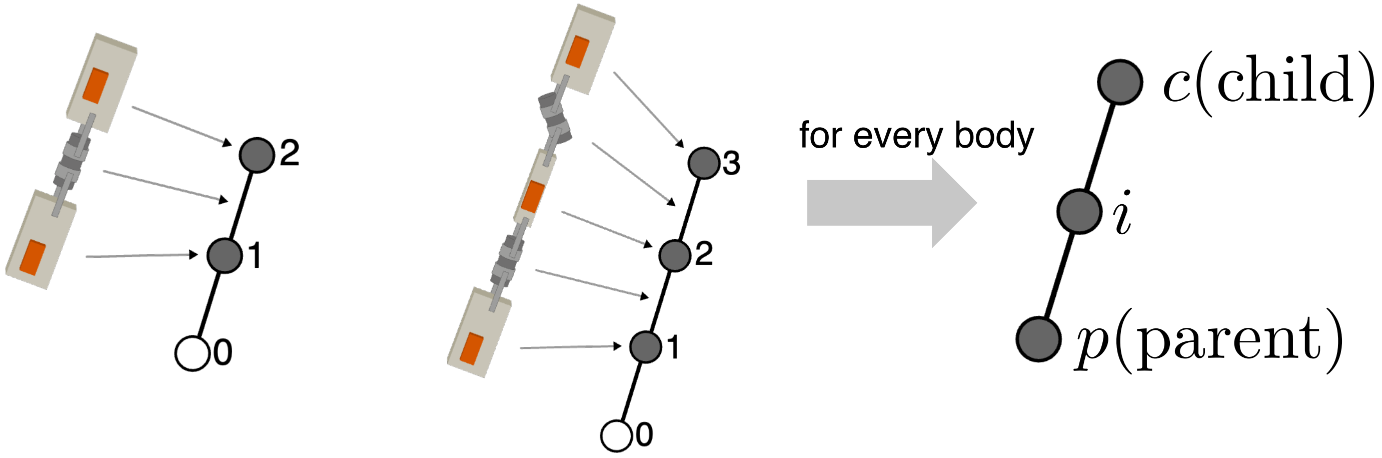
Recurrent Inertial Graph-based Estimator

State Estimation with IMUs / Methods

— The Recurrent Inertial Graph-based Estimator (RING) enables a mapping from IMU data to orientations that maintains global context while being parameter-invariant w.r.t. the graph of the tree.



— View kinematic chain as undirected graph and define neural network recursively.



Connectivity Graph

1. label bodies from 1 to N
2. store body index of parent body in array

$$\boldsymbol{\lambda}[i] = p$$

Architecture of RING

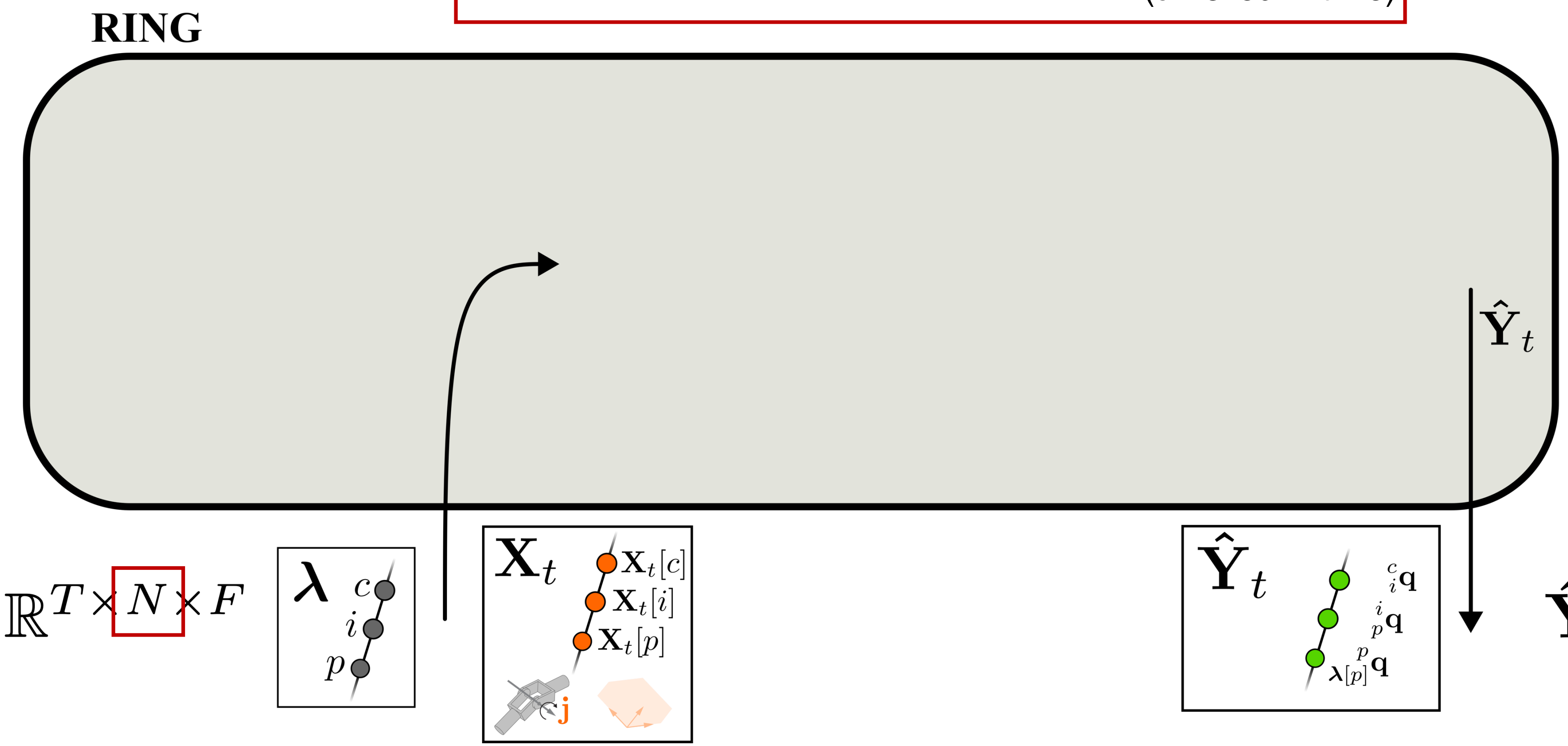
State Estimation with IMUs / Methods

— RING is an RNN that maps IMU- and joint axes data, and sampling rates to relative orientations.

$$\hat{\mathbf{Y}} = \texttt{ring}_\theta\left(\mathbf{X}, \boldsymbol{\lambda}\right)$$ (unrolled in time)

Dimensions
T.. # timesteps
N.. # bodies
F.. # features

$\mathbf{X} \in \mathbb{R}^{T \times \boxed{N} \times F}$



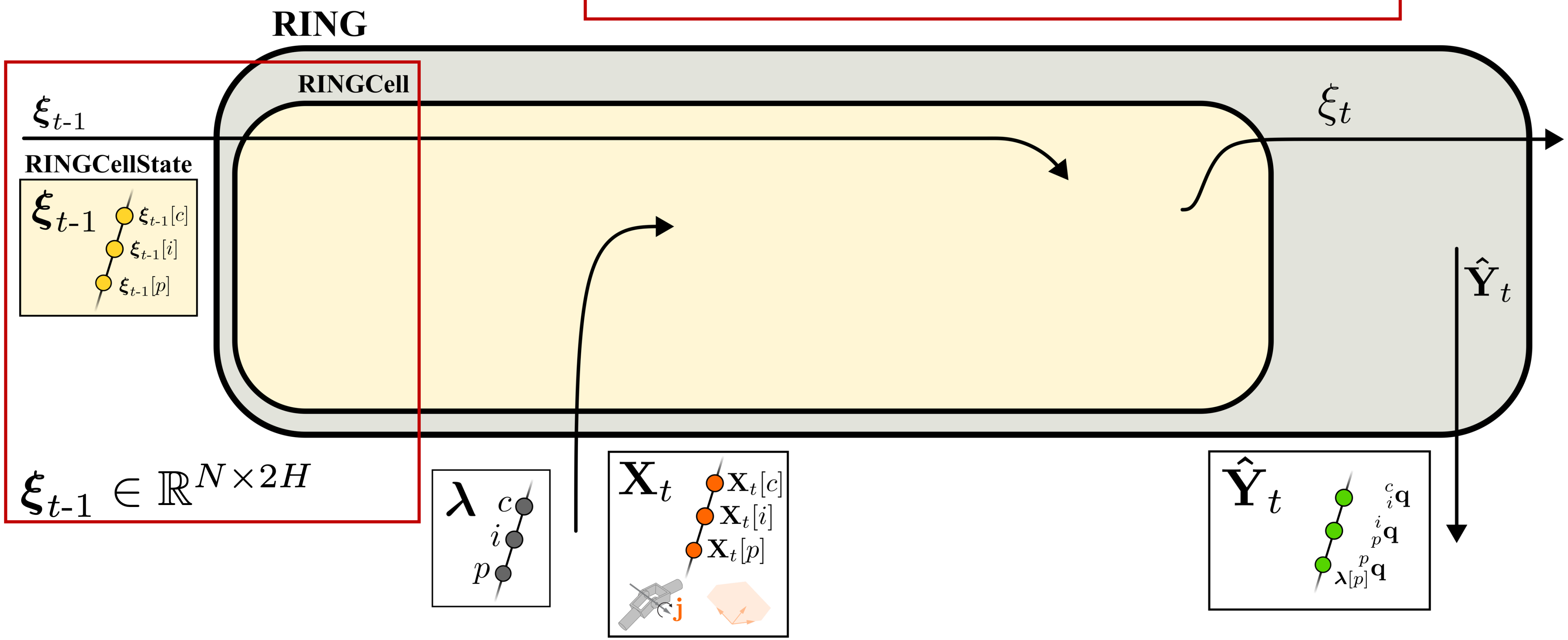
$\hat{\mathbf{Y}} \in \mathbb{H}^{T \times \boxed{N}}$

Architecture of RING

State Estimation with IMUs / Methods

— Internally, it uses an RNN-like inner cell \`RINGCell\` that updates the hidden state.

$$\boxed{\boldsymbol{\xi}_t = \texttt{ringCell}\left(\boldsymbol{\xi}_{t\text{-}1}, \mathbf{X}_t, \boldsymbol{\lambda}\right)}$$



Dimensions

T.. # timesteps

N.. # bodies

F.. # features

H.. hidden dim of GRU

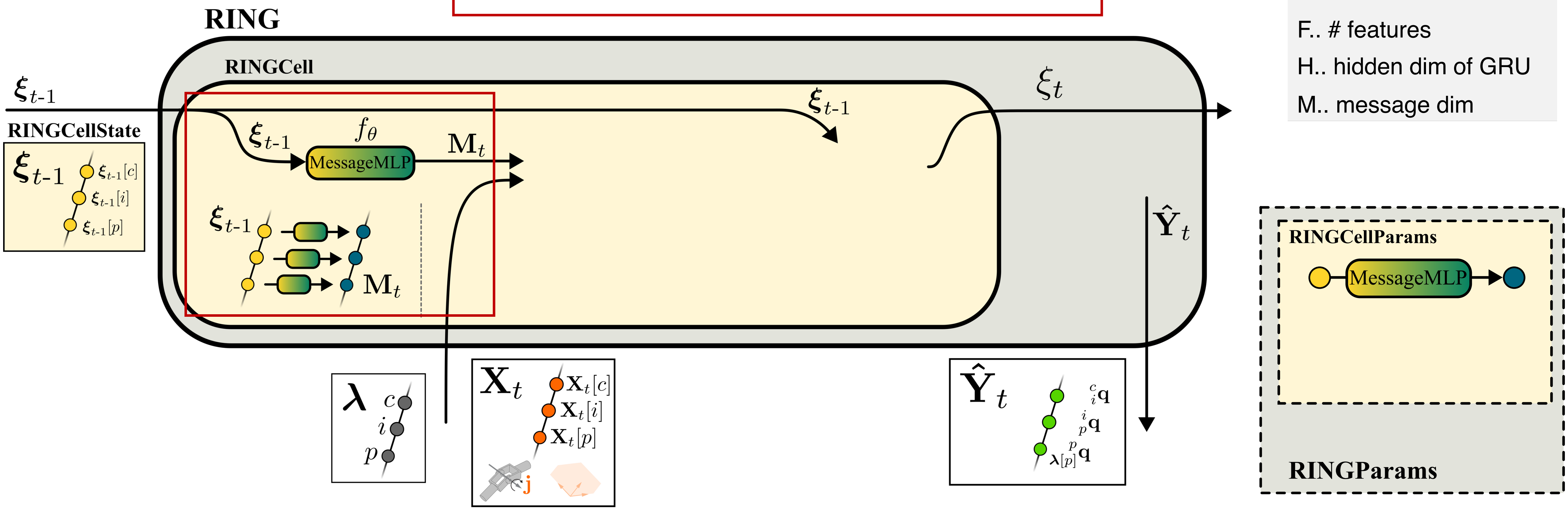
Architecture of RING

State Estimation with IMUs / Methods

— First, each node in the graph computes a message based on its last hidden state.

$$\boxed{f_\theta : \mathbb{R}^H \rightarrow \mathbb{R}^M \qquad \mathbf{M}_t \in \mathbb{R}^{N \times M}}$$

