Summarization: Port-Hamiltonian Neural ODE Networks on Lie Groups for Robot Dynamics Learning and Control

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Summarization†Generated based on Paper from Duong et al. (2024)
Topic: Lie Groups, Hamiltonian Mechanics, Dynamics Learning, Trajectory Tracking

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Abstract

This document summarizes the core contributions and methodology of the paper "Port-Hamiltonian Neural ODE Networks on Lie Groups for Robot Dynamics Learning and Control, Duong et al. [2024]", focusing on its' main ideas and the core blocks.

1 Overview: Core Questions and Answers

(1) What is the problem?

- **Accurate Robot Dynamics Modeling:** Learning robot dynamics *from data* for systems whose states evolve on a **matrix Lie group** (e.g., the $SE(3)$ manifold for rigid bodies), while ensuring the model respects **physical** laws (e.g. **energy conservation** and **kinematic constraints**).
- **Stabilization and Generalizability:** Developing a **unified control policy** capable of stabilization and **trajectory tracking** for different rigid-body mobile **UGVs**, **UAVs** or **UUVs** under **same** control design.

(2) Why need to solve this problem?

- Accurate dynamics models are critical for **safe**, **stable** control and **generalization (generalizing?)** to novel operational conditions.
- Necessity deriving from current situation (methods):
  - Traditional models (e.g. hand-designed) derived from first principles often *over-simplify* the system, resulting in modeling errors that simple parameter tuning cannot correct.
  - In contrast, standard *black-box* machine learning models require *large amounts of training data & computational* time (*impractical in mobile* robotics applications) and often fail to infer physical laws (like kinematic constraints and energy conservation).

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†**Disclaimer:** This summarization is for research and study purposes. It represents a personal interpretation and may contain inaccuracies. Feedback or corrections via email are highly appreciated.

(3) How is it different from prev.?

- Compared to structured learning:
  - Previous Hamiltonian/Lagrangian neural networks primarily operated on vector-valued states in Euclidean space and relied on parameterizations like Euler angles, which suffer from singularities.
  - This work embeds matrix Lie groups in a **higher-dimensional** space, allowing to train the model via the widely used **neural ODE network on Euclidean space**.
- Compared to Lie group networks:
  - Existing Lie group neural ODEs (for learning dynamics and normalizing flows) mostly focused on preserving structure during backpropagation, but they did provide physical system descriptions.
  - This work embeds **physical system descriptions** via incorporating **Hamiltonian mechanics**.
- In summarization, this work introduces a **port-Hamiltonian formulation** capable of embedding any general **matrix Lie group constraint** and explicitly models **energy-dissipation elements** (such as **friction** or **drag forces**).

(4) Why is it better than prev.? (Advantages)

- **Physics and Geometry Preservation:** By embedding port-Hamiltonian mechanics and matrix Lie group constraints directly into the neural ODE, the model automatically obeys **energy conservation** and **geometric constraints** ($SO(3)$ constraints and $SE(3)$ constraints) during *long-term trajectory predictions*.
- **Efficiency:** The structured model **converges faster** and achieves significantly **lower training loss and prediction errors** compared to *unstructured* or *black-box networks*.
- **Unified Model-based Controller:** It directly designs a unified, **system-agnostic** and **model-based** controller using *interconnection and damping assignment passivity-based control (IDA-PBC)*, allowing **stable trajectory tracking** for fully-actuated and underactuated robots **without requiring a priori knowledge** of system parameters.

(5) What is the approach itself?

- Port-Hamiltonian neural ODE network on a Lie group
  - 4 separate neural networks to **approximate physical components**:
    * kinetic energy T
    * potential energy V
    * energy dissipation matrix D
    * input matrix B
  - The networks dictate the continuous-time dynamics within an ODE solver to minimize the errors between predicted and true states.
- Unified Control Policy: It applies an energy-shaping and damping-injection strategy to reshape the learned system's energy landscape, so its global minimum aligns with the desired tracking trajectory.

(6) What are the applications of it?

- The approach (designed *dynamics models*) is applicable to rigid-body **mobile** robots, such as **unmanned ground vehicles (UGVs)**, **unmanned aerial vehicles (UAVs)** and **unmanned underwater vehicles (UUVs)**.
- Experiments both in *simulation* and ***real*** *PX4 quadrotors*.

2 The Structure

Summarized Block-Diagram The summarized block-diagram of *Port-Hamiltonian ODE* see fig. 1[1].

Original in Paper The original block-diagram see fig. 2.

3 Open Questions

References

T. Duong, A. Altawaitan, J. Stanley, and N. Atanasov. Port-hamiltonian neural ode networks on lie groups for robot dynamics learning and control. *IEEE Transactions on Robotics*, 40:3695–3715, 2024.

[1] For efficiency, this diagram was initially hand-drawn on paper and then converted into its current digital version using Nano Banana Pro.

