Physics-Informed Neural Network

이동로봇 튜토리얼 #3

박수환

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KYUNG HEE UNIVERSITY

Paper #1 Navigation

경희대학교
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논문 요약

- 2D-INS 물리 법칙을 Loss에 포함한 PINN 기반 순수 관성 내비게이션 프레임워크
- IMU 데이터로 위치·속도·Yaw를 물리 일관성 있게 추정하도록 제약 강화
- 기존 2D-INS·MoRPINet 대비 최대 94% 정확도 향상

논문 소개

MoRPI-PINN: A Physics-Informed Framework for Mobile Robot Pure Inertial Navigation

Arup Kumar Sahoo and Itzik Klein

Abstract—**A fundamental requirement for full autonomy in mobile robots is accurate navigation even in situations where satellite navigation or cameras are unavailable. In such practical situations, relying only on inertial sensors will result in navigation solution drift due to the sensors' inherent noise and error terms. One of the emerging solutions to mitigate drift is to maneuver the robot in a snake-like slithering motion to increase the inertial signal to noise ratio allowing the regression of the mobile robot position. In this work, we propose MoRPI-PINN as a physics-informed neural network framework for accurate inertial-based mobile robot navigation. By embedding physical laws and constraints into the training process, MoRPI-PINN is capable of providing an accurate and robust navigation solution. Using real-world experiments, we show accuracy improvements of over 85% compared to other approaches. MoRPI-PINN is a lightweight approach that can be implemented even on edge devices and used in any typical mobile robot application.**

Index Terms—**Scientific Machine Learning; Physics-informed Neural Networks; Inertial Navigation System; Mobile Robot; Accelerometer; Gyroscope; Yaw Angle; Dead Reckoning.**

TABLE
LIST OF ABBREVIATIONS

Abbreviation	Definition
Navigation	
INS	Inertial Navigation System
IMU	Inertial Measurement Unit
GNSS	Global Navigation Satellite System
RTK	Real-Time Kinematic
NED	North-East-Down (Coordinate Frame)
ECEF	Earth-Centered Earth-Fixed
Neural Networks	
PINN	Physics-informed Neural Network
AD	Automatic Differentiation
GT	Ground Truth
Error Metrics	
ATE	Absolute Trajectory Error
MATE	Mean Absolute Trajectory Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
NRMSE	Normalized Root Mean Squared Error

I. INTRODUCTION

THE study of mobile robots is crucial for modern industries and services, as they are deployed across various fields. It includes logistics, transportation, agriculture, healthcare, military operations, and data collection in hazardous environments [1], [2], [3], and [4]. In recent years, the market demand of mobile robots have been significantly increased, because of increase in application areas, advances in robot technology along with the cost reductions in electronic sensors and devices. As a result, around the globe, various companies are developing mobile robots to meet these demands and explore new markets.

Navigation plays a fundamental role in mobile robot design, enabling precise determination of position and orientation across diverse and often challenging environments. While operating outdoors, the navigation task depends on a variety of sensors, including cameras [5], LiDAR [6], Sonar [7], global navigation satellite systems (GNSS) [8], inertial navigation system (INS) [9], and odometers [10]. In indoors or tunnels the GNSS signals are unavailable while vision methods suffer from poor lighting conditions or featureless environments. In such real-world scenarios, the navigation solution depends only on the inertial sensor readings in a process known as pure inertial navigation [11], [12].

There, the navigation solution drifts due to errors and noise in the inertial measurement. To cope with the inertial drift Shurin and Klein [13] proposed the quadrotor dead-reckoning approach. Inspired by the natural movement of pedestrians [14], [15], they enforced periodic motion on quadrotors and designed a model-based approach for positioning. Later, similar model-based approaches were applied on mobile robots [16]. With the emergence of deep-learning approaches in the navigation field [17], [18], neural network solutions were designed for quadrotors [19] and mobile robots [20].

Recent advances in scientific machine learning, offers promising solutions to such challenges and uncovers novel scientific phenomena, particularly through physics-informed neural networks (PINNs). Unlike conventional deep neural networks (DNNs), PINNs embed physical laws typically expressed as differential equations (DEs) directly into the objetive function of neural network as a residual loss [21]. This integration ensures that model outputs adhere to governing physical principles, enhancing accuracy and interpretability while reducing reliance on extensive labeled data. PINNs leverage parallel computing and autometic differentiation, in order to address the computational inefficiencies of repeatedly solving DEs. In past few years, PINNs have demonstrated remarkable success across scientific and engineering domains, including anomaly detection [22], [23], fluid mechanics [24], solid mechanics

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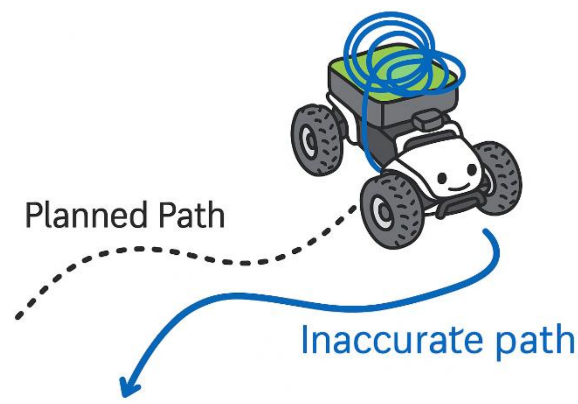
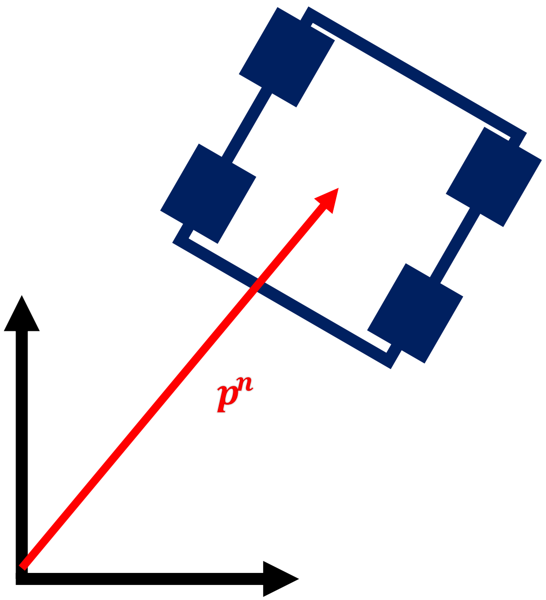
- IMU 단독 내비게이션은 센서 노이즈가 적분 과정에서 증폭되어 급격한 오차 누적 발생
- 직선 주행보다 주기적(Snake-like) 움직임이 높아진 SNR을 제공함을 실험적으로 확인
- 기존 2D-INS·학습기반 모델 모두 이러한 동적 환경에서 안정적 추정을 보장하지 못함



[1] A. K. Sahoo and I. Klein, "MoRPI-PINN: A physics-informed framework for mobile robot pure inertial navigation," arXiv preprint arXiv:2507.18206, Sep. 2025.