Dimensions
T.. # timesteps
N.. # bodies
F.. # features
H.. hidden dim of GRU
M.. message dim

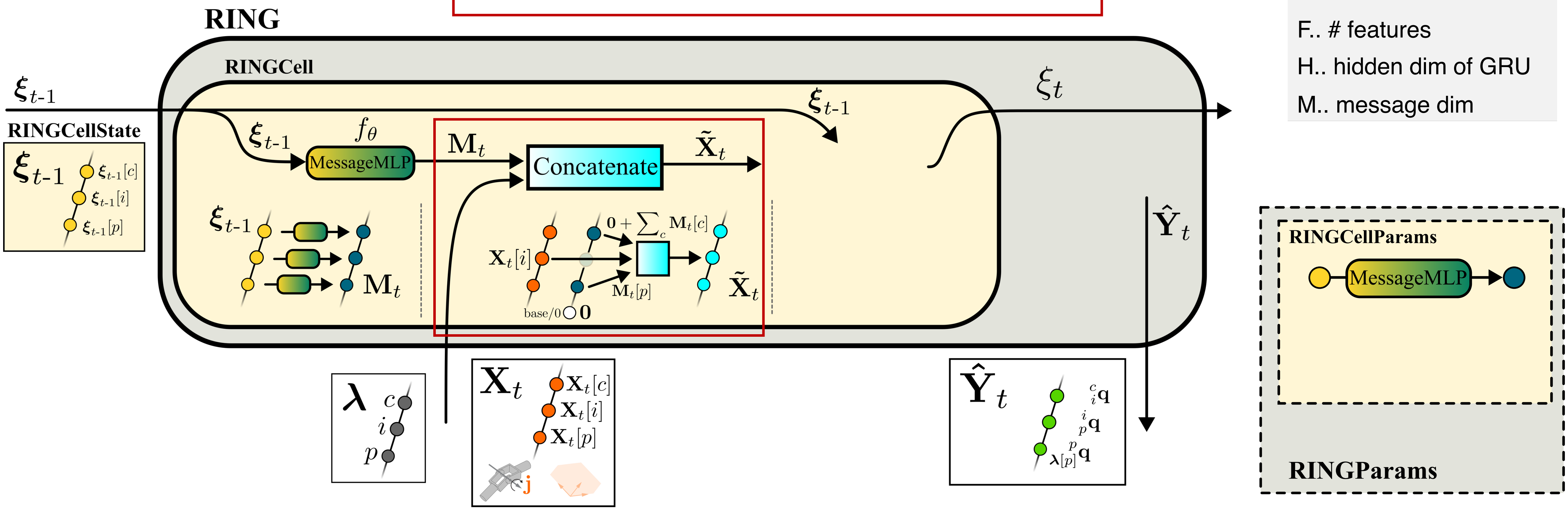


Architecture of RING

State Estimation with IMUs / Methods

— Second, messages are passed along the edges of the graph and an auxillary input computed.

$$\tilde{\mathbf{X}} \in \mathbb{R}^{N \times (2M+F)}$$



Dimensions
T.. # timesteps
N.. # bodies
F.. # features
H.. hidden dim of GRU
M.. message dim

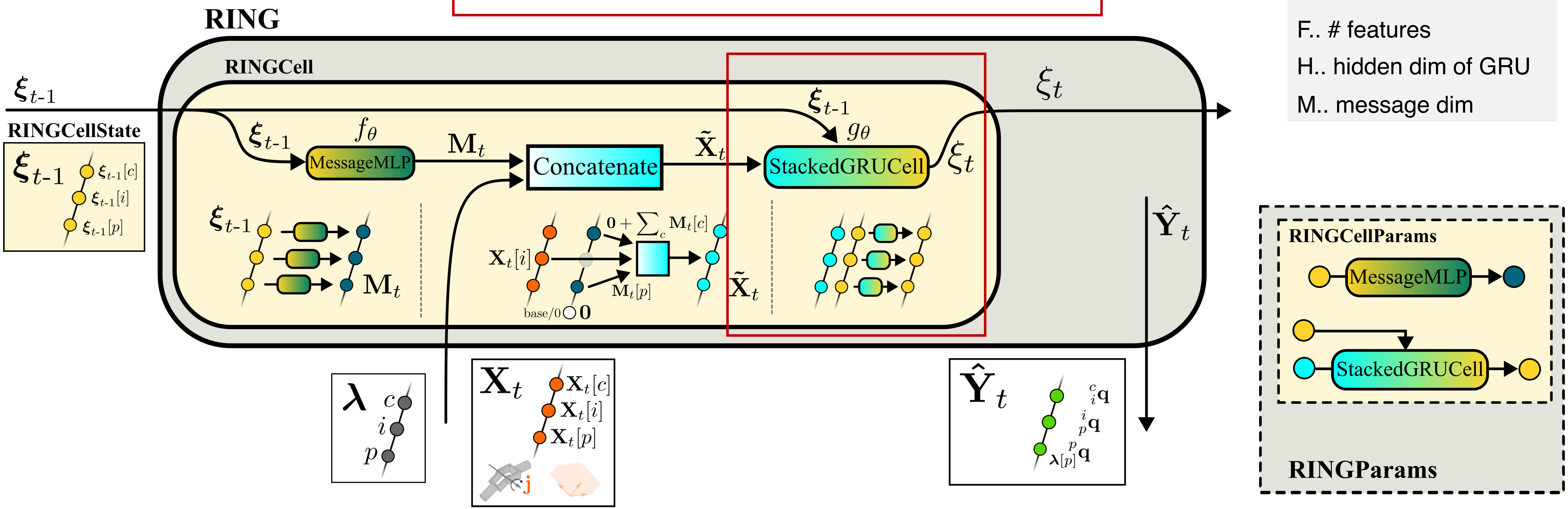
Architecture of RING

State Estimation with IMUs / Methods

— Third, hidden state is updated.

$$\boldsymbol{\xi}_t[i] = g_\theta\left(\boldsymbol{\xi}_{t\text{-}1}[i], \tilde{\mathbf{X}}[i]\right)$$

$$g_\theta : \mathbb{R}^{2H} \times \mathbb{R}^{2M+F} \rightarrow \mathbb{R}^{2H}$$



Dimensions

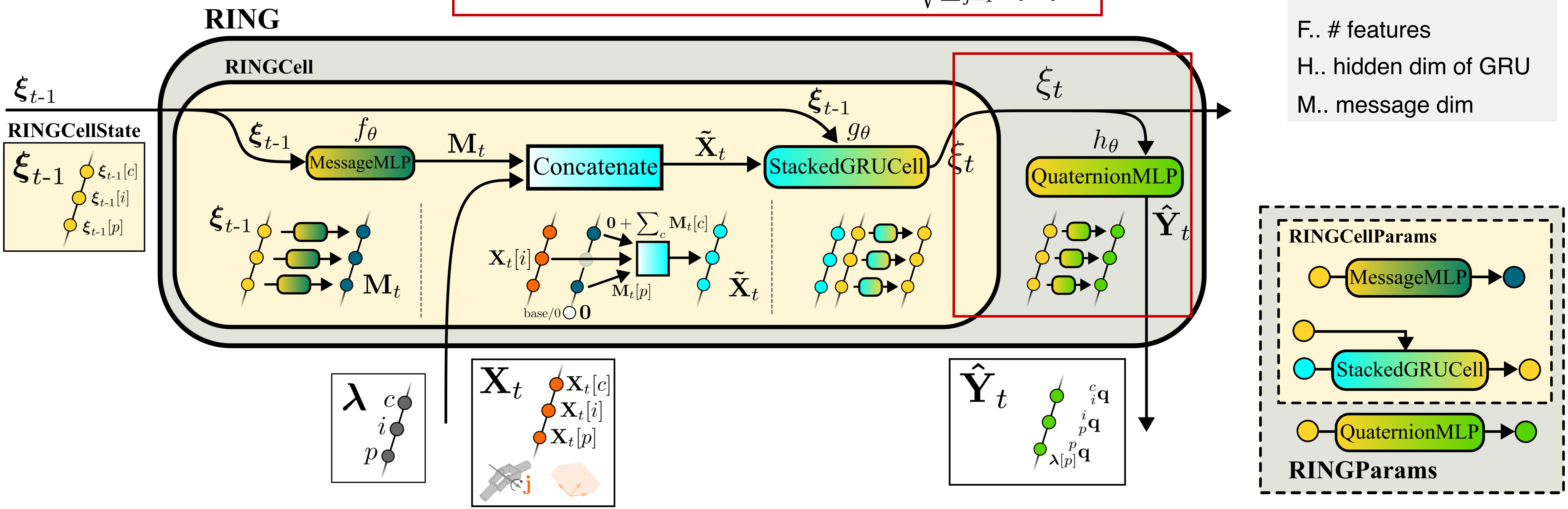
- T.. # timesteps
- N.. # bodies
- F.. # features
- H.. hidden dim of GRU
- M.. message dim

Architecture of RING

State Estimation with IMUs / Methods

— Fourth, unit quaternions are computed.

$$h_\theta : \mathbb{R}^H \rightarrow \mathbb{R}^4 \qquad \hat{\mathbf{Y}}_t[i] = \frac{\tilde{\mathbf{Y}}[i]}{\sqrt{\sum_{j=1}^4 \tilde{\mathbf{Y}}[i,j]^2}}$$

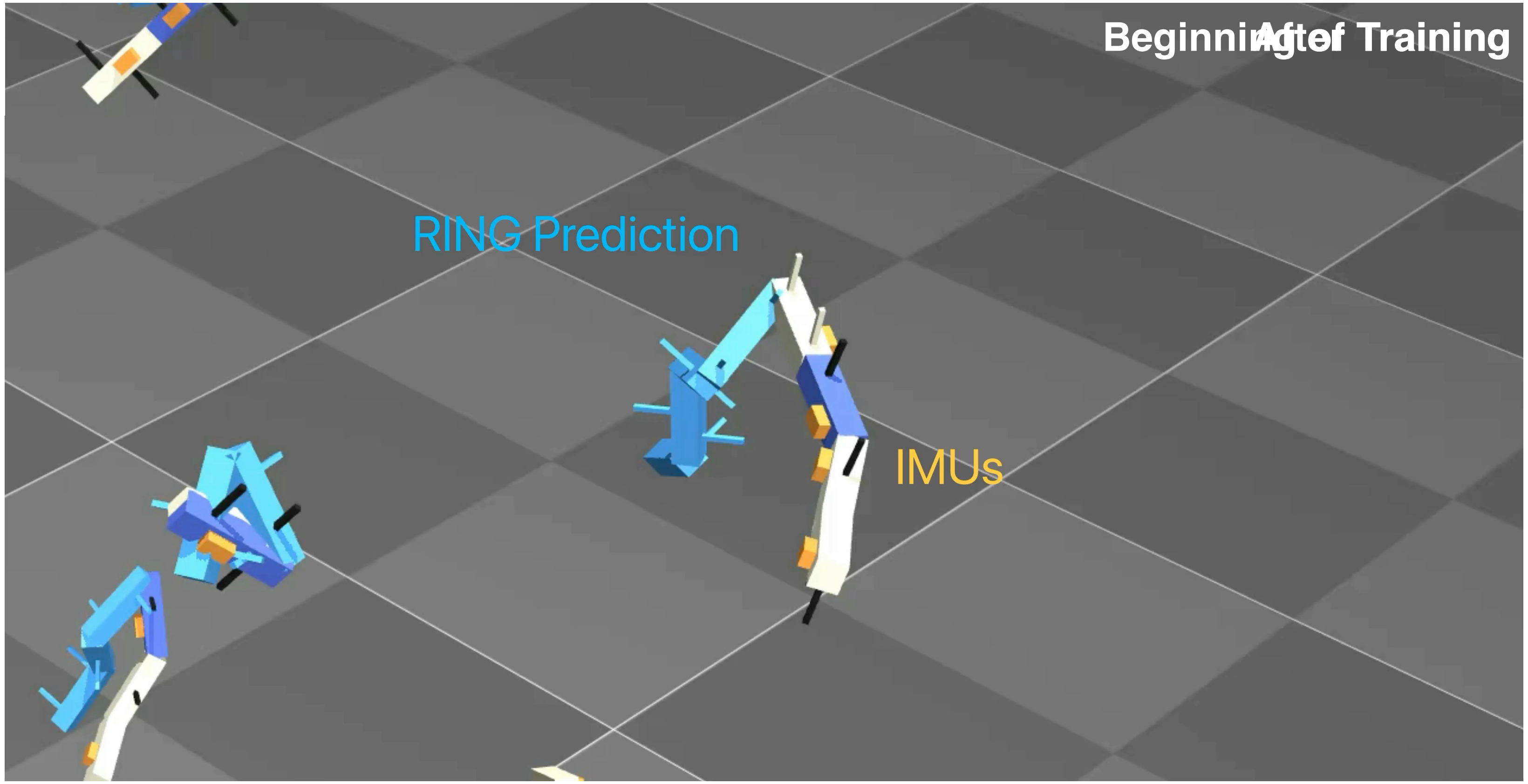


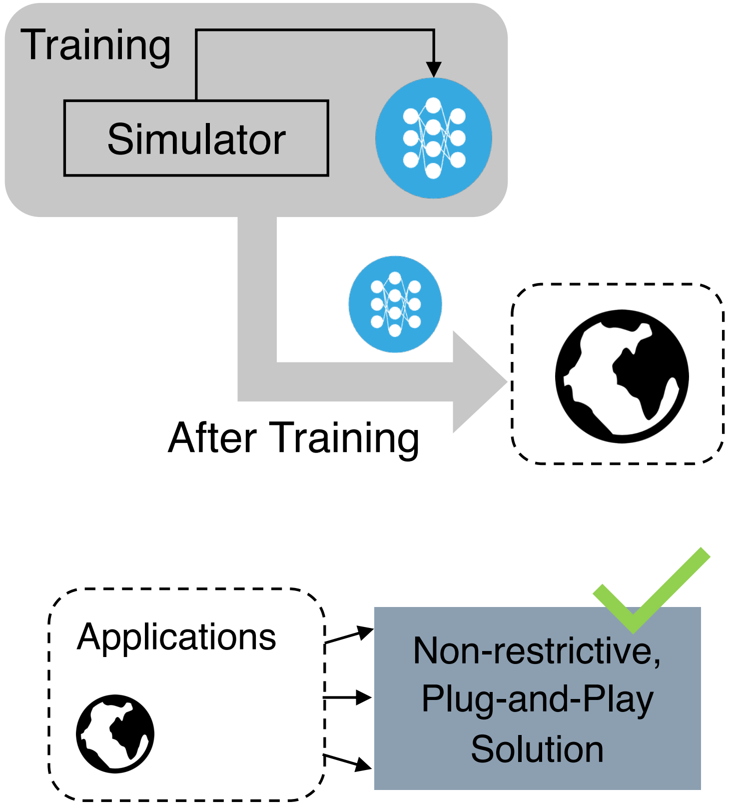
Dimensions
T.. # timesteps
N.. # bodies
F.. # features
H.. hidden dim of GRU
M.. message dim

Training of RING in Simulation

State Estimation with IMUs / Methods

— Combine domain randomizations with RING architecture to train a single non-restrictive, plug-and-play IMT solution.





