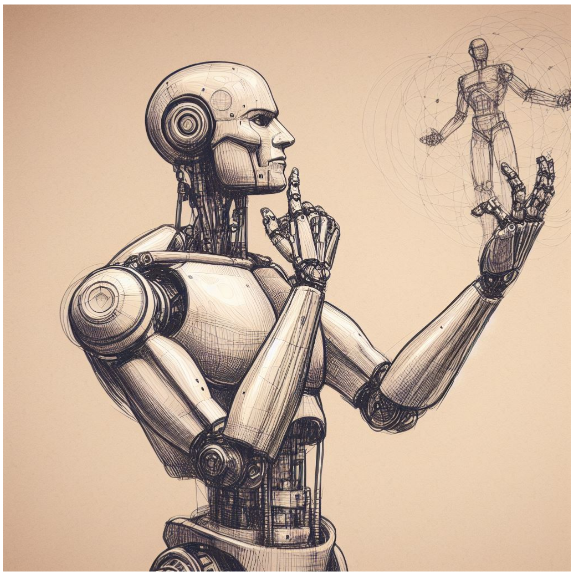
Thesis structure: Fernando Díaz Ledezma

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

Titel: **TODO**



Open TODOs

- ☑ Title
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Abstract

Vision

- For future robots, the seamless integration of the body schema stands as a foundational pillar that fosters learning, motor control, coordination, and advanced spatial awareness that improves their versatility and seamless interaction with their surroundings.
- As robots develop and steadily permeate many aspects of human life, they need actively engage in the exploration and development of models for their own bodies, i.e. autonomous self-discovery of their body schema.
- Inspired by humans, future robots should be able to skillfully employ their body schema for advanced locomotion and motion planning, precise grasping, intricate object manipulation, and to anticipate and adapt the interaction with other agents.
- Constant self-monitoring of the sensorimotor state and the internal body models becomes the norm for instantaneous error detection and correction. These

models can adapt steadily to different situations developing a spatial awareness of the physical self that enables the rapid planning and deployment of contingent motion strategies providing advanced interaction capabilities with the environment.

- Robots will be self-sufficient to perform monitoring, calibration, and adaptation of their body representation relying only on onboard sensing capabilities. Fundamental modalities will include somatosensation (proprioception and touch) and vision.

- Understanding their own body structure enables robots to interact more effectively with other robots and with humans by adjusting movements for safety. Additionally, robots can optimize their energy consumption by adapting their motions based on physical properties, contributing to energy-aware robotics.

Challenges

1. **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 based on robot sensing only remains unresolved.

2. **Limitations of Current Robot Learning Approaches:** Many current local and global machine learning frameworks for physical systems exclude structural knowledge and suffer from limited generalization capabilities and low sample efficiency. Additionally, learning a robot's physical attributes parts from the assumption of a known mechanical topology and is often exclusive to calibration and offline parametric identification routines performed in controlled spaces (laboratories).

3. **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.

4. **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

This work:

- Consolidates the necessary and sufficient proprioceptive signal quantities (afferent and efferent sensory inputs and commands) that enable robots to autonomously acquire, monitor, and adapt knowledge about their body structure and decouple them from the need for exteroceptive off-body sensors.

- Reformulates robot kinematic calibration and parametric robot system identification as a computational graph whose topology reflects a modular structure amenable to machine learning. The architecture of this graph is abstracted into a pipeline consisting of a sequence of online learning phases where streams of proprioceptive signals are merged with first-order principles, imposed by the system's embodiment, to enable the extraction of fundamental features of the robot body schema.

- Characterizes essential morphological properties of the broad class of tree-like floating base structures by studying the relationships among fundamental proprioceptive signals. The mechanical topology, i.e., the arrangement of links and joints, is initially inferred using model-free information-theoretic measures. Consequently, this topology is concurrently validated and employed to instantiate the kinematic description of the robot's body independent of exteroceptive off-robot calibration devices.