Paper #1 Navigation

기본 이론 소개



위치 업데이트 수식

$$\dot{\mathbf{p}}^n = \mathbf{v}^n,$$

$$\dot{\mathbf{v}}^n = \mathbf{C}_b^n\,\mathbf{f}_{ib}^b + \mathbf{g}^n,$$

$$\dot{\mathbf{C}}_b^n = \mathbf{C}_b^n\,\boldsymbol{\Omega}_{ib}^b.$$

IMU 센서 데이터

$$\mathbf{f}_{ib}^b = \begin{bmatrix} f_x \\ f_y \\ f_z \end{bmatrix}^T \qquad \boldsymbol{\omega}_{ib}^b = \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix}^T$$

회전관련

$$\boldsymbol{\Omega}_{ib}^b = \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix} \qquad \mathbf{C}_b^n(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

[1] A. K. Sahoo and I. Klein, "MoRPI-PINN: A physics-informed framework for mobile robot pure inertial navigation," arXiv preprint arXiv:2507.18206, Sep. 2025.

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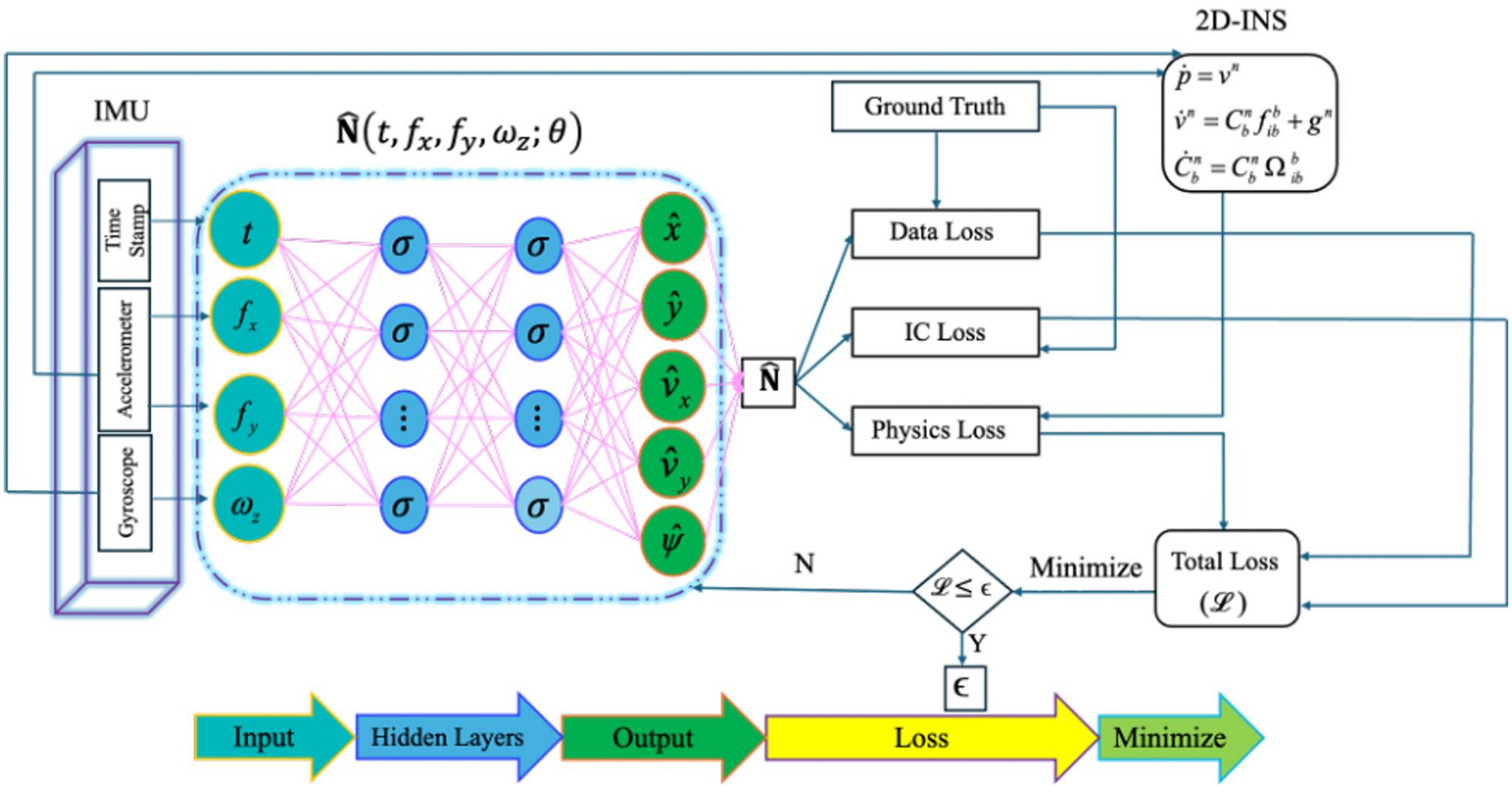
핵심 Framework



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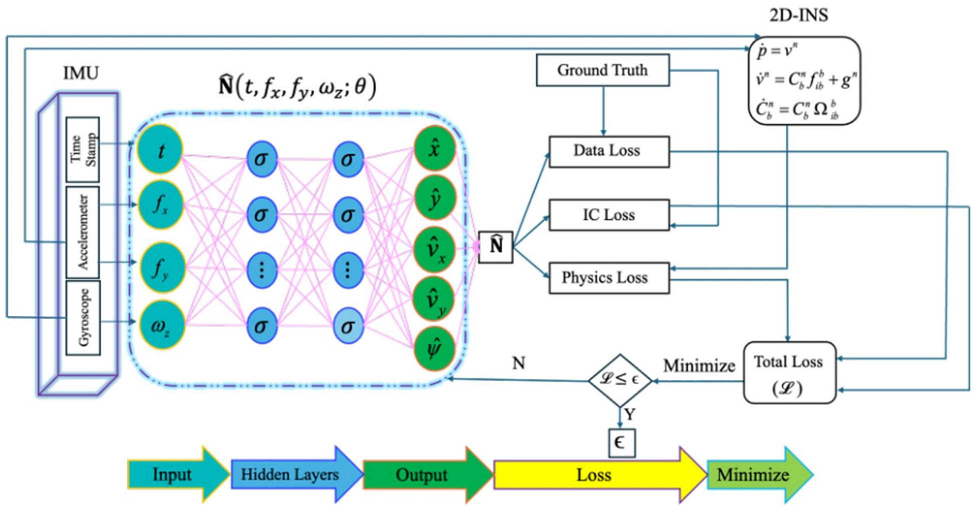
Paper #1 Navigation

핵심 Framework



Data Loss

$$\mathcal{L}_{\text{data}} = \frac{1}{N_{\text{data}}} \sum_{i=1}^{N_{\text{data}}} \left(\|\mathbf{p}_i - \hat{\mathbf{p}}_i\|^2 + \|\mathbf{v}_i - \hat{\mathbf{v}}_i\|^2 \right)$$

Init Loss

$$\mathcal{L}_{\text{init}} = \frac{1}{N_{\text{ic}}} \sum_{i=1}^{N_{\text{ic}}} \|\hat{\mathbf{p}}_i - \mathbf{p}_0\|^2$$