Results

Live Demonstration

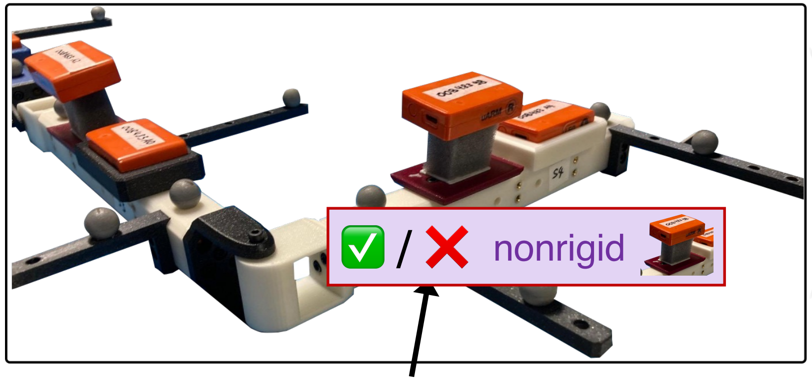
State Estimation with IMUs / Results

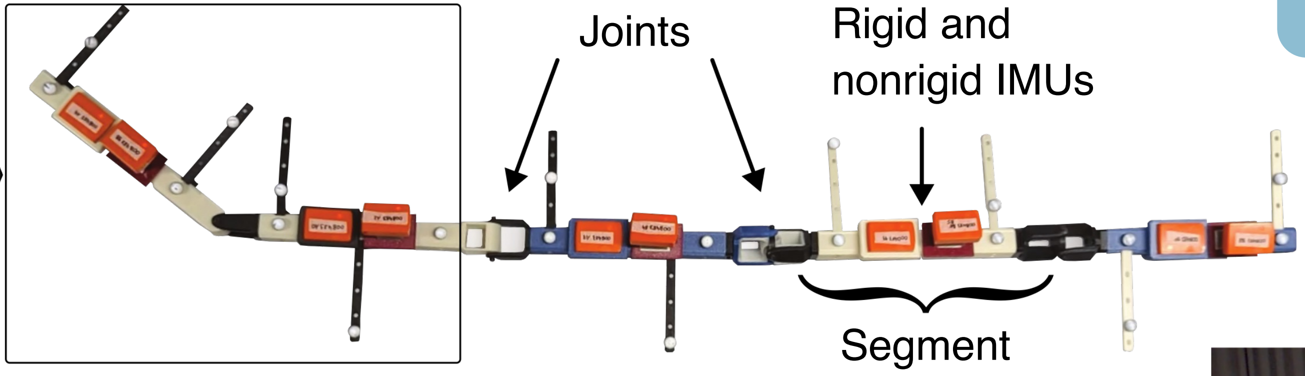
DEMO

Five-Segment Mechanical Kinematic Chain

State Estimation with IMUs / Results

— High-precision validation with optical motion capture and in a **controlled** environment.





✅ / ❌ nonrigid

Foam causes motion artifacts

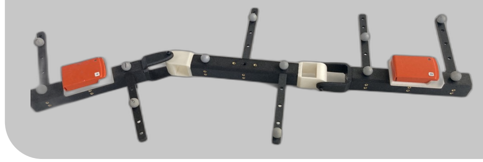
Challenges

✅ / ❌ calibr.

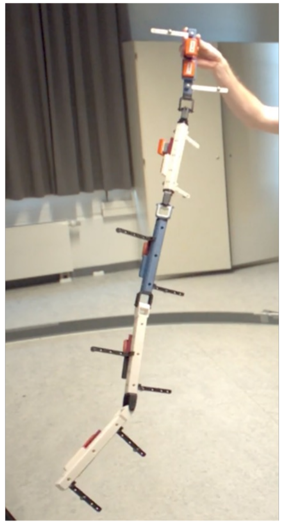
✅ / ❌ mag.-free

✅ / ❌ sparse

Smaller kinematic chains



Various types of motions



Real-world Kinematic Chain Tracking

State Estimation with IMUs / Results

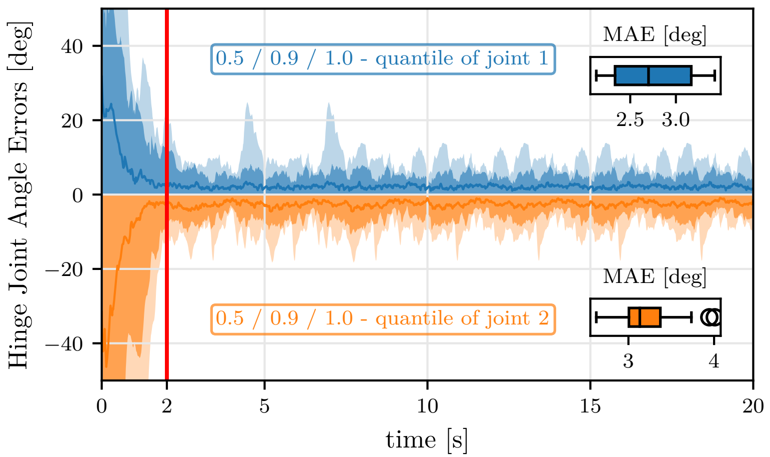
Sensors L. (2023)

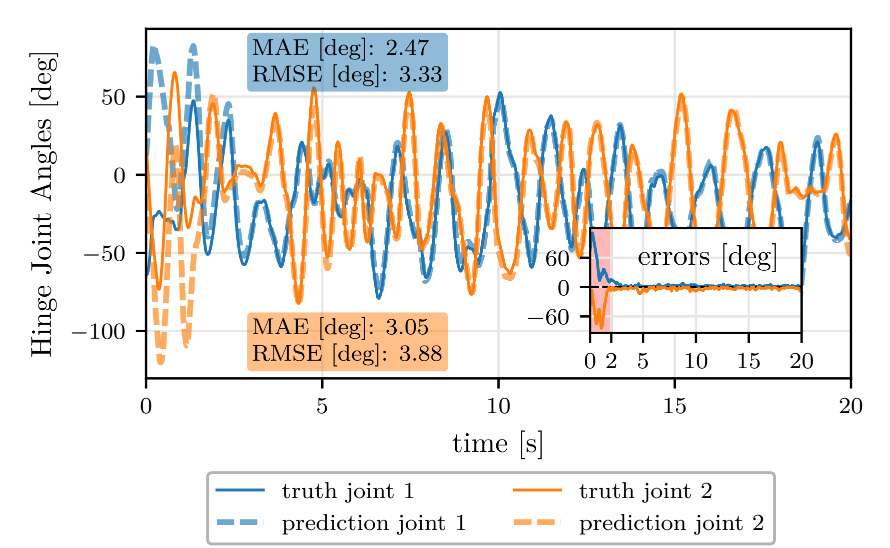
— Using three-segment kinematic chain, we show:

- Accurate tracking
- Fast initial convergence
- Long-term stability
- Ablation Study

DR 1	DR 2	DR 3	MAE [deg]
❌	❌	❌	73.6 +/- 27.0
✅	✅	✅	**3.25 +/- 0.29**

Exciting Motion ✅ mag.-free ✅ sparse





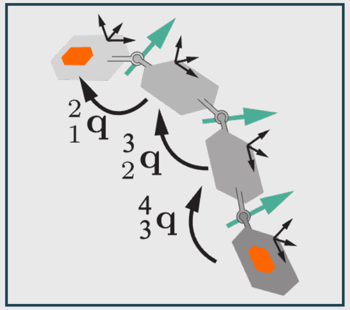
Broadly-Applicable Real-World Solution

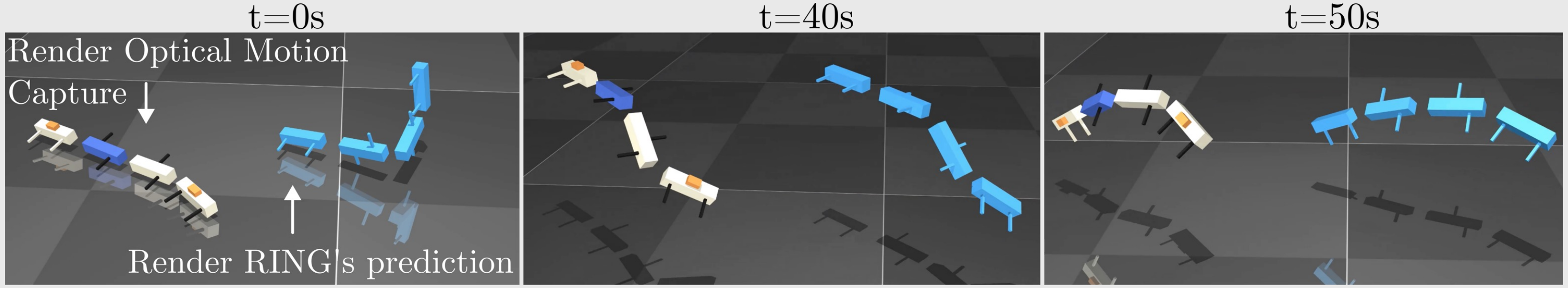
State Estimation with IMUs / Results

TMLR (2024) BMS (2024)

— Tracking of triple-hinge-joint kinematic chain with two magnetometer-free IMUs.

IMT Problem



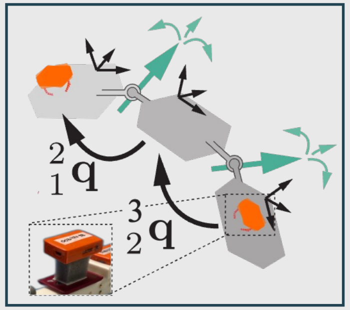


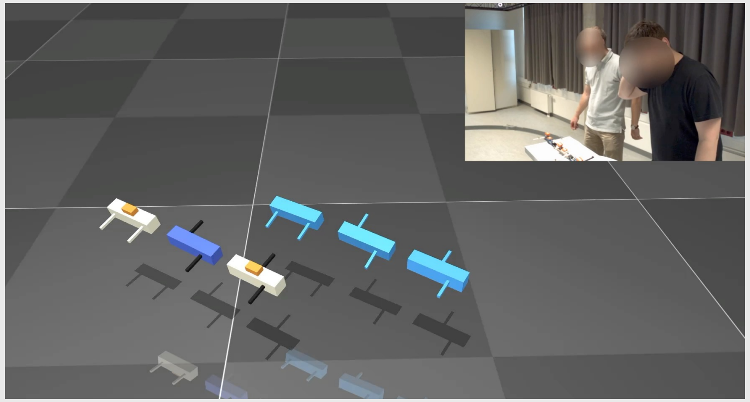
- ✅ mag.-free
- ✅ sparse

MAE: 7.78°

— Tracking of double-hinge-joint kinematic chain with unknown joint axes with two foam-attached, mag.-free IMUs.

IMT Problem



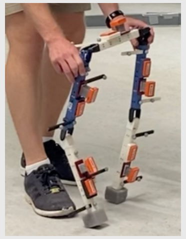


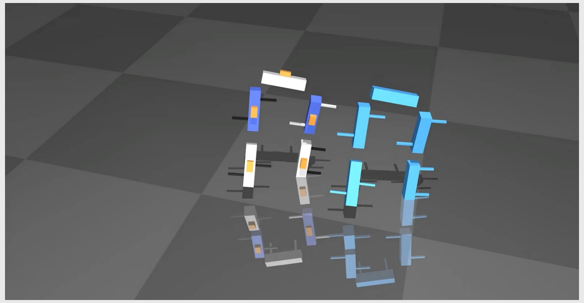
- ✅ mag.-free
- ✅ sparse
- ✅ calib.
- ✅ nonrigid

MAE: 8.10°

IMT Problem

...