- Complements the description of the robot body schema by instantiating the fundamental inertial properties of the links composing the inferred morphology. Given that these properties lie on the Riemannian manifold of symmetric positive definite matrices, a method is introduced to learn them online while ensuring physical feasibility at all times.

Impact

- While acknowledging the undeniable versatility and representational power of current end-to-end learning approaches, this work incites to reconsider their naive application to physical systems and promote the assessment of their limitations when they deliberately exclude principled knowledge. In contrast, the arguments and findings presented here reveal avenues for machine learning frameworks for embodied systems. This research exposes the untapped potential arising from the synergistic integration of existing structural knowledge with data-driven method.

- The outlined concepts and methods demonstrate that crucial aspects of a robot's body schema can be deduced through a fundamental set of proprioceptive signals. As future mobile robots are anticipated to feature a diverse, enhanced, and reliable array of on-board sensing modalities, extending beyond proprioception, the findings discussed in this thesis serve as a catalyst for research into the integration of these modalities. This integration, coupled with the online learning of body morphological and dynamic properties, holds the promise of refining and adapting body models, ultimately empowering robots with heightened levels of autonomy.

- This study contributes to an emerging research area that underscores building and maintaining a body schema as a crucial capability for embodied systems. Such a capability pertains robots characterized by conventional, immutable structures and a novel category of mechanical systems exhibiting dynamic morphologies and diverse multimodal sensory modalities. These systems will evolve their sense of self, recognizing the affordances inherent in their bodies..

Abstract (text version)

As robots become increasingly integral to human life, the imperative emerges for them to autonomously explore and construct models of their bodies. Robots should take cues from human capabilities, aspiring to build and utilize their body schema for advanced locomotion, finer manipulation, and adaptive interactions. Thus, a crucial foundation lies in seamlessly integrating the body schema to elevate learning, motor control, coordination, and spatial awareness. Furthermore, future robots should become self-sufficient entities that conduct monitoring, calibration, and adaptation exclusively through onboard sensing modalities. Standardizing constant self-monitoring nurtures spatial awareness and facilitates rapid error detection and correction. A profound understanding of their body structure will undoubtedly lead to enhanced, safe, and energy-aware interactions. However, current robot learning approaches encounter limitations, such as suboptimal generalization and sample efficiency, exhibiting a need for more structural knowledge. Versatile methods, like neural networks, confront challenges related to data and topology, confining learning to specific regions. On the other hand, learning robot physical attributes still rely on a presumed knowledge of the mechanical topology, often involving calibration and offline identification in controlled environments with a persistent reliance on external measurements, such as vision and motion-capturing systems. The research landscape generally reveals the lack of a unified framework that enables robots to build representations of their body schema to achieve improved body awareness and interaction capabilities. This study addresses these challenges by consolidating necessary and sufficient proprioceptive signal quantities, enabling robots to autonomously acquire knowledge about their body structure without relying on exteroceptive off-body sensors. It introduces an approach that reformulates robot kinematic calibration and system identification as a modular computational graph amenable to machine learning. This abstracted architecture, applied in online learning phases, seamlessly merges proprioceptive signals with first-order principles, extracting fundamental features of the robot body schema. Characterizing morphological properties of tree-like structures, the study infers mechanical topology through information-theoretic measures, validating and applying it independently of off-robot calibration. The research extends its scope by complementing the robot body schema by instantiating inertial properties, ensuring online learning and physical feasibility. Ultimately, this work challenges the uncritical application of end-to-end learning in physical systems, urging a reevaluation of its limitations when excluding principled knowledge. It underscores opportunities for machine learning frameworks in embodied systems, emphasizing the untapped potential of synergizing structural knowledge with data-driven methods. This study catalyzes future research in an incipient field

that underscores building and maintaining a body schema by demonstrating that fundamental properties of a robot's morphology can be deduced from proprioceptive signals. Its implications are far-reaching, addressing the needs of conventional and dynamic robotic structures with diverse sensory modalities that require a more profound sense of self.