Physics Loss

$$\mathcal{L}_{\text{phys}} = \frac{1}{N_{\text{phys}}} \sum_{i=1}^{N_{\text{phys}}} \left(\left\| \frac{d}{dt} \begin{bmatrix} \hat{x}(t_i) \\ \hat{y}(t_i) \end{bmatrix} - \begin{bmatrix} \hat{v}_x(t_i) \\ \hat{v}_y(t_i) \end{bmatrix} \right\|^2 + \left\| \frac{d}{dt} \begin{bmatrix} \hat{v}_x(t_i) \\ \hat{v}_y(t_i) \end{bmatrix} - \left(\mathbf{C}_b^n(\hat{\psi}(t_i)) \begin{bmatrix} f_x(t_i) \\ f_y(t_i) \end{bmatrix} + \begin{bmatrix} g_x \\ g_y \end{bmatrix} \right) \right\|^2 + \left(\frac{d\hat{\psi}(t_i)}{dt} - \omega_z(t_i) \right)^2 \right)$$

Total Loss $\boxed{\mathcal{L}_{\text{total}} = \lambda_{\text{data}} \mathcal{L}_{\text{data}} + \lambda_{\text{init}} \mathcal{L}_{\text{init}} + \lambda_{\text{phys}} \mathcal{L}_{\text{phys}}}$

[1] A. K. Sahoo and I. Klein, "MoRPI-PINN: A physics-informed framework for mobile robot pure inertial navigation," arXiv preprint arXiv2507.18206, Sep. 2025.

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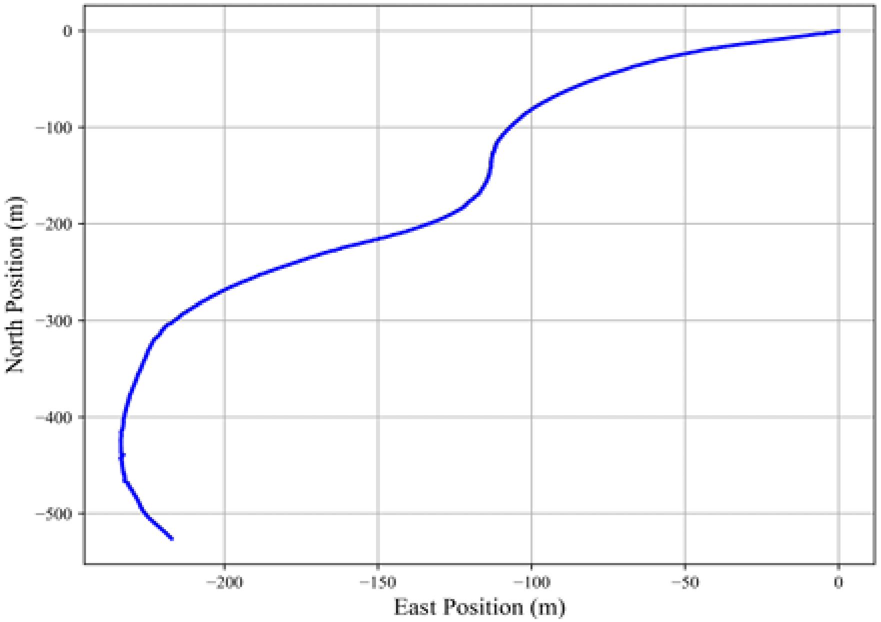
Train Data

Specification	Gyroscope	Accelerometer
Bias	$10\,^\circ/\mathrm{h}$	$0.03\,\mathrm{mg}$
Noise Density	$0.007\,^\circ/\mathrm{s}/\sqrt{\mathrm{Hz}}$	$120\,\mu\mathrm{g}/\sqrt{\mathrm{Hz}}$



[1] A. K. Sahoo and I. Klein, "MoRPI-PINN: A physics-informed framework for mobile robot pure inertial navigation," arXiv preprint arXiv:2507.18206, Sep. 2025.

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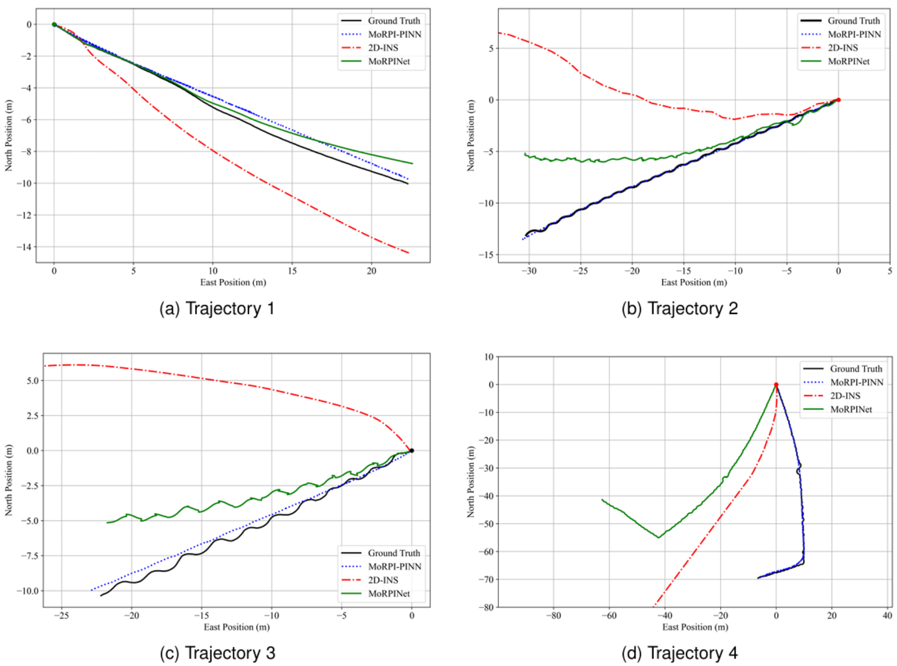
Experiment



