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Title: Learning The-Self: Leveraging Proprioception to Guide the Autonomous Discovery of the Robotic Body Schema

Titel: **TODO**

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Abstract

Vision

- For future robots, the seamless integration of the body schema stands as a foundational pillar that fosters motor control, coordination, and an advanced spatial awareness that improves their versatility and seamless interaction with its surroundings.

- Emulating humans, future robots should be able to skillfully employ the body schema for intricate object manipulation, precise grasping, adaptive responses to dynamic changes, and instantaneous error detection and correction.
- As robots develop and steadily permeate many aspects of human life, they should actively engage in the exploration and development of models for their own bodies, i.e. autonomous self-discovery a their body schema.
- Real-time self-monitoring becomes a norm, significantly impacting human-robot interaction, tool use, and object manipulation.
- Understanding their own body structure enables robots to interact more effectively with humans by adjusting movements for safety. Additionally, robots can optimize energy consumption by adapting their motions based on physical properties, contributing to sustainability in robotic applications.

Challenges

- **Limited Learning Approaches:** Learning a robot's physical attributes is often confined to calibration routines and offline identification methods, primarily for known kinematic structures and inertial parameters. However, this is not standardized for floating base robots like quadrupeds and humanoids.
- **Reliance on External Measurements:** Calibration and identification heavily depend on off-robot measurement devices, such as vision and motion-capturing systems, to discern kinematic structure properties. Despite various sensor signals from modern robots, determining the minimum set for constructing a body model remains unresolved.
- **Challenges in Learning Methods:** Many alternative learning methods, like neural networks, lack information about the body structure and require substantial data. Designing neural networks presents challenges in determining topology, and most data-based methods suffer from generalization limitations, confining learning to specific input-output regions.
- **Research Gaps and Unifying Scheme:** There are significant gaps in research, including unclear understanding of how object handling extends the robotic body schema and limited exploration of the mechanical arrangement of joints and links (mechanical topology). Additionally, there is a lack of a unifying scheme to integrate all learning stages for a fully characterized robotic body schema solely from knowledge about sensorimotor signals.

Contribution

- Identification of the proprioceptive signals and requisite sensor specifications necessary for enabling robots to autonomously acquire knowledge about their own body structure.

- Exploration of the influence of embodiment and first-order principles (FOP) in shaping the network topologies of parameterized operators, which serve as models for input-output mappings within robotic systems.
- Restructuring of the traditional kinematic calibration and parametric system identification processes for stationary-base robots into an online learning scenario, utilizing only the robot's proprioception and fundamental principles from kinematics and dynamics.

Overview of the Content

The contents of this thesis are subdivided into four main parts:

(a) **Model learning and body schema.** This chapter introduces the fundamentals of robotic calibration and system identification and their relation to the concept of body schema. The chapter elaborates on the different meanings of the body schema and the definition applying within the context of this thesis is provided. Finally the learning stages to characterize the robotic body schema from an engineering perspective are introduced and discussed.

(b) **Inferring the mechanical topology.** In this chapter, the concept of embodiment is presented and its significance to finding the robot structure is discussed. The fundamental idea that analyzing the relationships among the proprioceptive signals of a robot can convey information about the body structure as a result of embodiment is presented. Mutual information is pushed forward as a tool to unveil the mechanical topology of a robot given the right proprioceptive signals

(c) **Characterizing the kinematic structure.** This chapter extends the classical exteroception-based kinematic calibration methods with proprioception-based online learning. Departing from the conventional assumption that the mechanical topology is known, it is discussed how the combination of mutual information basic differential kinematic laws can be used to characterize the location and orientation of the robot joint axes.

(d) **Learning the inertial properties.** This chapter delves into the well established methods for robot inertial parameter identification and presents gradient-based online learning methods to produce valid sets of parameters. In particular the fundamental property that the inertial parameters lie on the manifold of symmetric positive definite matrices is exploited to present a Riemannian gradient descent method that operates on this manifold.