MAE: 5.22°

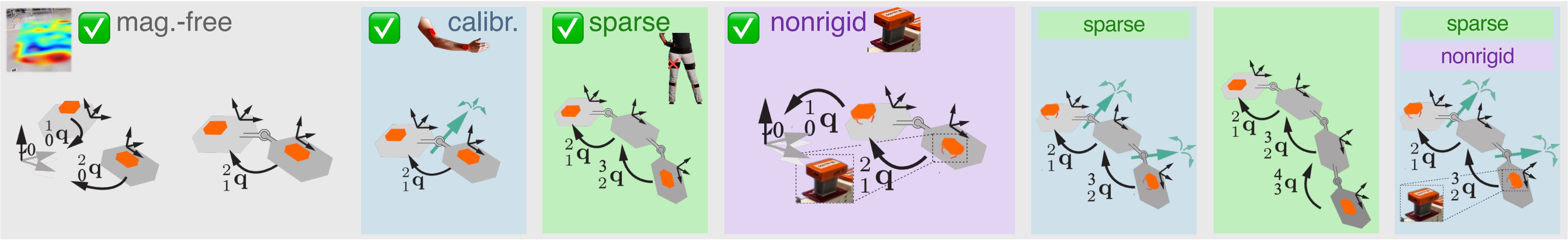
Broadly-Applicable Real-World Solution

State Estimation with IMUs / Results

TMLR (2024) BMS (2024)

— Previous methods are problem-specific and Not Applicable (NA) to many IMTPs, RING accurately solves all problems.

IMT Problems →



Methods ↓

(1)	2.06 ± 1.03	NA	NA	NA	$\geq$(5)	NA	NA	NA	NA
(2)	2.25 ± 0.81	$\geq$(5)	$\geq$(5)	NA	$\geq$(5)	NA	NA	NA	NA
(3)	2.09 ± 0.87	$\geq$(5)	$\geq$(5)	NA	$\geq$(5)	NA	NA	NA	NA
(4)	2.56 ± 0.93	$\geq$(5)	$\geq$(5)	NA	$\geq$(5)	NA	NA	NA	NA
(5)	1.61 ± 1.04	$\rightarrow$	19.3 ± 8.02	NA	9.20 ± 2.31	24.9 ± 17.6	NA	NA	NA
(5)+(6)	$\uparrow$	3.32 ± 2.12	NA	NA	$\uparrow$	7.00 ± 1.57	NA	NA	NA
(5)+(7)	$\uparrow$	4.15 ± 2.05	NA	NA	$\uparrow$	8.00 ± 2.78	NA	NA	NA
(5)+(6)+(8)	$\uparrow$	$\rightarrow$	3.18 ± 2.05	NA	$\uparrow$	8.50 ± 2.60	NA	NA	NA
(5)+(7)+(8)	$\uparrow$	$\rightarrow$	4.06 ± 2.23	NA	$\uparrow$	7.90 ± 2.48	NA	NA	NA
(9)	NA	NA	NA	5.60 ± 2.35	NA	NA	NA	NA	NA
RING	2.13 ± 0.91	3.52 ± 1.00	3.92 ± 1.40	4.14 ± 0.53	7.59 ± 2.85	5.56 ± 2.33	5.37 ± 0.71	6.78 ± 1.41	8.10 ± 1.19

Methods: Weber et al. (2021)(1), Madgwick (2010)(2), Mahony et al. (2008)(3), Seel & Ruppin (2017)(4), Laidig & Seel (2023)(5), Laidig et al. (2017)(6), Lehmann et al. (2020)(7),Olsson et al. (2020)(8), Bachhuber et al. (2023)(9)

— Because of its generalization capabilities, RING can be directly used for plug-and-play human IMT as well.

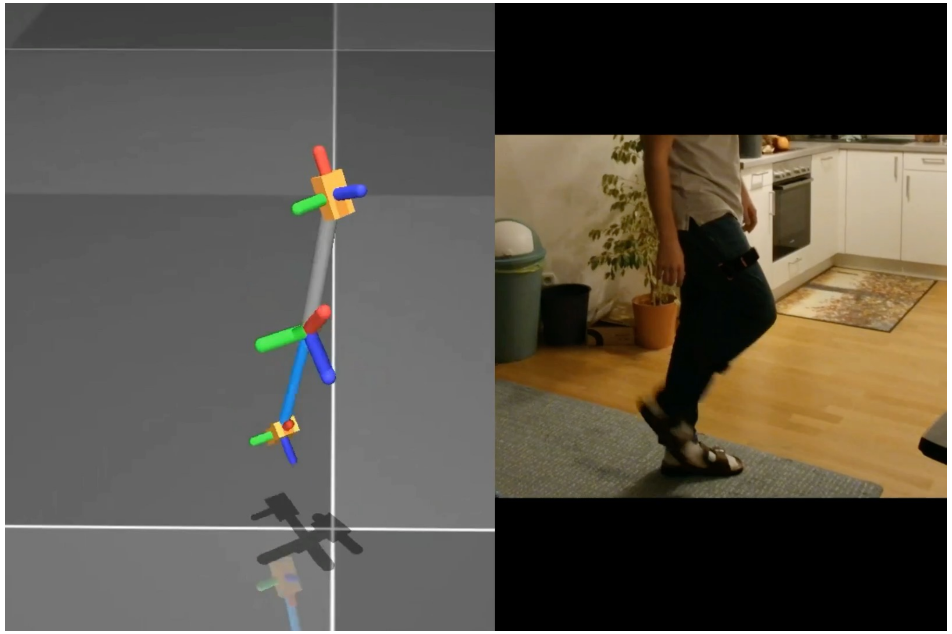
```python
import imt

solver = imt.Solver(graph=[-1, 0], Ts=0.01, body_names=["thigh", "shank"])
imu_data = {
    "thigh": dict(acc=acc1, gyr=gyr1),
    "shank": dict(acc=acc2, gyr=gyr2)
}
quaternions, _ = solver.step(imu_data)
```

GitHub github.com/simon-bachhuber/imt

python Package Index

Plug-and-Play Knee Tracking



both orientations and geometry are estimated from IMU data

— Overall, RING enables non-restrictive, plug-and-play IMT in a broad range of applications.

Knee

plug-and-play

indoors and outdoors application

supports sparse sensor setups

different motion patterns

different joints

different # IMUs

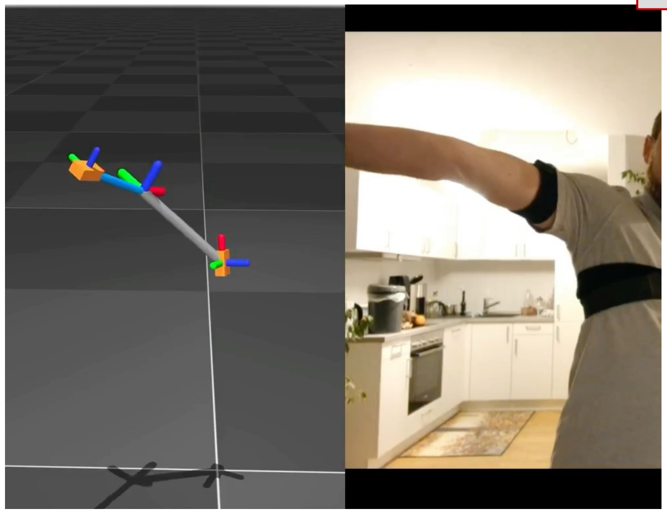
DOFs can be unknown

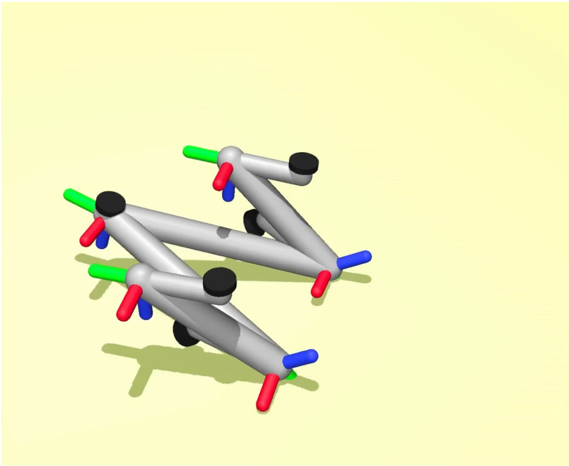
can be used with or without joint axes information

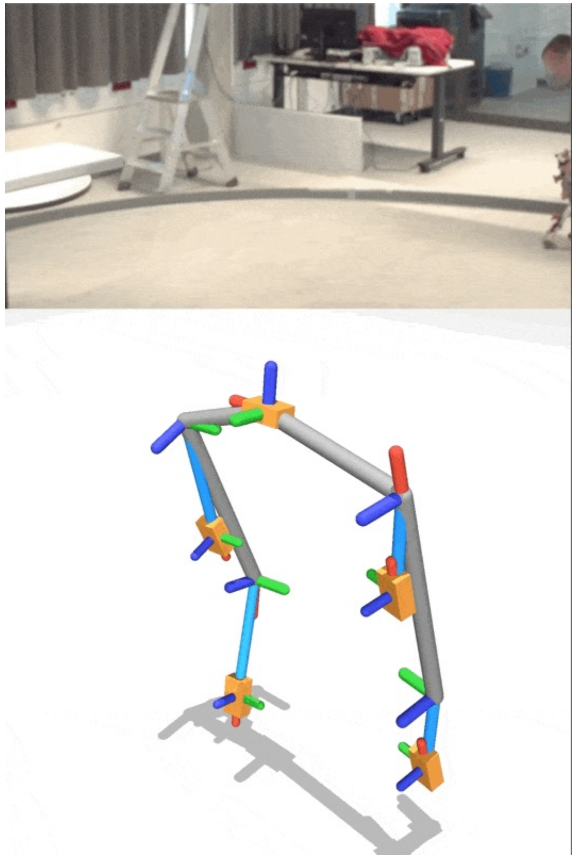
no calibration of IMUs required

can compute orientations, joint angles, geometry

Sho





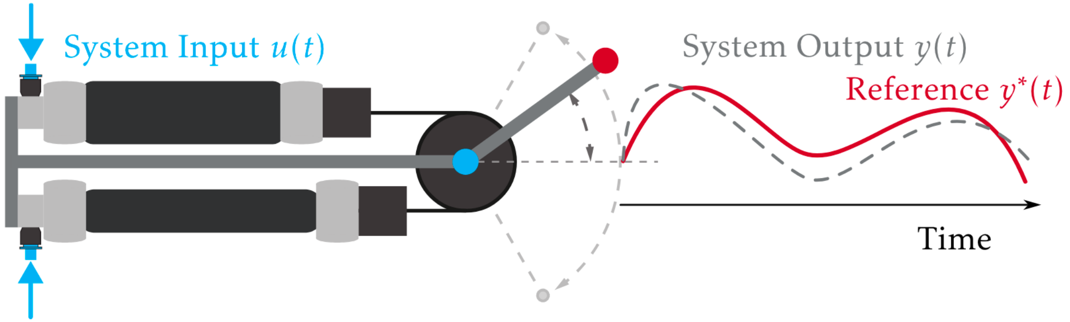


Motion Control with Neural ODEs

Reference Tracking in Unknown Nonlinear Dynamics

Motion Control with Neural ODEs

— reference tracking in systems with unknown nonlinear dynamics

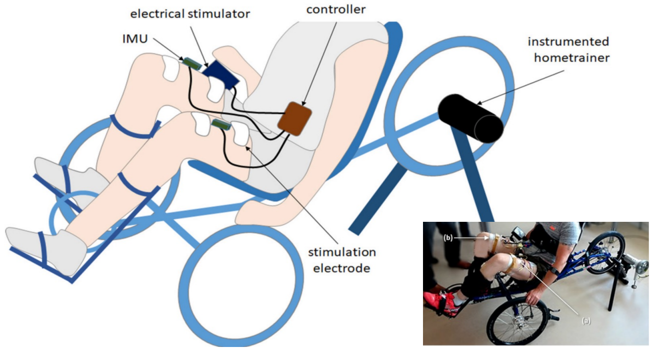


Applications

paraplegic cycling

→

FES-induced Cycling



From Sijobert et al. (2019)

— the current state of the art does not address the four challenges simultaneously

Challenges for Non-restrictive, Plug-and-Play Motion Control

allows for non-repetitive motions

no model required

Reinforcement Learning

Partially Observable Markov Decision Processes

Optimal Control

Iterative Learning Control

data-efficient

no state information required

Method Overview Reference Tracking

Motion Control with Neural ODEs

allows for non-repetitive motions	no model required
ANODEC	
data-efficient	no state information required

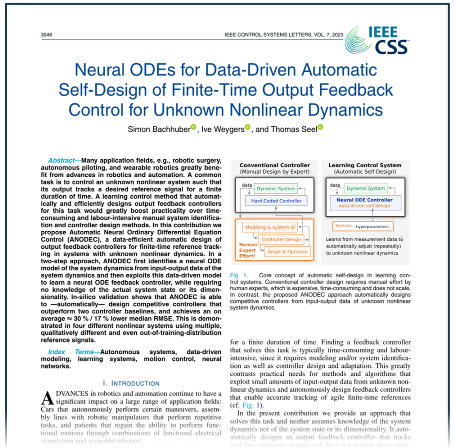
↓

GitHub
github.com/simon-bachhuber/chain_control

— Propose Automatic Neural ODE Control (**ANODEC**), a data-efficient learning control method, and extensive validation in simulation.