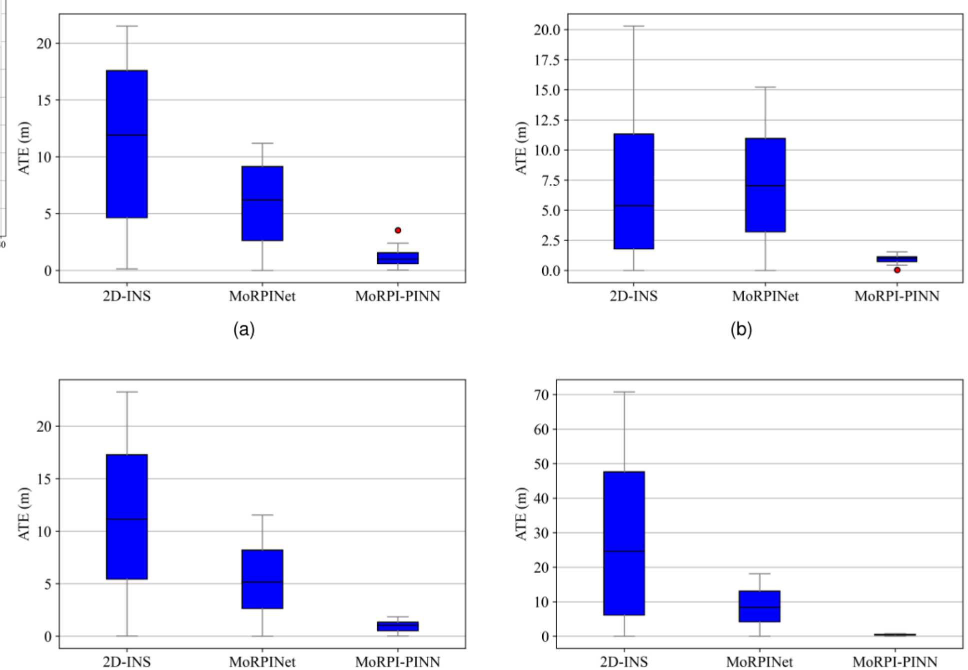
(a) Trajectory 1

(b) Trajectory 2

(c) Trajectory 3

(d) Trajectory 4

$$\mathrm{ATE}(\mathbf{p}_i, \hat{\mathbf{p}}_i) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|\mathbf{p}_i - \hat{\mathbf{p}}_i\|^2}$$



(a)

(b)

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Paper #2 Friction Estimation

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논문 요약

- PINN 기반 마찰 모델링으로 고비선형(static/dynamic friction)까지 정밀하게 추정
- UKF에 PINN 마찰을 직접 측정치로 입력, 모델 불확실성·외란 상황에서도 견고한 토크 추정
- 실험에서 RNEA 대비 토크 추종·에너지 효율·외란 대응 능력 크게 향상

논문 소개

IEEE ROBOTICS AND AUTOMATION LETTERS, VOL. 10, NO. 6, JUNE 2025 5705

Physics-Informed Neural Networks With Unscented Kalman Filter for Sensorless Joint Torque Estimation in Humanoid Robots

Ines Sorrentino, Giulio Romualdi, *Member, IEEE*, Lorenzo Moretti, Silvio Traversaro, *Member, IEEE*, and Daniele Pucci, *Associate Member, IEEE*

***Abstract*—This paper presents a novel framework for whole-body torque control of humanoid robots without joint torque sensors, designed for systems with electric motors and high-ratio harmonic drives. The approach integrates Physics-Informed Neural Networks (PINNs) for friction modeling and Unscented Kalman Filtering (UKF) for joint torque estimation, within a real-time torque control architecture. PINNs estimate nonlinear static and dynamic friction from joint and motor velocity readings, capturing effects like motor actuation without joint movement. The UKF utilizes PINN-based friction estimates as direct measurement inputs, improving torque estimation robustness. Experimental validation on the ergoCub humanoid robot demonstrates improved torque tracking accuracy, enhanced energy efficiency, and superior disturbance rejection compared to the state-of-the-art Recursive Newton-Euler Algorithm (RNEA), using a dynamic balancing experiment. The framework's scalability is shown by consistent performance across robots with similar hardware but different friction characteristics, without re-identification. Furthermore, a comparative analysis with position control highlights the advantages of the proposed torque control approach. The results establish the method as a scalable and practical solution for sensorless torque control in humanoid robots, ensuring torque tracking, adaptability, and stability in dynamic environments.**

***Index Terms*—Humanoid robot systems, calibration and identification, humanoid and bipedal locomotion.**

I. Introduction

THE ongoing evolution of humanoid robotics is expanding the boundaries of functionality, safety, and integration into human environments. Humanoid robots are designed for tasks like locomotion, manipulation, and human-robot interaction, demanding safe adaptability, compliant interaction, and precision, which can be facilitated by introducing compliance in the robot's joints [1], [2], [3]. Joint torque control is widely adopted among various control strategies as it enables compliance and adaptability. However, it typically relies on direct torque measurements, often impractical due to cost, integration complexity, and sensor limitations [4], [5], [6]. As a result, many humanoid robots without joint torque sensors rely on rigid control strategies that use predefined joint trajectories. While such approaches are effective in controlled environments, they often fail in dynamic, real-world scenarios where precise torque estimation is crucial for robust interaction with unpredictable surroundings. To address the limitations of current sensorless torque control methods, this paper introduces a novel framework that synergistically integrates Physics-Informed Neural Networks (PINNs) for complex friction modeling and an Unscented Kalman Filter (UKF) for robust joint torque estimation.

Existing methods estimate joint torques in real-time by combining sensor data (e.g., motor currents, joint positions, and velocities) with advanced algorithms [7], [8], [9]. A common model-based approach is the Recursive Newton-Euler Algorithm (RNEA) [8], [9], [10]. RNEA estimates joint torques based on rigid-body dynamics but is prone to inaccuracies from unmodeled dynamics, including friction, gearbox elasticity, sensor noise, and unmeasured external contacts [7], [11], [12]. Alternatively, some solutions compute joint torques from motor current and encoder data. While these offer fast response, they often assume rigid gear transmission, neglecting elastic deformations and backlash in high-ratio gears [13]. Sensorless variable impedance control is another approach, dynamically adjusting joint stiffness and damping based on interaction forces estimated from motor currents and encoders. Still, its accuracy heavily relies on precise robot dynamics models [14].

These torque estimation methods are all limited by complex friction dynamics, which sensorless control frameworks commonly address through friction estimation and compensation strategies. While basic models like Coulomb and viscous friction offer limited accuracy [8], [13], advanced models such as LuGre and Stribeck capture more intricate friction effects [15], [16]. Recent advancements have integrated physics-based modeling with data-driven techniques to estimate friction dynamics under

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- 다수의 휴머노이드 로봇은 관절 토크 센서가 없거나, 비용·무게·내구성 문제로 장착이 불가능
- 토크를 추정하려면 마찰, 관성, 비선형성까지 포함해야 하는데 기존 모델링만으로는 정확하지 않음

[2] I. Sorrentino et al., "Physics-informed neural networks with unscented Kalman filter for sensorless joint torque estimation in humanoid robots," IEEE Robotics and Automation Letters, vol. 10, no. 6, pp. 5705–5712, 2025

Paper #2 Friction Estimation

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기존 방법의 한계

Model Based Method (RNEA)

- **마찰 모델 자체가 단순함 → 실제 마찰 재현 불가**
  - RNEA는 마찰을 Coulomb + viscous처럼 단순화하여 실제 복잡한 마찰을 재현하지 못함
  - 기어박스·트랜스미션의 비선형 마찰(static, Stribeck, stick-slip 등)을 RNEA만으로는 표현 불가
- **모델 불일치→ 토크 추정 오차 증가**
- **환경·마모 변화에 유연하지 않음**
  - 마찰은 온도·마모·기어박스 상태에 따라 계속 변하지만 RNEA는 고정 파라미터만 사용