Impact

- This thesis demonstrated that given the proper set of proprioceptive measurements, all signals that can be obtained from state-of-the-art sensors, properties of the body schema can be learned

- This thesis has shown that robotic system identification need not be constrained to a laboratory and that the technology and methods exist to infer the robot morphology and characterize its inertial properties producing physically feasible sets of the inertial parameters by learning on the appropriate space
- The work in this thesis proved that indeed mutual information is a measure to evaluate the nonlinear relationships among sensorimotor signals and study how this relationships correspond the embodiment of the robot

Summary for BIB (English)

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Kurzzusammenfassung für BIB (Deutsch)

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Introduction

Motivation

- Robots learning models of their bodies have diverse applications, including effective tool usage, object manipulation, increased autonomy, and safety in human-robot interactions.
- The ability for robots to learn models of their bodies is inspired by the concepts of the physical self and body schema in humans, aiming to emulate aspects of human cognition and adaptability.
- Robots with awareness of their physical self gain a holistic understanding of their own bodies, integrating sensory information and motor control.
- The body schema in robotics serves as a foundational element, contributing to motor control, spatial awareness, and efficient learning, enabling robots to adapt and interact effectively.
- Robots with self-modeling capabilities can autonomously adapt to changes in their physical structure, facilitating modifications, repairs, and adjustments.
- They exhibit better motor control and coordination, allowing for more precise and efficient movements in diverse environments.
- Robots with a constantly adapting representation of their bodies can detect discrepancies between intended and actual movements, enabling autonomous identification and correction of errors or malfunctions.
- Self-aware robots reduce dependence on human intervention by autonomously adapting to changes, detecting errors, and making corrections, leading to increased reliability.

Problem Statement

- The learning of a robot's physical attributes is typically confined to calibration routines for known kinematic structures and conventional offline system identification methods, such as those for instantiating inertial parameters.
- In contrast to the conventional identification processes for fixed-base robots, particularly robotic arms, the procedures for floating base robots, such as quadrupeds, hexapods, and humanoids, lack standardization.
- There is a strong dependence on off-robot measurement devices for calibration and identification, commonly involving exteroceptive measurements like vision, laser metrology, and motion-capturing systems, to determine the properties of the kinematic structure.
- Among the various proprioceptive and exteroceptive signals provided by modern robots' sensor suites, the determination of a minimum set necessary to construct a body model is yet to be established.

- Many alternative learning-driven methods exist for robots to develop models of themselves, such as locally weighted projection regression, support vector regression, and Gaussian processes regression. Actually, recent frameworks often rely on end-to-end learning (primarily artificial neural networks) requiring substantial data and lacking information about the body structure.
- Designing neural networks for specific problems demands expert determination of the best topology, including the number of nodes and layers, connectivity, and activation functions. Generalization proves challenging, as the architecture must balance accuracy with avoiding overfitting, necessitating large amounts of training data for unknown scenarios.
- Most data-based methods suffer from generalization limitations, being confined to learning only a region of the input-output space.
- The integration of state-of-the-art machine learning techniques with well-established first-order principles from mechanics for more effective and efficient learning algorithms remains an area with many opportunities for development.
- A desired feature in learning mechanisms is the ability to use available prior information and integrate it into frameworks to alleviate data needs, enhance generalization capabilities, and simultaneously provide more information about the body structure and its properties.
- Exploration methodologies designed to collect data are inherently limited by the stringent requirement to ensure the safety of the robot and potential humans in proximity.
- The understanding of how the handling and manipulation of objects extend the robotic body schema remains unclear.
- Besides kinematic calibration and standard inverse kinematics problems, there is limited research on learning the mechanical arrangement of joints and links within the kinematic chain, known as the mechanical topology.
- While there is a general consensus that embodiment shapes the relationships among sensorimotor signals, the connections between sensorimotor regularities and body knowledge are not well understood.
- As the statistical properties of signals and their relationships may vary depending on the motion policy, a desired method should exhibit plasticity to reflect these effects.
- There is a lack of a unifying scheme that breaches the gaps to define a synergistic integration of all the learning stages required to produce a fully characterized a robotic body schema from only knowledge about the sensorimotor signals.