Control Sys. (2023)

S. Bachhuber, I. Weygers, and T. Seel, “Neural ODEs for Data-Driven Automatic Self-Design of Finite-Time Output Feedback Control for Unknown Nonlinear Dynamics,” IEEE Control Systems Letters, vol. 7, pp. 3048–3053, 2023


3048 IEEE CONTROL SYSTEMS LETTERS, VOL. 7, 2023

Neural ODEs for Data-Driven Automatic Self-Design of Finite-Time Output Feedback Control for Unknown Nonlinear Dynamics

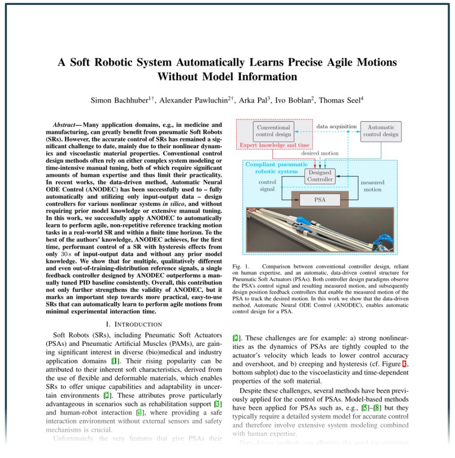
Simon Bachhuber, Ive Weygers, and Thomas Seel

→

— Use ANODEC to create a pneumatic soft actuator that learns to perform agile motions from only 30 seconds of IO data.

IROS (2024)

S. Bachhuber, A. Pawluchin, A. Pal, I. Boblan, and T. Seel, “A Soft Robotic System Automatically Learns Precise Agile Motions Without Model Information,” in 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024

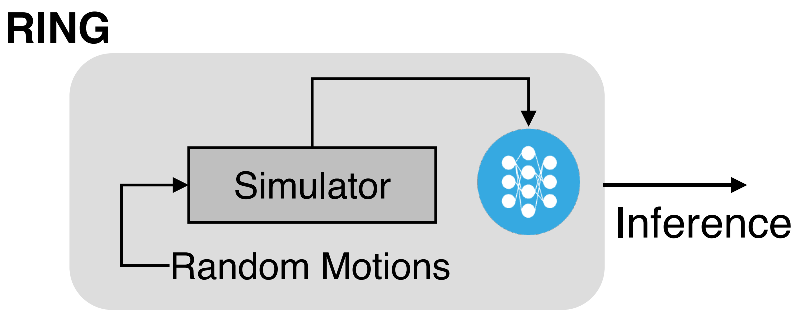

A Soft Robotic System Automatically Learns Precise Agile Motions Without Model Information

Simon Bachhuber, Alexander Pawluchin, Arka Pal, Ivo Boblan, Thomas Seel

Parallels to Inertial Motion Tracking

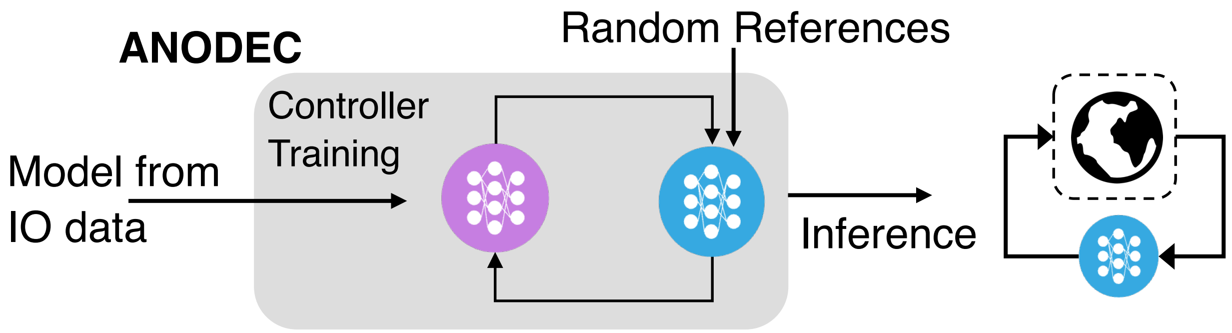
Motion Control with Neural ODEs

State Estimation with IMUs



- Objective: Learn filter
- Simulator: Model-based
- Motions: Random, exciting motions that are being simulated
- Domain Randomizations: Randomize the properties of the model and the virtual sensors

Motion Control with Neural ODEs



- Objective: Learn feedback controller
- Simulator: Data-driven
- Motions: Random step functions; references that the controller tries to realise
- Domain Randomizations: Randomize by transforming the IO behaviour of the model

Validation in Simulation and Experiment

Motion Control with Neural ODEs

— Extensive validation of ANODEC on two simulated systems and a pneumatic soft actuator in two configurations.

Control Sys. (2023)

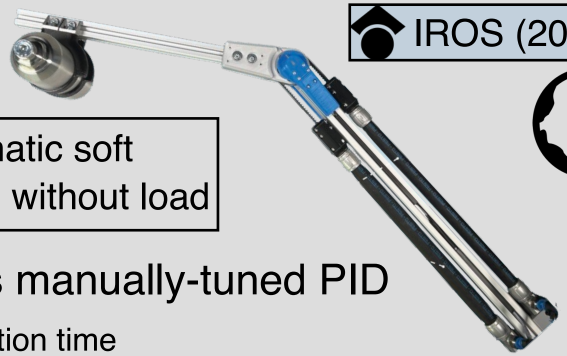
ANODEC
plug-and-play

IROS (2024)

simulated double pendulum dynamics

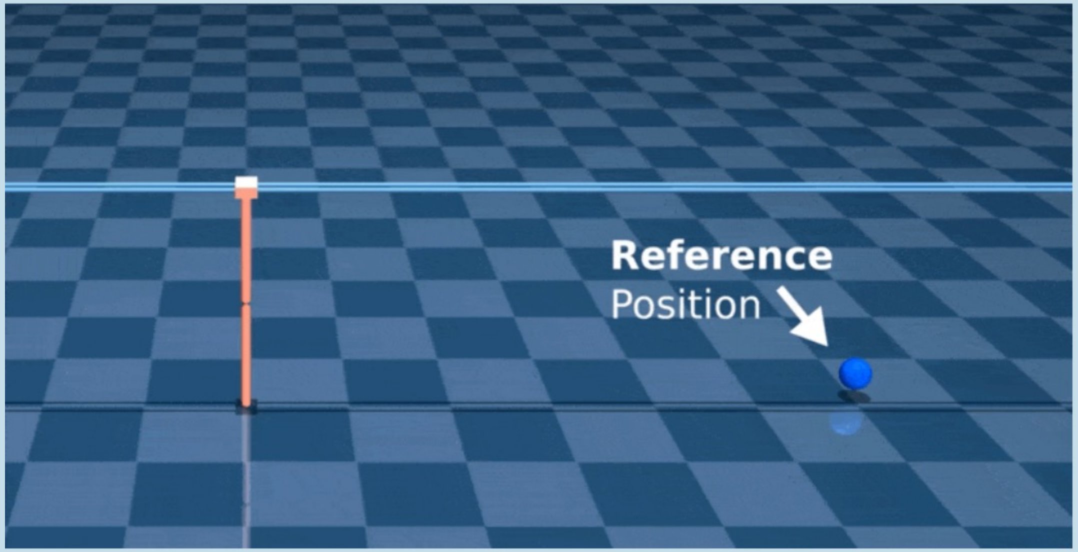
simulated Ackermann steering dynamics

real-world pneumatic soft actuator with and without load



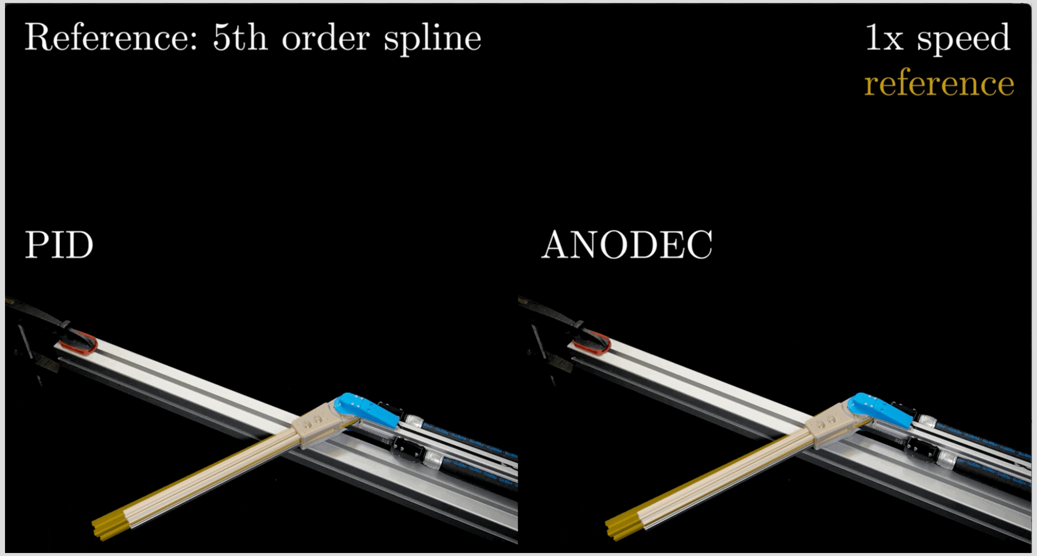
outperforms two common baselines

after two minutes of interaction time



outperforms manually-tuned PID

after 30 seconds of interaction time

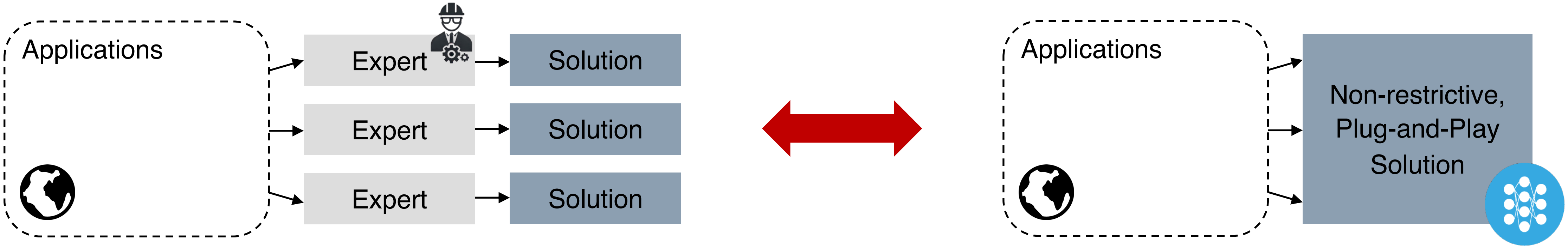


Summary and Conclusion

Viability of RNNs and Sim-to-Real Transfer

Summary and Conclusion

Core Research Question: How can the combination of RNNs and Sim-to-Real Transfer contribute to the development of non-restrictive, plug-and-play solutions for motion state estimation and solutions for motion control?



Viability of RNNs and Sim-to-Real Transfer

Summary and Conclusion

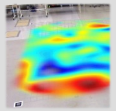
Core Research Question: How can the combination of RNNs and Sim-to-Real Transfer contribute to the development of non-restrictive, plug-and-play solutions for motion state estimation and solutions for motion control?

Motion State Estimation

RNNs and Sim-to-Real-Transfer

Motion Control

RING

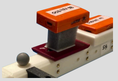


magnetometer-free

automatic calibration

sparse sensing

reduces motion artifacts



ANODEC

allows for non-repetitive motions

no model required

data-efficient

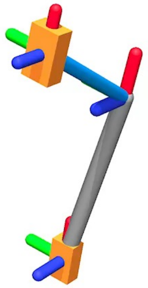
no state information required

Final Conclusion and Impact

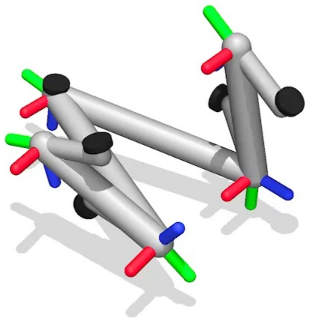
Summary and Conclusion

- The combination of RNNs and Sim-to-Real Transfer has enabled novel solutions for motion state estimation as well as for motion control. These solutions advance the state of the art by providing a more flexible approach that reduces reliance on expert knowledge and lowers calibration and data collection overhead.