Summary for BIB (English)

This thesis explores the potential for enhanced robot autonomy through a self-discovery-oriented body schema, proposing a unified online learning framework exclusively reliant on proprioception and leveraging structural knowledge. It infers the robot morphology and associated inertial description. The work urges reconsidering end-to-end learning for physical systems, emphasizing the need for a synergistic integration of principled knowledge and sensorimotor data.

Kurzzusammenfassung für BIB (Deutsch)

TODO

Introduction

Motivation

1. Empowering Robots
    - Autonomous self-discovery is imperative for robots integrating into human life.
    - Awareness of the physical self through the body schema is foundational.
    - It enables the integration of sensory information and motor control.
    - The evolving body schema serves as a dynamic map for interactions.
    - Enhances robot motor control, precision, and coordination.
    - Facilitates efficient learning, adapting to diverse environments.
2. Learning and the Body Schema
    - The body schema is indispensable for multifaceted robot capabilities.
    - Learning contributes to body schema development, forming a dual relationship.
    - Detects structure in sensorimotor signals, aiding body schema construction.
    - Incorporating body schema into learning refines skills and assimilates knowledge.
    - Enhances motor control through adaptive internal body representations.
    - Empowers robots to learn diverse tasks, providing versatility in dynamic settings.
3. Enhancing Locomotion, Manipulation, and Adaptability
    - A well-integrated body schema improves adaptability and interaction.
    - Enables precise and coordinated movements, advanced locomotion, and motion planning.
    - Enhances manipulation capabilities with human-like dexterity and precision.
    - Coordination with other agents, both robots and humans, becomes more refined.
    - Anticipatory and adaptive capabilities are fundamental for safe and effective interactions.
4. Constant Self-Monitoring for Autonomy
    - Continuous self-monitoring is fundamental for future robotic systems.
    - Achieved through internal models and uninterrupted sensorimotor signals.

- Enables dynamic, real-time understanding of the robot's state.
- Successive error detection and correction phases enhance reliability.
- Rapid formulation and execution of contingency motion strategies in dynamic environments.

5. Onboard Sensing for Self-Sufficiency

    - True autonomy requires robots to rely exclusively on onboard sensing.
    - Somatosensation (proprioception and touch) and vision are fundamental modalities.
    - Liberates robots from external dependencies, enhancing self-sufficiency.
    - Enables dynamic responses to changes in surroundings in real-time.
    - Enhances autonomy and adaptability, previously unseen with off-board sensing.

6. Safety- and Energy-Awareness

    - The body schema serves as a predictive tool, fostering safety in interactions.
    - Facilitates dynamic adjustments in movements to prioritize safety.
    - Enables seamless coordination with other robots and humans, averting collisions.
    - Comprehension of body structure optimizes energy consumption.
    - Dual capability enhances safety and contributes to energy-aware robotics, fostering efficiency and collaboration.

Problem Statement

- **Challenges and limitations of current learning Approaches:**

  1. Most of recent model learning endeavors in the robotics research has, unfortunately, excluded consideration of structural knowledge and rather centered around learning forward and inverse models with global or local focus [25].
  2. Standard global machine learning techniques like Gaussian process regression suffer from the course of dimensionality and rapidly become computationally intractable, alternative local methods such as Locally Weighted Projection Regression (and support vector regression) exhibit high sensitivity to hyperparameters and problematic generalization.
  3. The rise in computational power and the availability of data has brought end-to-end learning methods to prominence. With deep learning as the flagship, these global methods have lead to remarkable results. Yet, they have had the unwanted effect of making deliberately neglecting prior principled knowledge more widespread.
  4. In spite the prowess and potentials of deep learning approaches, such exclusion of available prior knowledge makes it difficult to determine dedicated neural networks architectures (number of nodes and layers, connectivity, and activation functions) [2], [6] but, just like other learning techniques, deep learning approaches they still face problems related to the high demands of data to train (low sample efficiency), extensive training times, and performance that is tied to the training data, i.e. challenged generalization [26], [29].
  5. In general, most data-driven learning methods suffer from generalization limitations, confining learning to specific input-output regions.