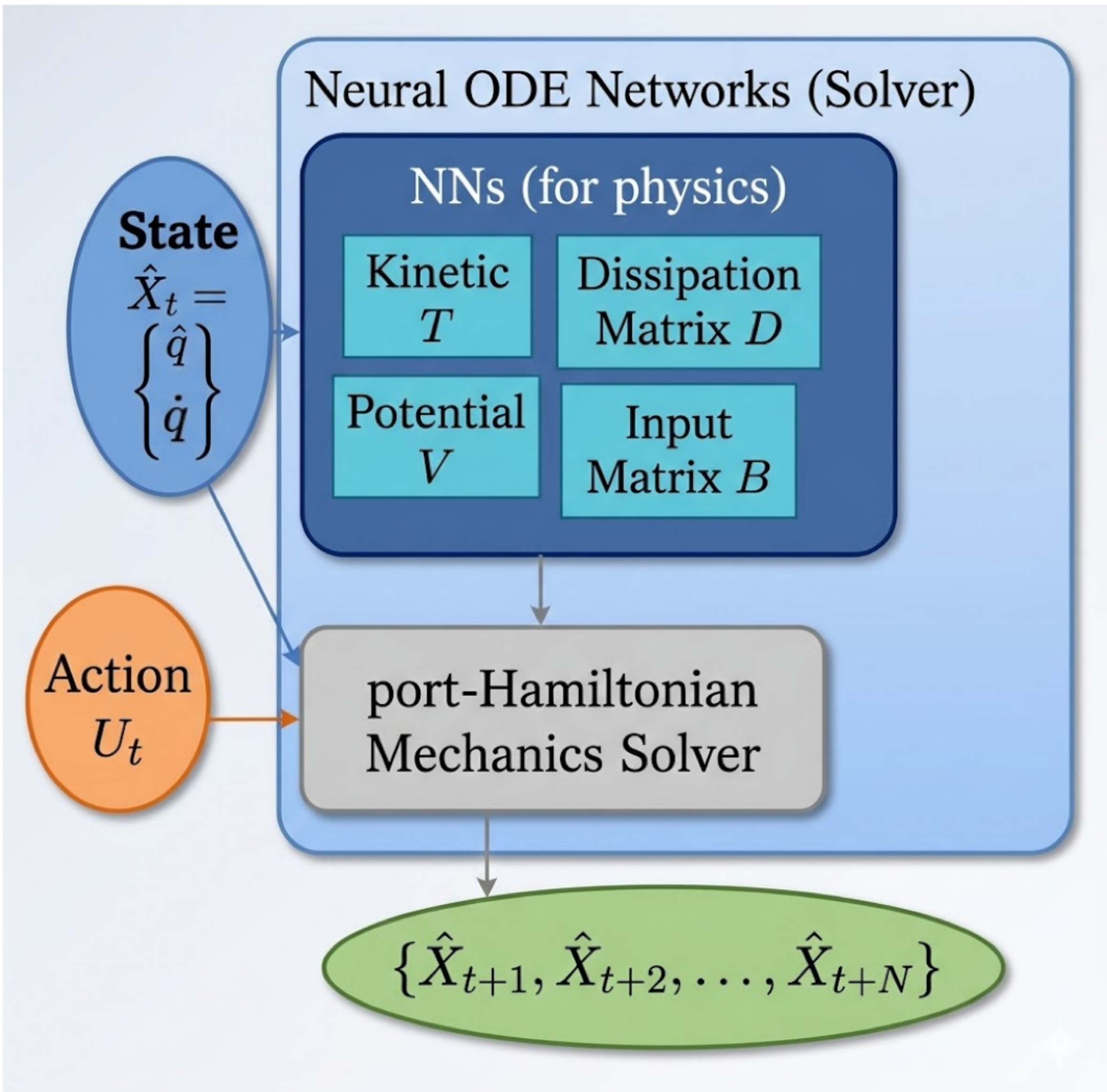

Figure 1: Summarized Block-Diagram of Port-Hamiltonian ODE

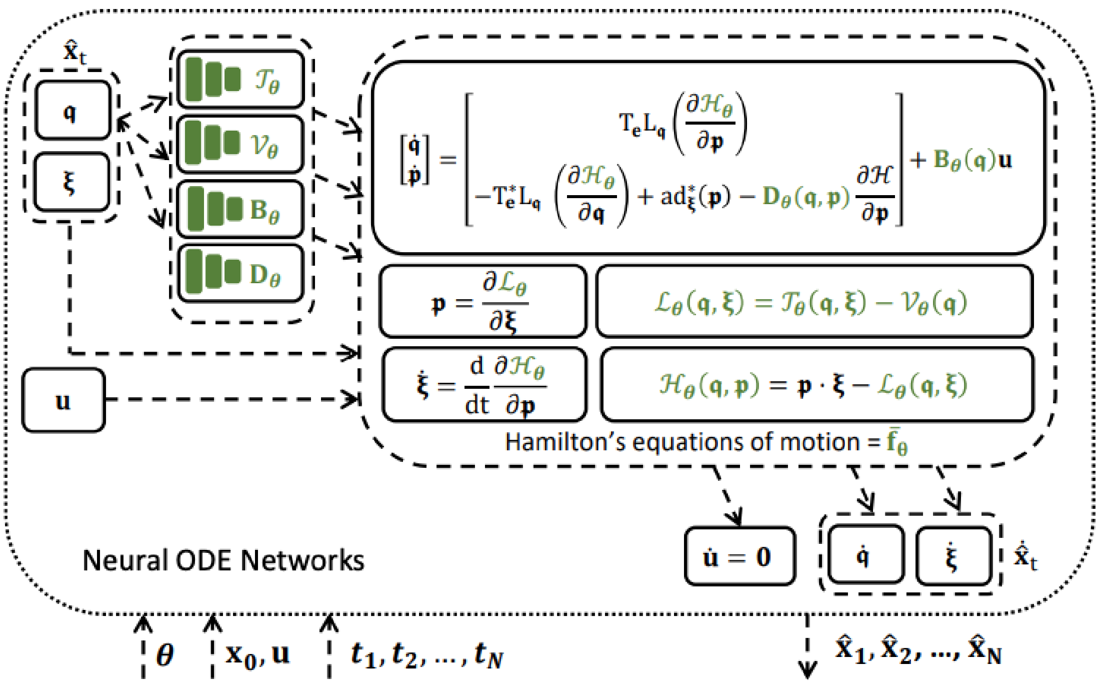

Fig. 2: Architecture of port-Hamiltonian neural ODE network on matrix Lie group. The trainable terms are shown in green.

Figure 2: Original Block-Diagram in Paper