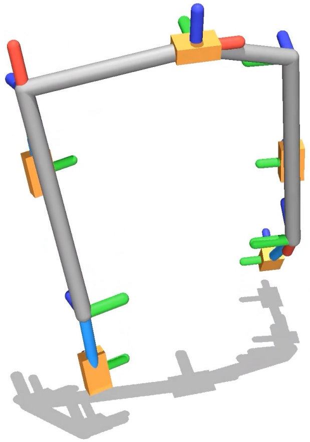
VR/AR



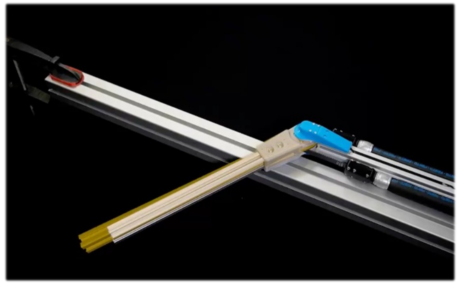
diagnostics



gait analysis



assistive devices



Publications in 1st and 2nd Authorship

Summary and Conclusion

S. Bachhuber, I. Weygers, and T. Seel, “Dispelling Four Challenges in Inertial Motion Tracking with One Recurrent Inertial Graph-based Estimator,” 2024 IFAC Symposium on Biological and Medical Systems, vol. 58, no. 24, pp. 117–122, 2024

BMS (2024)

S. Bachhuber, I. Weygers, D. Lehmann, M. Dombrowski, and T. Seel, “Recurrent Inertial Graph-Based Estimator: A Single Pluripotent IMT Solution,” Transactions on Machine Learning Research, vol. 10, 2024

TMLR (2024)

S. Bachhuber, D. Lehmann, E. Dorschky, A. D. Koelewijn, T. Seel, and I. Weygers, “Plug-and-play sparse inertial motion tracking with sim-to-real transfer,” IEEE Sensors Letters, vol. 7, no. 10, pp. 1–4, 2023

Sensors L. (2023)

S. Bachhuber, D. Weber, I. Weygers, and T. Seel, “RNN-based observability analysis for magnetometer-free sparse inertial motion tracking,” in 2022 25th International Conference on Information Fusion (FUSION), 2022, pp. 1–8

FUSION (2022)

S. Bachhuber, A. Pawluchin, A. Pal, I. Boblan, and T. Seel, “A Soft Robotic System Automatically Learns Precise Agile Motions Without Model Information,” in 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 11368–11373

IROS (2024)

M. Meindl, **S. Bachhuber**, and T. Seel, “Reference-Adapting Iterative Learning Control for Motion Optimization in Constrained Environments,” in 2024 IEEE 63rd Conference on Decision and Control (CDC), 2024*

M. Meindl, **S. Bachhuber**, and T. Seel, “AI-MOLE: Autonomous iterative motion learning for unknown nonlinear dynamics with extensive experimental validation,” Control Engineering Practice, vol. 145, p. 105879, 2024*

S. Bachhuber, I. Weygers, and T. Seel, “Neural ODEs for Data-Driven Automatic Self-Design of Finite-Time Output Feedback Control for Unknown Nonlinear Dynamics,” IEEE Control Systems Letters, vol. 7, pp. 3048–3053, 2023

Control Sys. (2023)

opensource software

tested and documented

GitHub

github.com/simon-bachhuber/imt

github.com/simon-bachhuber/ring

github.com/simon-bachhuber/diodem

github.com/simon-bachhuber/chain_control

python Package Index

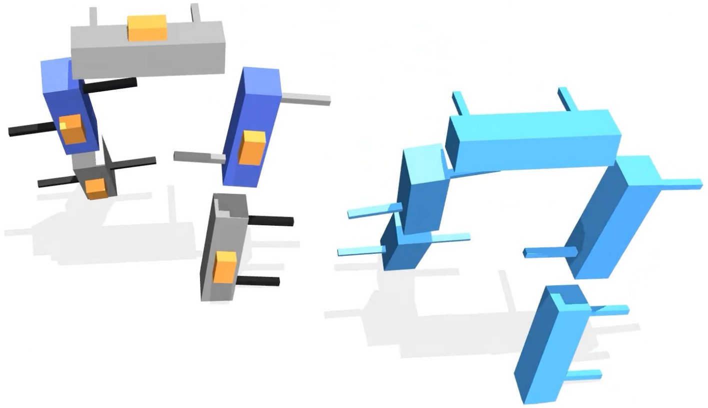
imt-imt

imt-ring

imt-diodem

*not included in thesis

Thank you for your attention!



IMUs and Inertial Motion Tracking

State Estimation with IMUs

— Inertial Measurement Units (IMUs, or inerital sensors) have become small and affordable.

Apollo IMU (1969, ~0.5m)

MEMS IMU (2019, ~1cm)

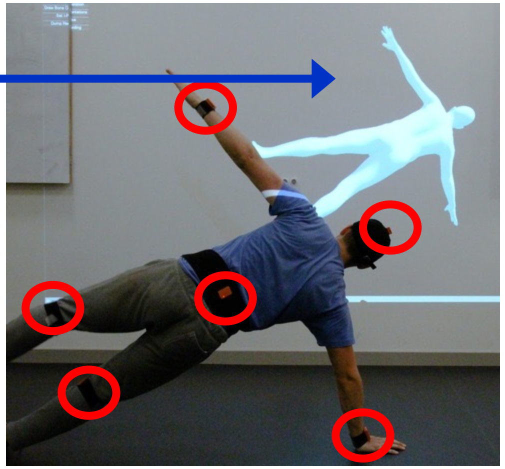
- lightweight, wireless, and battery-powered
- 3D gyroscope (angular velocity)
- 3D accelerometer (gravity + change of velocity)
- 3D magnetometer (Earth’s magentic field + others)

— Inertial Motion Tracking (IMT) tracks human or robot motion using wearable IMUs. Typically, one IMU per segment.

IMUs

IMT algorithms

Orientations / Visualised Pose



— In many real-world applications, IMT algorithms are faced with several challenges.

diagnostics cerebral palsy in infants

drop foot detection

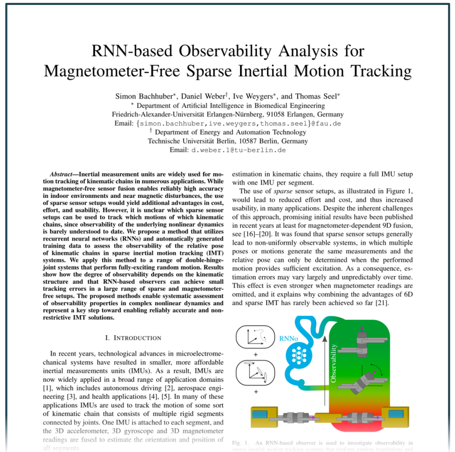
Method Overview Inertial Motion Tracking

Paper (2022) Observability Analysis

- **First**, train one RNN for each IMT problem, demonstrating observability of individual IMT problems in-silico.

Bachhuber et al. 2022

S. Bachhuber, D. Weber, I. Weygers, and T. Seel, “RNN-based Observability Analysis for Magnetometer-Free Sparse Inertial Motion Tracking,” 2022 International Conference on Information Fusion


RNN-based Observability Analysis for Magnetometer-Free Sparse Inertial Motion Tracking

- **Second**, develop domain randomisations to overcome the sim-to-real gap; evaluate the trained RNN on real-world data.

Bachhuber et al. 2023

S. Bachhuber, D. Lehmann, E. Dorschky, A. D. Koelewijn, T. Seel, and I. Weygers, “Plug-and-Play Sparse Inertial Motion Tracking With Sim-to-Real Transfer,” IEEE Sensors Letters


Sensor signal processing

Plug-and-Play Sparse Inertial Motion Tracking With Sim-to-Real Transfer

I. INTRODUCTION

- **Third**, unify the individual solutions by training a single RNN on all observable IMTPs.

Bachhuber et al. 2024

S. Bachhuber, I. Weygers, D. Lehmann, M. Dombrowski, and T. Seel, “Recurrent Inertial Graph-Based Estimator (RING): A Single Pluripotent Inertial Motion Tracking Solution,” Transactions on Machine Learning Research


Published in Transactions on Machine Learning Research (10/2024)

Recurrent Inertial Graph-Based Estimator (RING): A Single Pluripotent Inertial Motion Tracking Solution

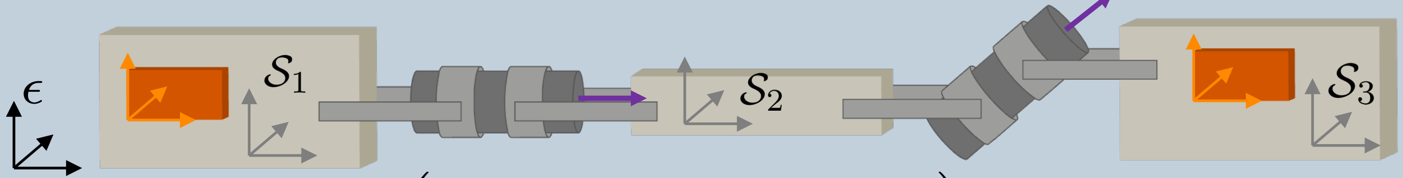
Abstract

Simulated IMT Problem

Paper (2022) Observability Analysis

— Consider a single IMT problem: **magnetometer-free, sparse** three-segment kinematic chain tracking.

$$\boldsymbol{y}_t = (\boldsymbol{\omega}_1(t)^\intercal, \boldsymbol{\rho}_1(t)^\intercal, \boldsymbol{\omega}_3(t)^\intercal, \boldsymbol{\rho}_3(t)^\intercal)^\intercal$$



$$\boldsymbol{x}_t = \left({}^{\mathcal{S}_1}_{\epsilon}\mathbf{q}^\intercal(t), {}^{\mathcal{S}_2}_{\mathcal{S}_1}\mathbf{q}^\intercal(t), {}^{\mathcal{S}_3}_{\mathcal{S}_2}\mathbf{q}^\intercal(t)\right)$$

Filtering Task

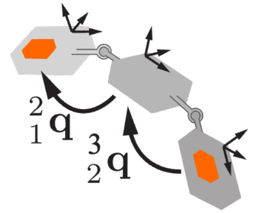
Estimate state $\boldsymbol{x}_t \in \mathbb{H}^3$

from measurements

$\boldsymbol{y}_{1:t} \in \mathbb{R}^{t \times 12}$

IMT Problem

Sparse 3-Segment Kinematic Chain



— Simulate randomly-exciting motion; compute virtual IMU and groundtruth pose data.

seed

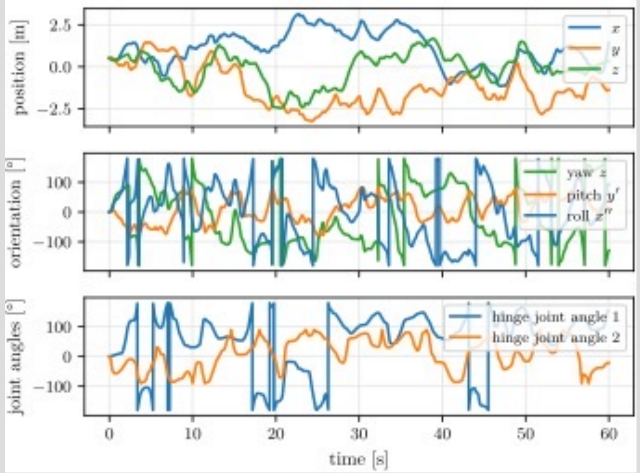
random position ${}_{\mathcal{E}}\boldsymbol{r}_1(t)$

➕

random global orientation ${}^{\mathcal{S}_1(t)}_{\mathcal{E}}\mathbf{q}$

➕

random joint angles $\varphi_1(t), \varphi_2(t)$



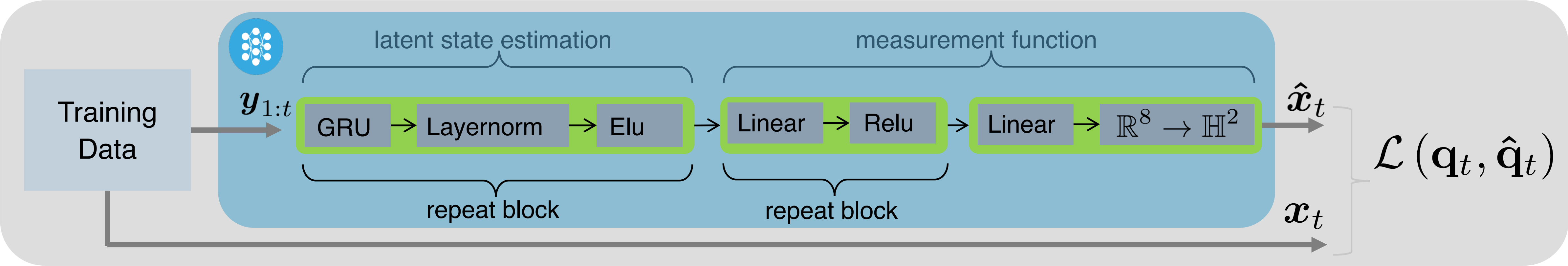
simulated acc. & gyr.

Training Data

RNN-based Observer

Paper (2022) Observability Analysis

- Train RNN-based Observer (RNNO) that maps timeseries of inertial data to rotational state.