Neural Network

- **데이터 의존적 → 일반화 성능 약함**
  - 훈련 데이터 분포 바깥(새 동작·새 속도·새 환경)에서는 성능 급격히 저하
- **물리 기반 제약 부재 → 비물리적 추정 가능**
- **환경 변화(온도·마모 등)에 적응 어려움**
  - 마찰 특성이 계속 변하지만,NN은 고정된 데이터 기반 모델이라 외란·마모 변화에 취약

PINN은 물리식 + 학습을 결합해 두 방식의 단점을 동시에 극복

[2] I. Sorrentino et al., "Physics-informed neural networks with unscented Kalman filter for sensorless joint torque estimation in humanoid robots," IEEE Robotics and Automation Letters, vol. 10, no. 6, pp. 5705–5712, 2025

Paper #2 Friction Estimation

기본 이론 정리

로봇 동역학 식

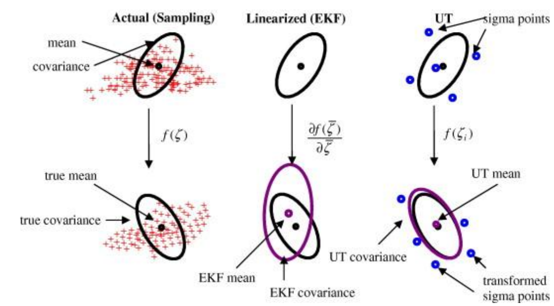
$$M(q)\begin{bmatrix} {}^{B}\alpha^{g}_{A,B} \\ \ddot{s} \end{bmatrix} + C(q,\ {}^{B}\nu_{A,B}) = B\boldsymbol{\tau} + \sum_{k} J_k^{\top}(q)\, f^{k}_{\text{ext}}$$

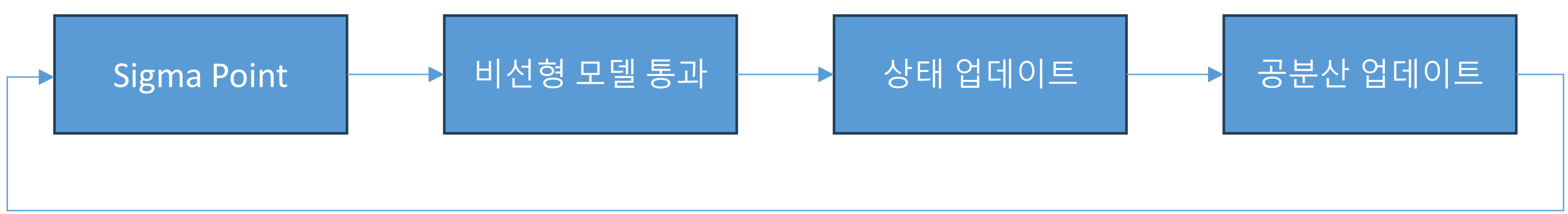
모터 동역학 식

$$k_t I_m = J_m\,\ddot{\theta} + \frac{1}{R}\tau_F + \frac{1}{R}\tau$$

UKF

- 시그마 포인트 기반 비선형 칼만 필터
- 기존 EKF에서 비선형 함수를 선형화하는 과정을 생략한 상태로 샘플링을 통한 근사화 전략을 사용
- 동역학·마찰 불확실성에 강한 확률적 상태 추정 제공





$$x_k = \begin{bmatrix} \dot{s}^{\top} & \hat{\tau}_m^{\top} & \hat{\tau}_F^{\top} & \hat{f}_{FT}^{\top} & \hat{f}_{ext}^{\top} & \hat{\alpha}_{acc}^{\top} & \hat{\omega}_{gyro}^{\top} \end{bmatrix}_k^{\top} \qquad y_k = \begin{bmatrix} \dot{s}^{\top} & I_m^{\top} & \tau_F^{\top} & f_{FT}^{\top} & \alpha_{acc}^{\top} & \omega_{gyro}^{\top} \end{bmatrix}_k^{\top}$$

[2] I. Sorrentino et al., "Physics-informed neural networks with unscented Kalman filter for sensorless joint torque estimation in humanoid robots," IEEE Robotics and Automation Letters, vol. 10, no. 6, pp. 5705–5712, 2025

Paper #2 Friction Estimation

PINN

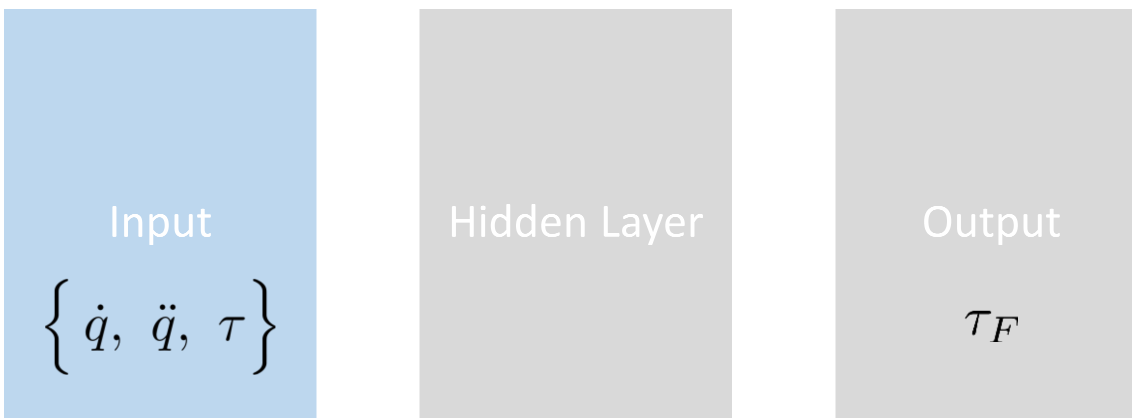
- 조인트 속도값의 Noise, 모터 속도를 차분으로 진행해 부정확성을 방지하기 위해 1틱이 아닌 Buffer형태로 입력
- 마찰토크로 Stribeck – Coulumb –Viscous 마찰모델 기반으로 마찰토크를 만들도록 제약 (정확하지만 구조가 복잡해 모델 기반으로는 추정이 어려움)

Stribeck – Coulumb –Viscous

$$\tau_F(\dot{q}) = \tau_c \,\mathrm{sgn}(\dot{q}) + (\tau_s - \tau_c)\exp\left(-\left|\frac{\dot{q}}{v_s}\right|^{\alpha}\right) + b\,\dot{q}$$

Total Loss

$$\mathcal{L} = \mathcal{L}_{\mathrm{data}} + \mathcal{L}_{\mathrm{physics}} = (1-\lambda)\,\frac{1}{N}\sum_{i=1}^{N}\left(\tau_{F,\mathrm{pred}} - \tau_{F,\mathrm{true}}\right)^2 + \lambda\,\frac{1}{N}\sum_{i=1}^{N}\left(\tau_{F,\mathrm{pred}} - \tau_{F,\mathrm{physics}}\right)^2 .$$