Research Questions and Contributions

Research questions

Overall the research questions addressed in this thesis pertain the learning of the robotic body schema, at least from the engineering perspective. In particular:

Q 1 *Which measurements are required to fully automate robot kinematics and inverse dynamics learning based on knowing only the adjacency graph along with kinematic and dynamic first-order principles?*

Q 2 *How to transform robot system identification or end-to-end learning with meta parameter guessing into an automated learning scheme that determines both the structure and dynamical properties of the robot with minimal information?*

Q 3 *How to leverage the inherent structure of the robot's sensorimotor system to gradually develop an understanding of the body structure despite being initially oblivious to its physical characteristics?*

Contribution 1: Robot body structure as a learning problem

This thesis

(a) Determines the type of proprioceptive signals and corresponding sensor requirements to enable robots to learn their body schema

(b) Reformulates the classical kinematic calibration and parametric system identification of fixed base robots as an online learning problem that relies solely on the robot's proprioception and first-order principles from kinematic and dynamics

(c) Discusses how embodiment and first-order principles (FOP) define network topologies of parameterized operator that model input-output mappings in robotic systems

Contribution 2: Inferring the robot morphology

(a) An application of classical gradient descent to learn three different representations of the robot kinematics; namely, modified Denavit-Hartenberg parameters, Euler angles, and angle axis representation

(b) A demonstration that the given certain number of sensors with appropriate modalities the mechanical topology a tree-structure robot can be extracted by studying the mutual information among the signals

(c) A method to infer the robot morphology, that is, the mechanical topology and the location and orientation of the robot's joint axes based only on the proprioceptive signals

Contribution 3: Online learning of physically feasible inertial parameters

(a) An offline learning (optimization) with constraints is presented to show that learning physically feasible inertial parameters of a manipulator can be done from joint data; i.e., joint position, velocity, acceleration, and torque

(b) An online learning driven by state-of-the-art gradient descent method to facilitate the online learning of feasible inertial parameters applied to floating base robots

(c) Introduce the Riemannian AMS gradient descent method, an optimization method for online learning on the manifold of symmetric positive definite matrices to guarantee the physical feasibility of the parameters at all times during the learning process

State of the art

Impact

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Ch. Introduction

General

- The concept of body schema
- The body schema in robotics
- The body schema learning problem.
- Related work (State of the Art)

Motivation

- Objectives of the research.
- Research questions or hypotheses.
- Significance of the study.

Research questions and contribution

TODO

The body schema learning problem

- The body schema
- The body learning problem
- Related work
- Different approaches to learn body properties
- Open research problems
- Contribution

Conclusion

Ch. Theoretical Framework

- The body schema in neuroscience
- The body schema in robotics
- Sensorimotor learning in robotics
  - Fundamentals
  - Taxonomy
    Artificial neural networks
  - Statistical learning
    Probabilistic learning
  - Decomposition
- Discussion
- The robot proprioceptive signals

Introduction

- Robot kinematics
- Robot dynamics
- A modular view on learning

Conclusion

Ch. A Learning Perspective on the Inertial Parameters

Introduction

- Classical system identification approach
- The advantages of online learning
- Relation to adative control
- The power of gradient descent
- Differential geometry
- Learning the inertial parameters the right way

Conclusion

Learning the kinematic description

Introduction

Conclusion

The robot body topology

Introduction

Conclusion

Conclusion

- One potential application area: Self-discovery in robots is crucial for applications in prosthetics and wearable robotics, allowing devices to align with the user's body for natural and comfortable support.