- Minimize the squared angle error using truncated backpropagation through time.

$$\mathcal{L}(\mathbf{q}_t, \hat{\mathbf{q}}_t) = \tilde{\mathcal{L}}(\mathbf{q}_t^* \otimes \hat{\mathbf{q}}_t)^2 \quad \text{where } \tilde{\mathcal{L}}(\mathbf{q}_{\text{err}}) = 2\underline{\arctan}\left(\frac{\sqrt{\mathrm{q}_x^2 + \mathrm{q}_y^2 + \mathrm{q}_z^2}}{\mathrm{q}_w}\right)$$

arctan instead of typical arccos for better numerical stability

Numerically-Stable Inclination Loss

$$\tilde{\mathcal{L}}_{\text{incl}}(\mathbf{q}_{\text{err}}) = \underline{\tilde{\mathcal{L}}}(\mathcal{P}(\mathbf{q}_{\text{err}}))^2$$

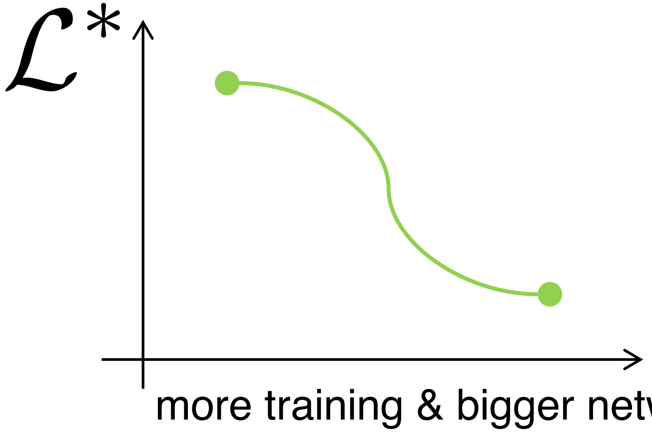
$$\mathcal{P}(\mathbf{q}) = \left(\underline{\tilde{\mathcal{L}}}([\mathrm{q}_w, 0, 0, \mathrm{q}_z]^\intercal) @ [0, 0, -1]^\intercal\right) \otimes \mathbf{q}$$

Observability Analysis

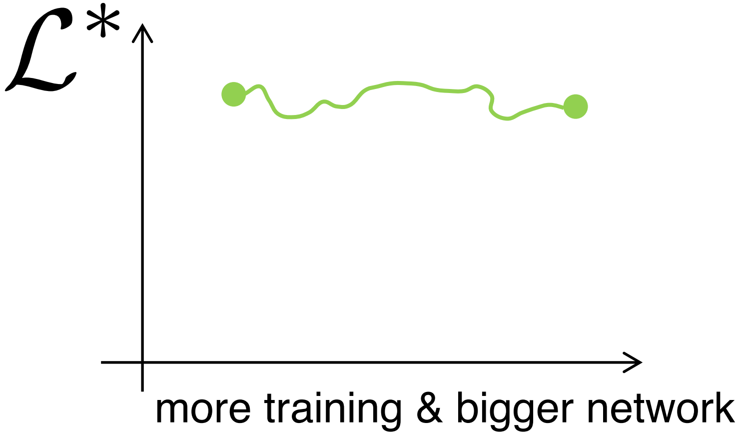
Paper (2022) Observability Analysis

— Increase amounts of training data and network size to assess observabiliy.

Data from **observable** IMT system



Data from **non-observable** IMT system



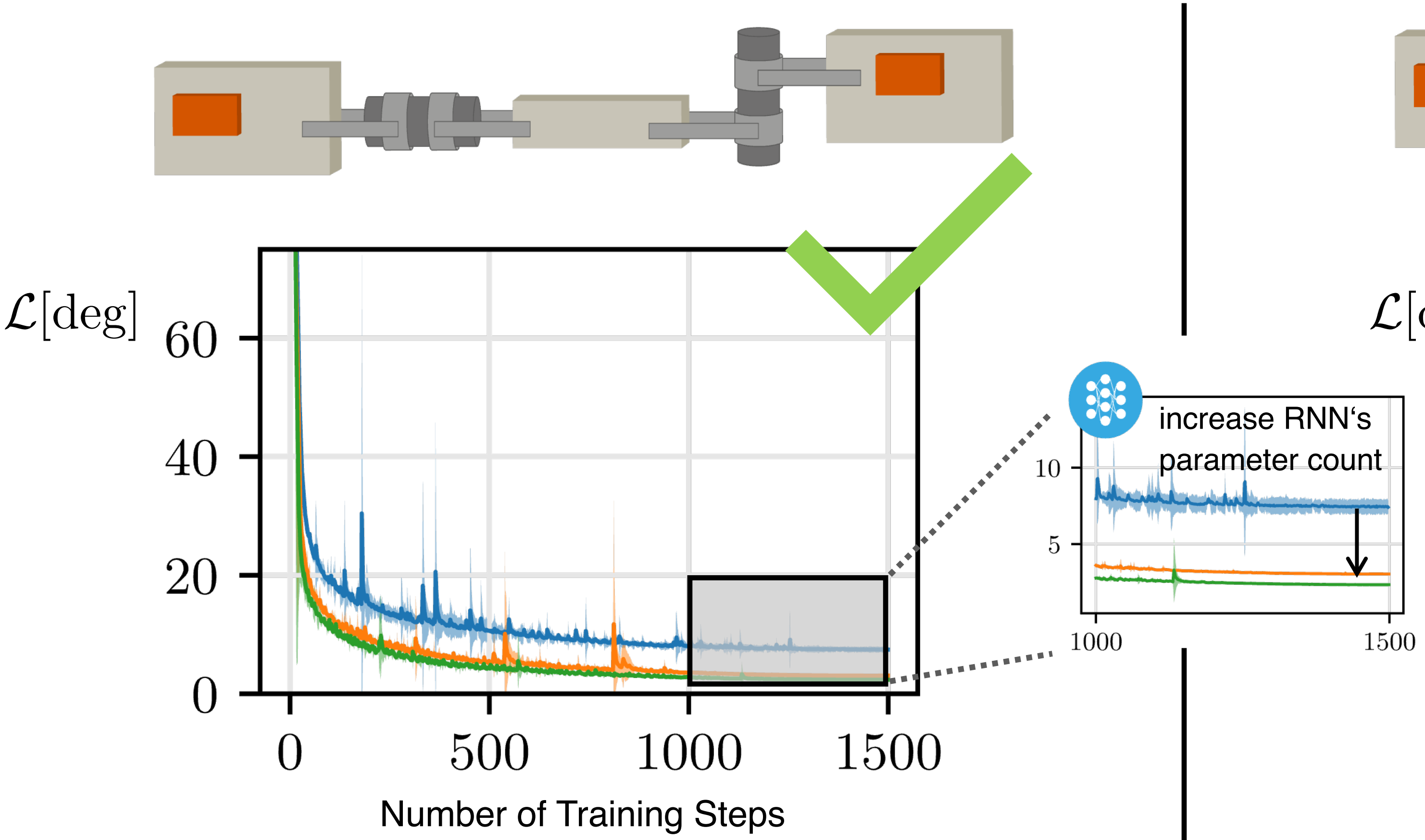
Argument 1: ***If a system is non-observable, then RNNO cannot converge to low error****, even if the amount of training data is increased, even if the parameter count of the RNN is increased, and even if the noise and bias levels are reduced.*

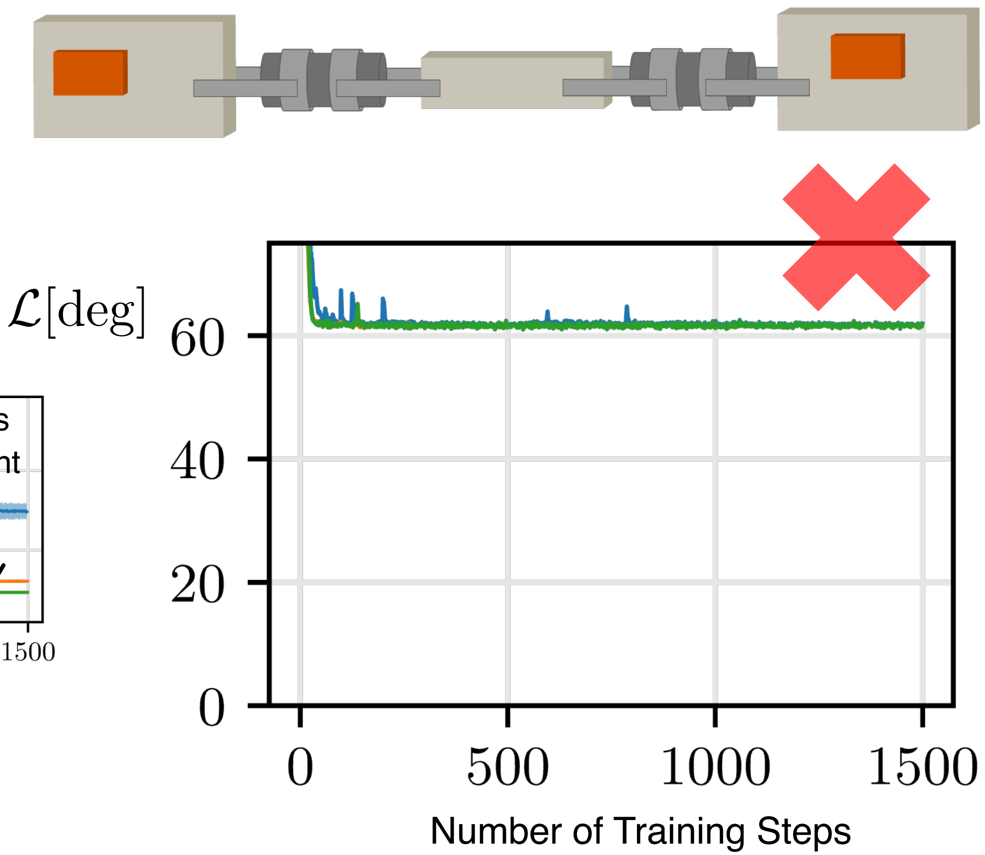
Argument 2: ***If an RNNO converges to a small residual error, then observability is proven by example****. The error should exhibit some dependence on the RNN's parameter count, the amount of training data, and the noise and bias levels.*

Observabiliy Analysis

Paper (2022) Observability Analysis

— Observabiliy of magnetometer-free, sparse three-segment KC **depends on joint axes directions**.