- **Limitations of conventional system identification:**

  1. The learning of a robot's physical attributes parts from the assumption of a known mechanical topology and is often exclusive to calibration routines for known kinematic structures [13] and conventional offline system identification methods performed in controlled spaces (laboratories). [16], [30].
  2. In contrast to the conventional identification processes for fixed-base robots, the procedures for floating base robots are not as standardized [1], [17].
  3. Besides kinematic calibration and standard inverse kinematics problems, classical robotics research offers limited insights on learning the mechanical arrangement of joints and links that define the essence of the kinematic chain, known as the mechanical topology.

- **Reliance on External Measurements:**

1. 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 based on robot sensing only remains unresolved.
2. 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.

- **Inference of body knowledge**:
  - In parallel to the current model learning and conventional system identification approaches there is a relatively young research area that underscores building and maintaining internal body models as a crucial capability for embodied systems
  - Learning the physical self and developing a body schema are pivotal for robotics, enhancing spatial awareness, motor control, and adaptability [24]. The body schema serves as a dynamic map, enabling precise movements and fostering efficient learning. As robots encounter diverse environments, their adaptive body schema allows them to navigate real-world scenarios effectively [12].
  - As acknowledged in current works [5], and in spite of the very much desired distributed and multimodal properties of a body schema, in robotics it is certainly relevant to capture the body morphology.
  - There has been discussion of the challenges inherent to deep learning approaches involving. . . [29]
  - Recent remarkable achievements towards learning a body schema for robots have been made, yet the are strongly dependent bur depend on (off-body) vision [5], [10], [11], [19], [22], [28]
  - Some other works require tactile inputs[8], [18], [31]
  - Few efforts explore combinations of these modalities, like the combination of vision and tactile input[7], somatosensation (proprioception and touch)[21], and the consideration of all these modalities [15], [23], [27]
  - Very few works have even contemplated the need to learn the mechanical topology of the robot and the advantages it might bring [3], [4]

- **Research Gaps:**
  1. Among the various proprioceptive and exteroceptive signals provided by modern robots' sensor suites, the determination of a fundamental set necessary to construct a body schema is yet to be established.
  2. A desired feature in machine learning for embodied systems is the ability to use available prior information and integrate it into their frameworks to alleviate data needs, enhance generalization capabilities, and simultaneously provide more information about the body structure and its

properties. Only recently, have interesting insights [9] and works [20] appeared that address this in depth.

3. Despite the recognized significance of frameworks that capture structural properties of physical systems.
4. Integrating structural knowledge into these frameworks is essential for enhancing their overall effectiveness and addressing these challenges.
5. For embodied systems, 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.
6. Unclear understanding of how object handling extends the robotic body schema
7. Limited exploration of the mechanical arrangement of joints and links (mechanical topology).
8. There is a lack of a unifying scheme that narrows the gap to define the relevant learning stages and their corresponding integration required to produce a robot body schema from knowledge about the sensorimotor signals and first-order principles that captures essential properties of the robot body (physical self).
9. Leveraging engineering approaches for system identification and modern online learning techniques to provide a first realized robot body schema has not been extensively explored.
10. While there is a general consensus that embodiment shapes the relationships among sensorimotor signals, the connections between sensorimotor regularities and body structural knowledge in robotics are not well understood [14].
11. 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.

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

1. Determines the type of proprioceptive signals and corresponding sensor requirements to enable robots to learn their body schema
2. 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
3. Discusses how embodiment and first-order principles (FOP) define network topologies of parameterized operators that model input-output mappings in robotic systems

Contribution 2: Inferring the robot morphology

1. 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
2. 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

3. 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

1. 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
2. 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
3. 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

Overview of the Content

The thesis discusses four main topics:

1. **Model learning and body schema.** Introduction of 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.
2. **Inferring the mechanical topology.** In this section, 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
3. **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.
4. **Learning the inertial properties.** This section 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.

State of the art

Impact

See abstract

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.

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