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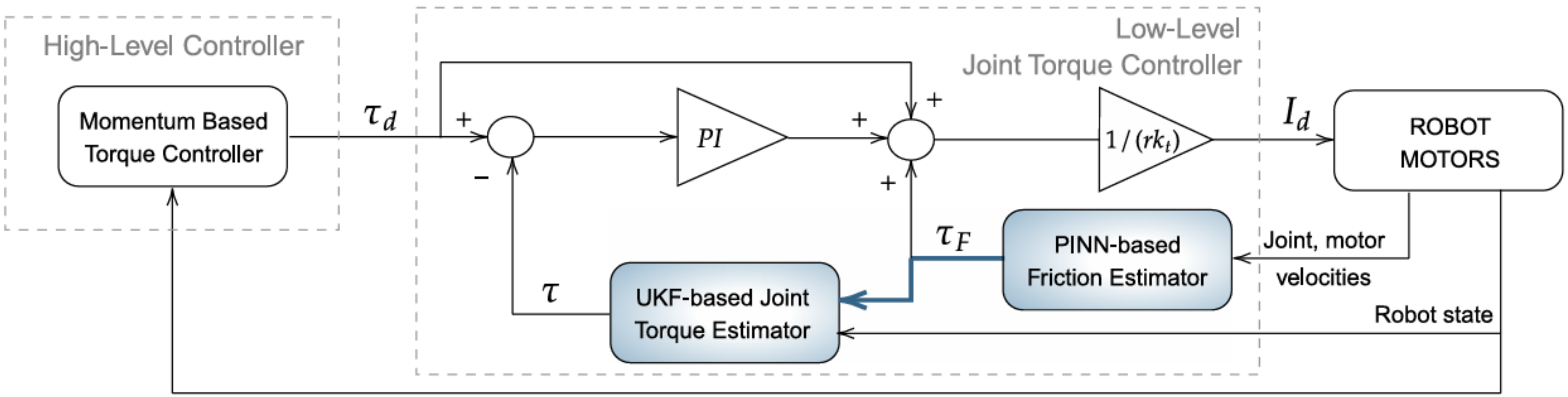
Paper #2 Friction Estimation

Framework



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Paper #2 Friction Estimation

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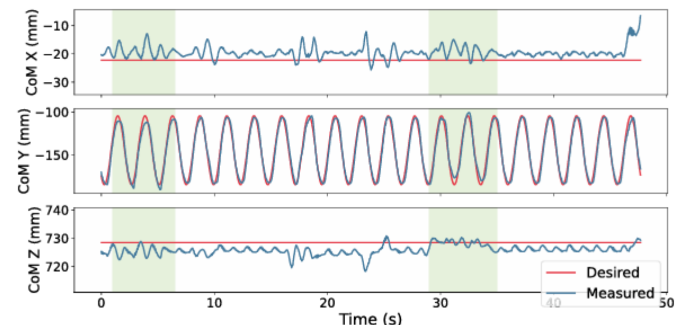
Experiment #1 Without Disturbances

Control Architecture	Mean Error (mm)	Max Error (mm)
Feedforward	[1.2, 13.1, 1.9]	[3.1, 24.2, 4.6]
RNEA No Compensation	[0.8, 6.5, 0.7]	[2.3, 15.2, 2]
UKF No Compensation	[3.2, 11.5, 6.4]	[7.2, 20.6, 7.5]
Feedforward PINN	[2.8, 9.4, 1.1]	[4.4, 25.4, 2.5]
RNEA-PINN	[2.8, 3.8, 3.8]	[8.2, 18.1, 6.7]
UKF-PINN	[2.9, 8.1, 0.6]	[4.5, 17.5, 1.3]

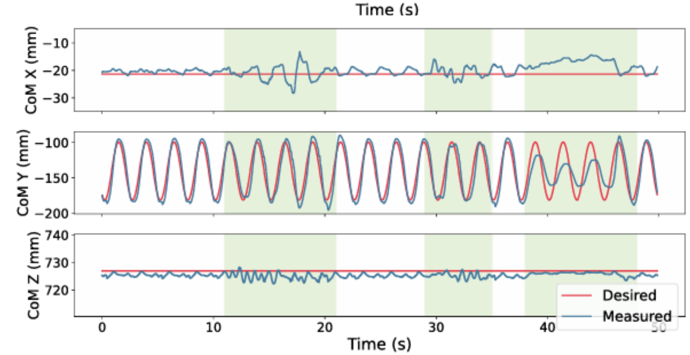
Control Architecture	MSE	RMSE	MAE
RNEA No Compensation	19.2	4.37	2.82
UKF No Compensation	4.13	2.03	1.45
RNEA-PINN	49.43	7.03	4.12
UKF-PINN	1.18	1.08	0.7

Experiment #2 With Disturbances

Rnea - PINN



UKF-PINN



[2] I. Sorrentino et al., "Physics-informed neural networks with unscented Kalman filter for sensorless joint torque estimation in humanoid robots," IEEE Robotics and Automation Letters, vol. 10, no. 6, pp. 5705–5712, 2025

Paper #3 Modeling Estimation

논문 요약

- OPI-PINNPC 구조를 제안하여 Payload가 달라져도 동역학을 안정적으로 예측할 수 있도록 했음
- 실시간 Payload 질량·위치 정보를 추정하여 PINN의 physics-loss에 직접 입력함으로써 모델 불확실성을 크게 감소시켰음
- PINN을 NMPC의 수치적분 대체 모델로 사용하여 예측 속도·계산 효율성을 동시에 확보했음

논문 소개

IEEE ROBOTICS AND AUTOMATION LETTERS, VOL. 10, NO. 11, NOVEMBER 2025 11275

PINN-Based Predictive Control Combined With Unknown Payload Identification for Robots With Prismatic Quasi-Direct-Drives

Haolin Li, Haotang Chen, Yikang Chai, Hang Zhao, Ye Zhao, Yu Han, and Jianwen Luo

Abstract—This study introduces a unified control framework that addresses the challenge of precise robots with Quasi-Direct-Drives under unknown payloads, named as online payload identification-based physics-informed neural network predictive control (OPI-PINNPC). By integrating online payload identification with physics-informed neural networks (PINNs), our approach embeds identified payload parameters directly into the neural network's loss function, ensuring physical consistency while adapting to changing load conditions. The physics-constrained neural representation serves as an efficient surrogate model within our nonlinear model predictive controller, enabling real-time optimization despite the complex dynamics of robots with Quasi-Direct-Drives. Experimental validation on our robot platform demonstrates 35% improvement in position and orientation tracking accuracy across diverse payload conditions, with substantially faster convergence compared to previous adaptive control methods. Our framework provides an adaptive solution for maintaining tracking performance under variable payload conditions without sacrificing computational efficiency.

Index Terms—Physics-informed neural network, nonlinear model predictive control, quadruped locomotion, identification.