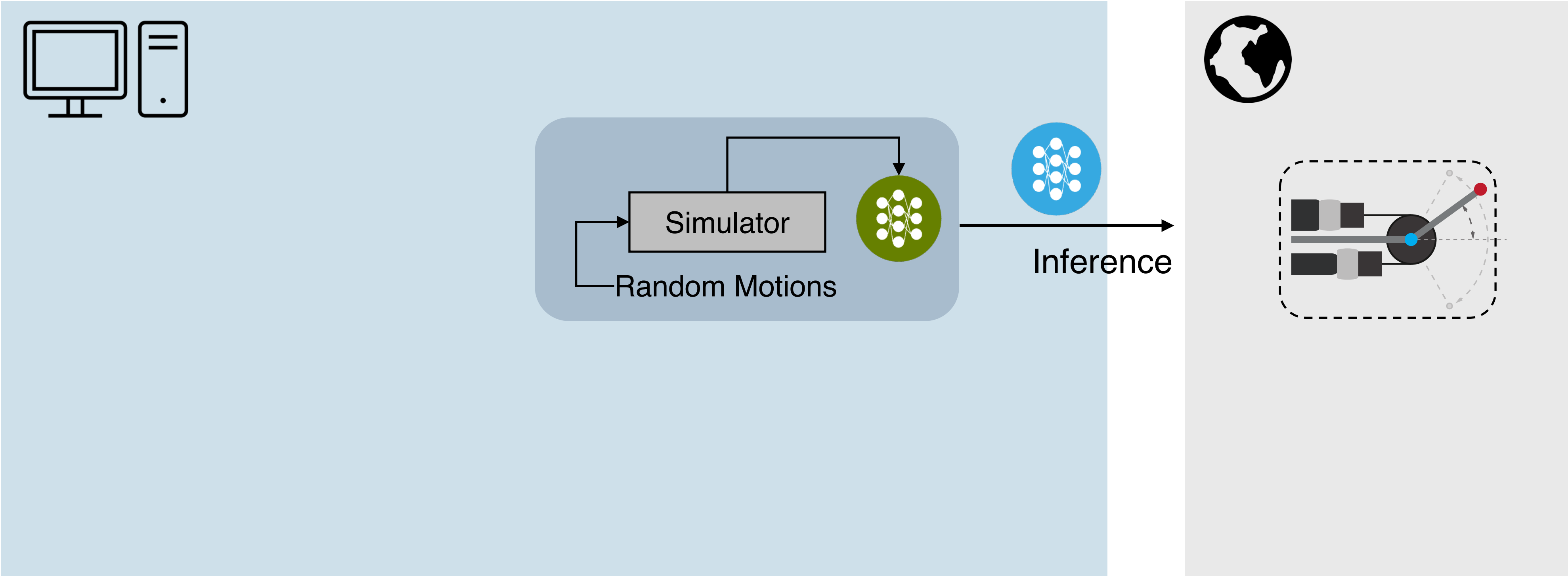




Automatic Neural ODE Control

Motion Control with Neural ODEs

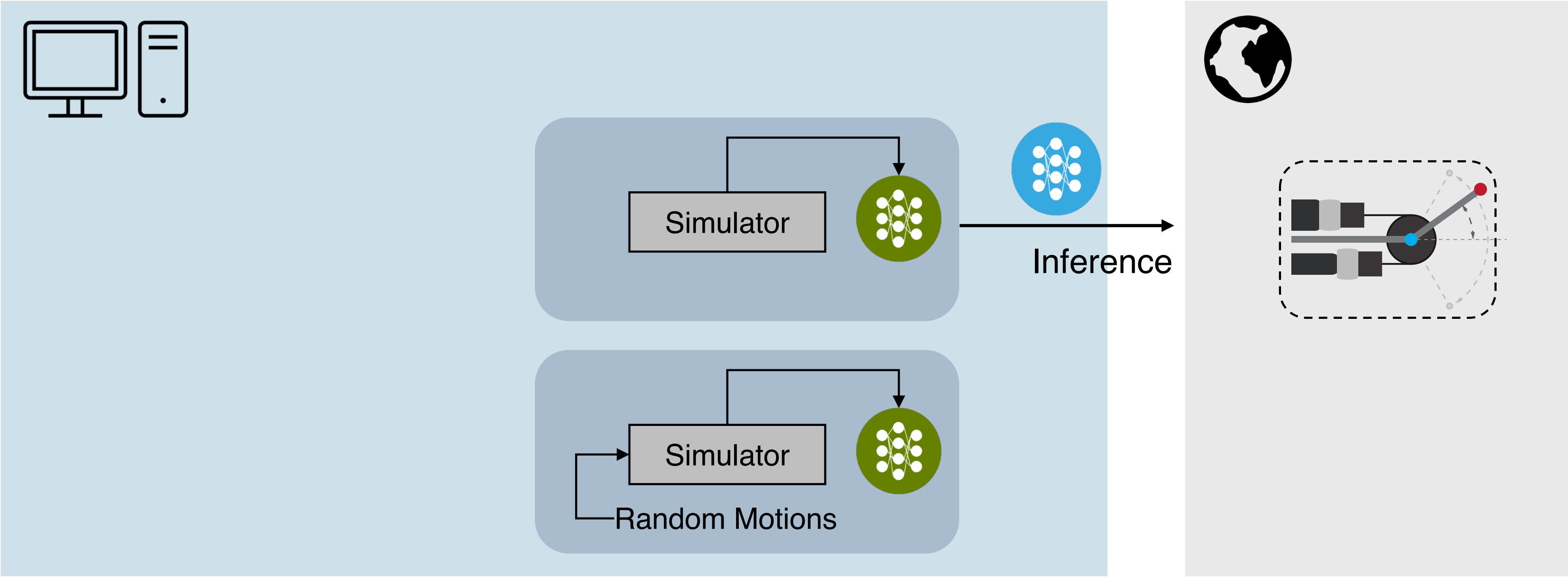
— ANODEC optimizes controller parameters by simulating closed-loop dynamics with random reference motions.



Automatic Neural ODE Control

Motion Control with Neural ODEs

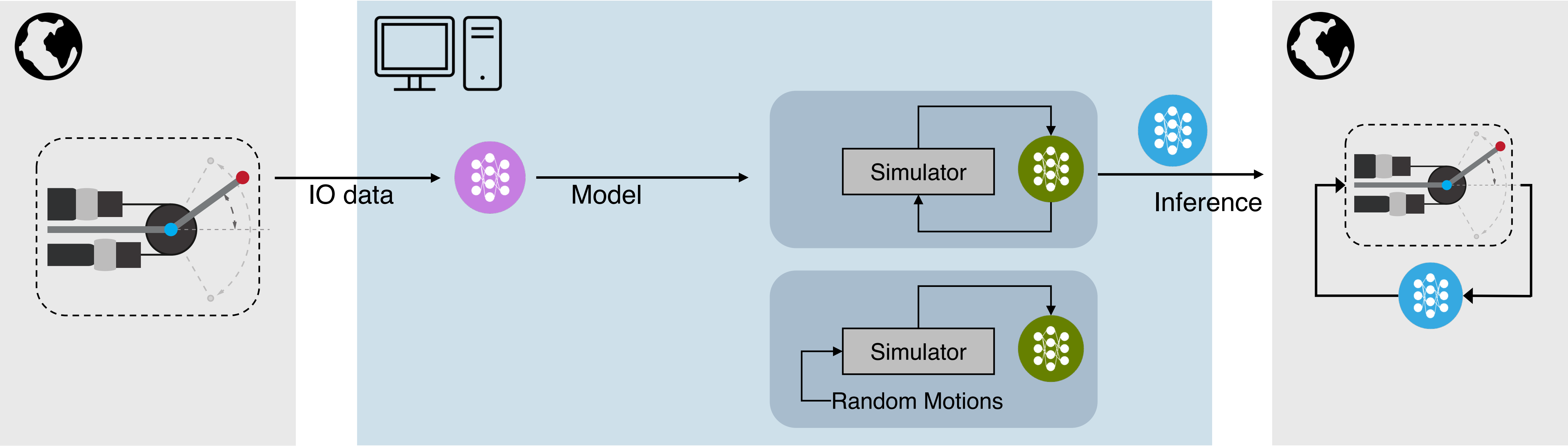
— ANODEC optimizes controller parameters by simulating closed-loop dynamics with random reference motions.



Automatic Neural ODE Control

Motion Control with Neural ODEs

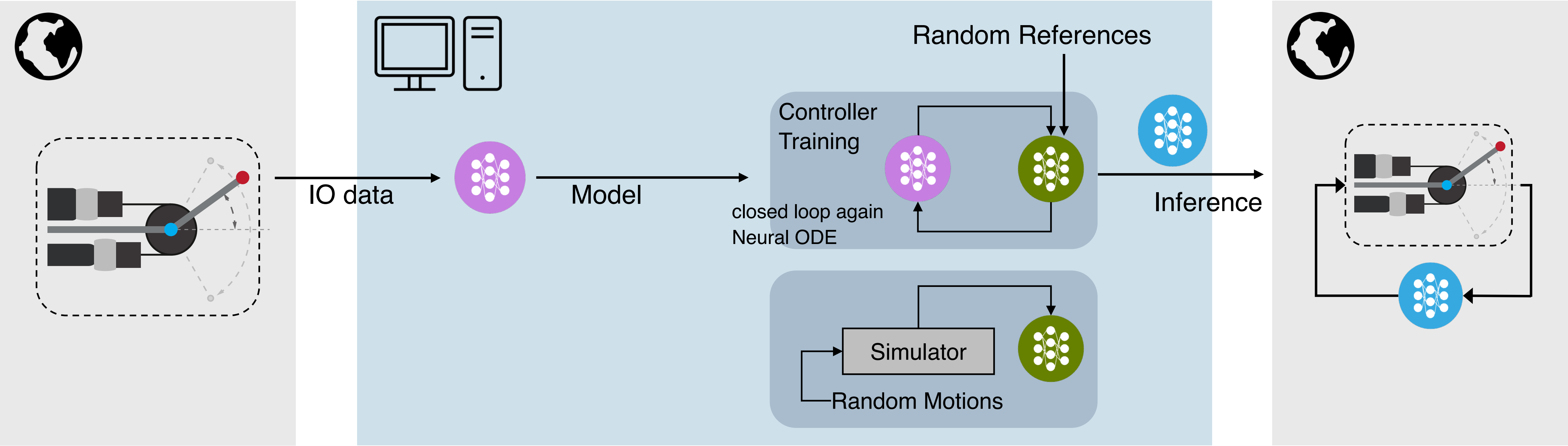
- ANODEC optimizes controller parameters by simulating closed-loop dynamics with random reference motions.
- First, learn Neual ODE Model from input-output data



Automatic Neural ODE Control

Motion Control with Neural ODEs

- ANODEC optimizes controller parameters by simulating closed-loop dynamics with random reference motions.
- First, learn Neual ODE Model from input-output data
- Second, learn Neural ODE Controller by forward simulation using random references

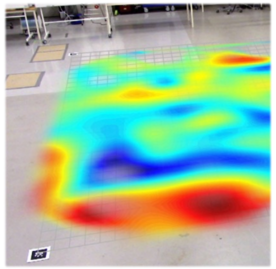


Addressing All Four Challenges

State Estimation with IMUs

— We want a non-restrictive method that can tackle all four **challenges**.

✅ mag.-free

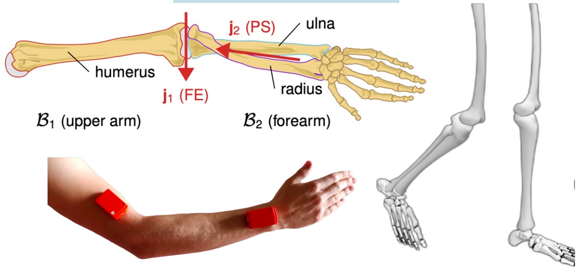


reliable outdoors and indoors

✅ sparse

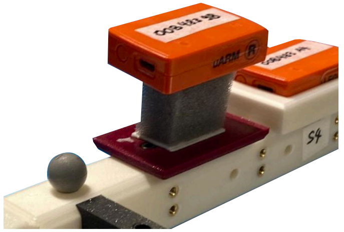
allows for sparse sensor setups

✅ calib.



reduces expert knowledge and calibration & modelling efforts

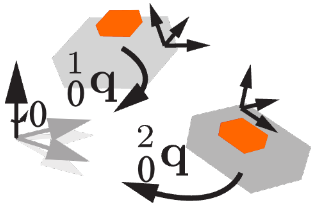
✅ nonrigid



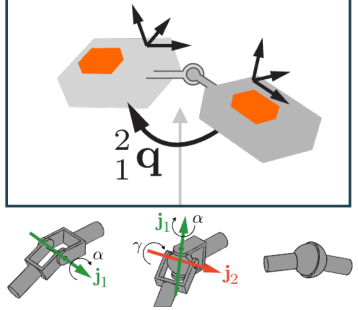
robust to nonrigid attachment and reduces motion artifacts

— Such a method will be broadly applicable to diverse **IMT problems**:

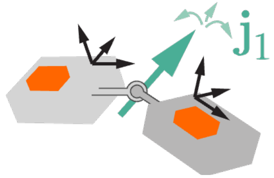
Inertial Orientation Estimation



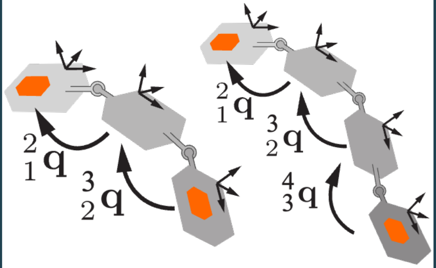
Magnetometer-free Heading Correction



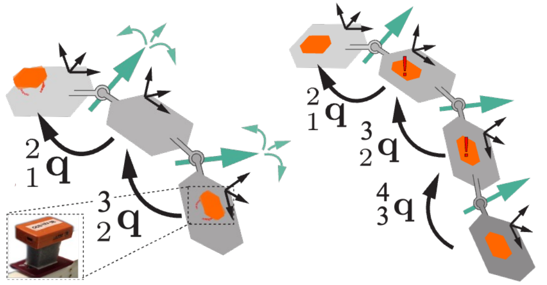
Estimating Joint Axes Directions



Sparse N-Segment Kinematic Chain



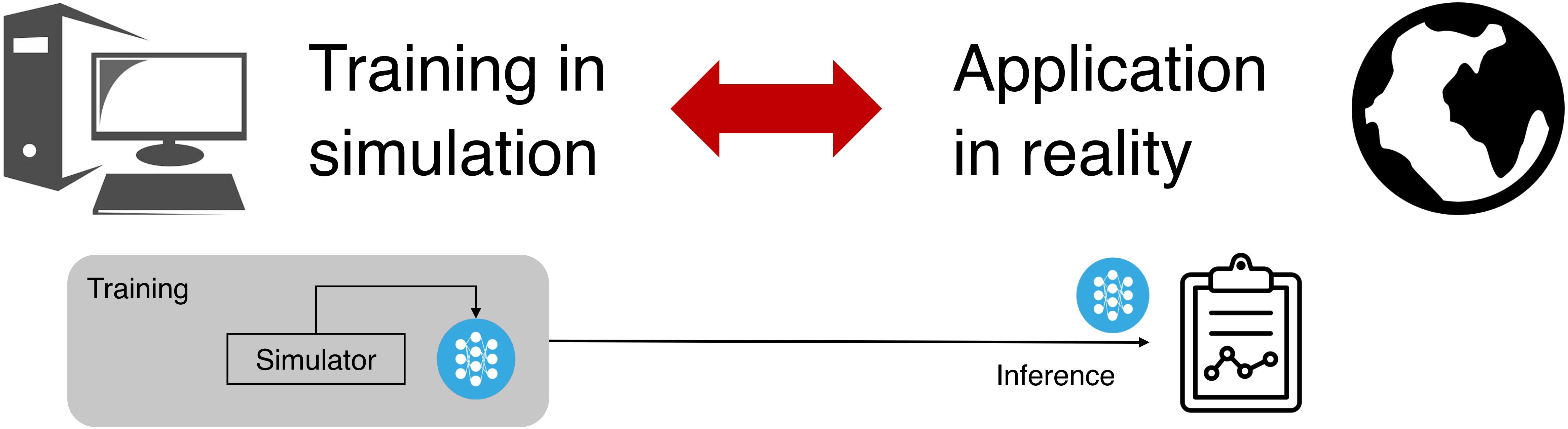
Complex Combinations



Zero-Shot Transfer

State Estimation with IMUs / Methods

- Train RNN in simulation; **after training RNN is a real-world IMT filter**
- Overcome sim-to-real gap with extensive **domain randomizations**



Generalising to Multiple IMT Problems

State Estimation with IMUs / Methods

— How can we train a single NN with a fixed set of parameters despite different input/output shapes?