I. INTRODUCTION

NONLINEAR Model Predictive Control (NMPC) has emerged as a powerful and versatile control strategy, particularly in the realm of robotic systems [1], [2], [3], [4]. Robotic systems such as robotic manipulators or quadruped robots, with their complex dynamics and multiple degrees of freedom, present unique challenges for motion control. Traditional control methods often struggle to meet these demands due to the highly nonlinear and coupled dynamics [5], [6], [7]. NMPC addresses these challenges by leveraging a predictive model of the system to optimize control inputs over a finite horizon [8], [9]. Unlike linear control approaches [10], NMPC fully embraces the nonlinearities inherent in system dynamics, leading to more accurate and effective control strategies [11]. It considers the future states and constraints of the robot, enabling it to anticipate and react to changes in terrain, disturbances, or desired trajectories in real-time [12]. This predictive capability is crucial for tasks such as dynamic walking, running, and jumping, where the robot must adapt rapidly to maintain stability and achieve its objectives [13]. Compared with analytical methods [14], [15], NMPC incorporates constraints like joint limits, friction, and contact forces into optimization, ensuring control inputs are both optimal and safe for robot's hardware [16], [17]. NMPC's flexibility enables adaptation to different robot designs and operational scenarios [18], [19]. Recent advances in computing and optimization have made NMPC practical for real-time controls. However, accurately modeling nonlinear dynamics in NMPC constraints remains challenging under uncertainties or disturbances, especially with the unknown parameters of the locomotion model under varying payloads [20], [21]. Therefore, it is common in traditional methods to incorporate parameter identification modules to handle model uncertainties. For example, the Risk-Sensitive Extended Kalman Filter proposed in [22] effectively adapts to dynamically changing inertial parameters. [23] proposes an estimation method for the center of mass and full momentum of humanoid robots for controlling the momentum of humanoid robots.

As robotic systems have grown increasingly complex, traditional machine learning models and purely physics-based approaches face distinct limitations: the former typically sacrifice physical interpretability and consistency, while the latter struggle to adapt to real-time variations and uncertainties [24], [25], [26]. Physics-informed Neural Networks (PINNs) have emerged as a groundbreaking methodology in robot modeling and control, effectively bridging the gap between conventional physics-based techniques and contemporary machine learning [27], [28], [29].

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- QDD 로봇은 Payload 변화에 민감해 기존 모델만으로는 정확한 제어가 어려웠음
- Payload 포함 동역학은 비선형 요소가 많아 기존 방식만으로는 정확한 추정이 어려웠음
- 실시간 Payload 추정 + PINN + NMPC 결합으로 안정적 예측제어를 구현했음

[3] H. Li, H. Chen, Y. Chai, H. Zhao, Y. Zhao, Y. Han, and J. Luo, "PINN-Based Predictive Control Combined With Unknown Payload Identification for Robots With Prismatic Quasi-Direct-Drives," IEEE Robotics and Automation Letters, vol. 10, no. 11, pp. 11275–11282, Nov. 2025

Paper #3 Modeling Estimation

사전지식

Payload 포함 동역학

$$\begin{cases} m\ddot{r} = \sum F_{ci} - \sum m_i g - m_p g, \\ I\dot{\theta} = \sum r_{ci} \times F_{ci} + \sum r_i \times (m_i g) + r_p \times (m_p g). \end{cases}$$

- 해당 부분을 PINN으로 학습하여 최적화 반영이 쉽게 함
- Numerical integration 없이 빠른 예측 가능
- 비선형 동역학을 더 정확하게 반영

Payload 포함 MPC

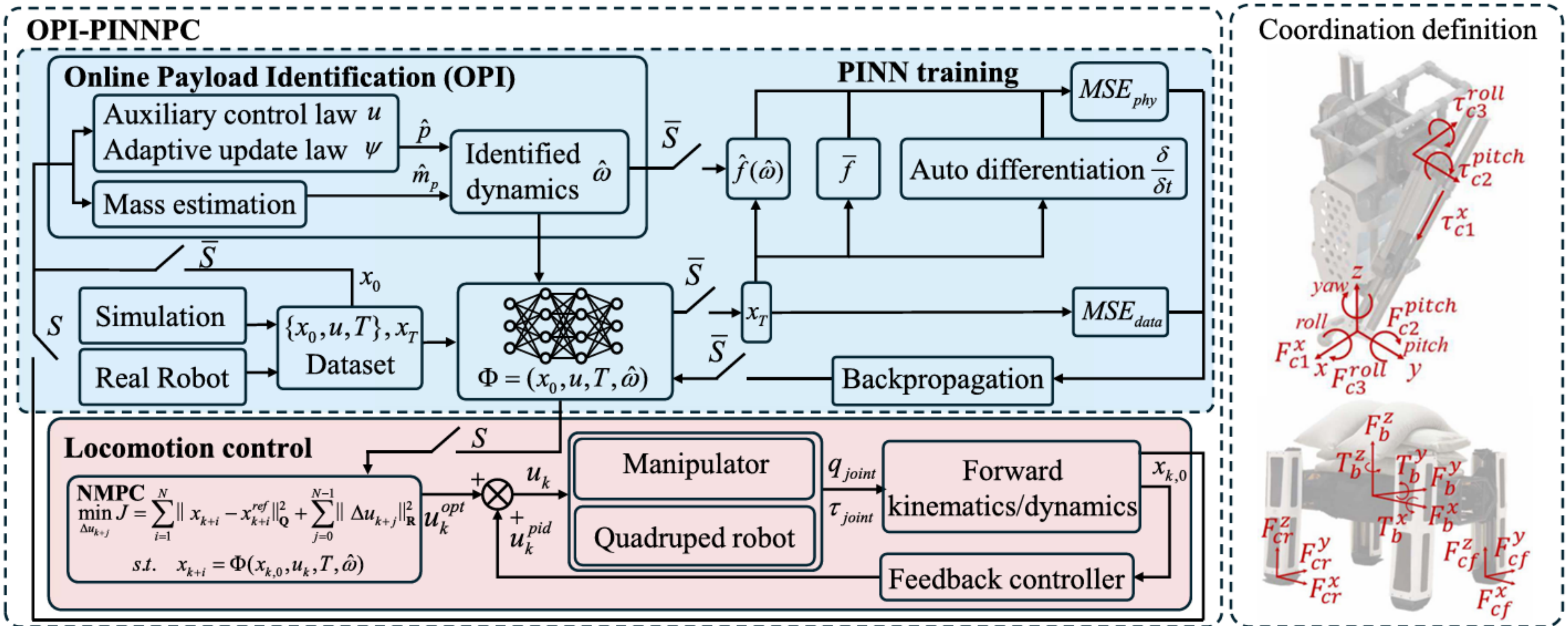
$$\min_{\Delta u_{k+j}} \left(\sum_{i=1}^{N} \|x_{k+i} - x_{k+i}^{\mathrm{ref}}\|_Q^2 + \sum_{j=0}^{N-1} \|\Delta u_{k+j}\|_R^2 \right)$$

$$\text{s.t.} \begin{cases} x_{k+i+1} = \boxed{\Phi(x_{k+i},\, u_{k+i},\, T,\, \hat{\omega})}, \\ u_{k+i+1} = u_k + \sum_{j=0}^{i} \Delta u_{k+j}, \\ u_{\min} \leq u_{k+i} \leq u_{\max}, \\ \Delta u_{\min} \leq \Delta u_{k+i} \leq \Delta u_{\max}, \\ x_{\min} \leq x_{k+i} \leq x_{\max}, \\ \forall i = 0, \ldots, N-1. \end{cases}$$

[3] H. Li, H. Chen, Y. Chai, H. Zhao, Y. Zhao, Y. Han, and J. Luo, "PINN-Based Predictive Control Combined With Unknown Payload Identification for Robots With Prismatic Quasi-Direct-Drives," IEEE Robotics and Automation Letters, vol. 10, no. 11, pp. 11275–11282, Nov. 2025

Paper #3 Modeling Estimation

Framework



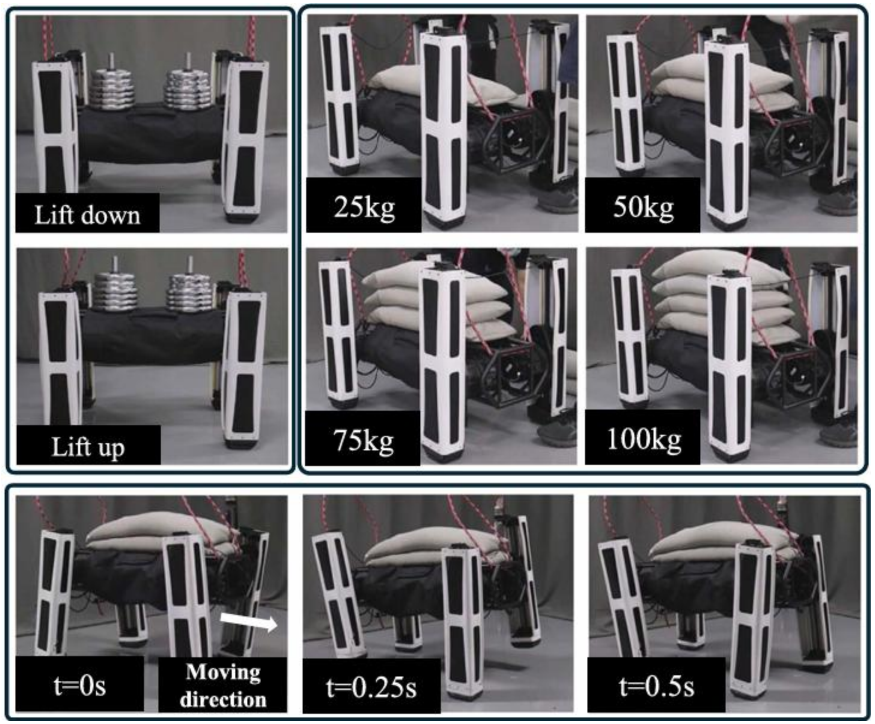
$$MSE_{\text{data}} = \frac{1}{N_{\text{data}}}\sum_{i=1}^{N_{\text{data}}} \left\|\Phi(x_k,\, u_k,\, T,\, \hat{\omega}) - x_{k+1}\right\|^2.$$

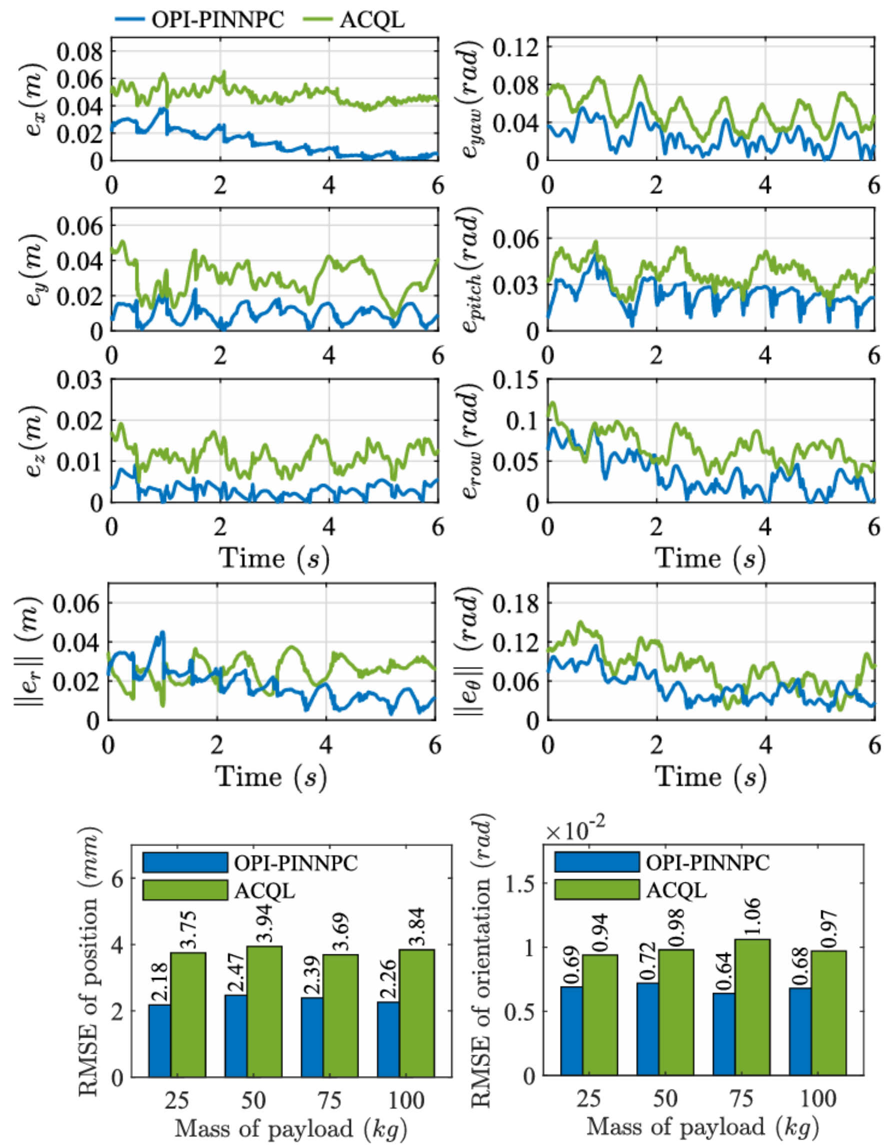
$$MSE_{\text{phy}} = \frac{1}{N_{\text{phy}}}\sum_{i=1}^{N_{\text{phy}}} \left\|\dot{\Phi}(x_k,\, u_k,\, T,\, \hat{\omega}) - \tilde{f}(x_k,\, u_k,\, \hat{\omega})\right\|^2.$$

[3] H. Li, H. Chen, Y. Chai, H. Zhao, Y. Zhao, Y. Han, and J. Luo, "PINN-Based Predictive Control Combined With Unknown Payload Identification for Robots With Prismatic Quasi-Direct-Drives," IEEE Robotics and Automation Letters, vol. 10, no. 11, pp. 11275–11282, Nov. 2025

Paper #3 Modeling Estimation

Experiment





[3] H. Li, H. Chen, Y. Chai, H. Zhao, Y. Zhao, Y. Han, and J. Luo, "PINN-Based Predictive Control Combined With Unknown Payload Identification for Robots With Prismatic Quasi-Direct-Drives," IEEE Robotics and Automation Letters, vol. 10, no. 11, pp. 11275–11282, Nov. 2025

감사합니다