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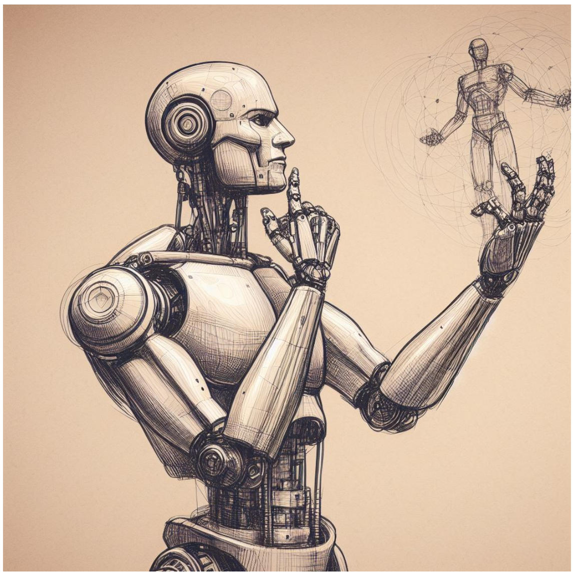
Title: Learning The-Self: Leveraging Proprioception to Guide the Autonomous Discovery of the Robot Body Schema

Titel: **TODO**



Open TODOs

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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 embodied 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. More importantly, the generally exhibit a lack of fundamental structural knowledge of the complex systems at hand. 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 reveals the lack of a unified foundational 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 disembodied 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 presents a method to infer mechanical topology through information-theoretic measures, validating and applying it independently from off-robot calibration. The research extends its scope by complementing the robot body schema by instantiating inertial properties, ensuring both the online learning and physical feasibility. The discussed methods are supported by experimental work in real and simulated robots with several degrees of freedom. 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)

In dieser Arbeit wird das Potenzial für eine verbesserte Roboterautonomie durch ein selbstentdeckungsorientiertes Körperschema untersucht, indem ein einheitlicher Online-Lernrahmen vorgeschlagen wird, der ausschließlich auf Propriozeption beruht und strukturelles Wissen nutzt. Daraus werden die Morphologie des Roboters und die zugehörige Inertialbeschreibung abgeleitet. Die Arbeit regt dazu an, das End-to-End-Lernen für physische Systeme zu überdenken und betont die Notwendigkeit einer synergistischen Integration von prinzipiellem Wissen und sensomotorischen Daten.

Introduction

Motivation

1. Empowering Robots to Learn and Control their Bodies
    - 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. Essential for Locomotion, Manipulation, and Increased 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 meaningful and refined.
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 and interaction strategies in dynamic environments.

5. Embodied 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

    - Enhanced locomotion and manipulation, self-monitoring, and embodied sensing lead to anticipatory and adaptive capabilities fundamental for safe and effective interactions.
    - The body schema is a fundamental element for prediction, fostering transparent and safe 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

A robust understanding of the body is crucial for enhancing robot locomotion, manipulation, and interaction. Thus, the capability of robots to acquire, refine, and adapt body models is essential to achieve genuine autonomy.

Existing learning frameworks in robotics largely ignore the robot physical structure, instead relying solely on local or global approaches to capture input-output relationships [26]. Local methods, while effective in certain scenarios, suffer from limited generalization and hyperparameter sensitivity [10], [32], while global methods risk overfitting and computational overload REF. Deep learning, the standard end-to-end learning framework, also faces challenges despite advancements in computational power and data availability. These challenges include the difficulty in designing suitable network architectures [2], [6], low sample efficiency, extended training times, and limited generalization [27], [30]. In general, the shortcomings of current learning approaches often stem from a lack of consideration or deliberate neglect of prior prior principled knowledge about the robot.

Efforts in cognitive robotics stress the pivotal role of the body schema as an internal body model necessary for spatial awareness, motor control, and adaptability [13], [25]. Nonetheless, consensus is lacking on what constitutes a robot body schema. Relying predominantly on off-body vision, some approaches interpret learning the body schema as learning the properties of the kinematic structure, with only a few discussing the discovery of the mechanical topology to allow for self-modeling and monitoring [3], [4]. [5], [11], [12], [20], [23], [29]. Alternatively, others view the body schema as learning the sensorimotor associations between proprioceptive, tactile, and visual modalities [7], [16], [22], [24], [28], but they provide limited insights into the robot's physical structure.

Building a robot body schema is in essence connected to model-based robotics, as the latter provides methods for identifying physical attributes of the robot body grounded on known kinematic structures. Nevertheless, while calibration routines [14] and offline system identification [17], [31] for fixed-base systems are effective in controlled environments, there is a lack of standard methods for floating base robots [1], [18]. Notably, none of these methods were conceived for their integration into incremental learning frameworks. Moreover, while model-based robotics addresses the kinematic calibration and forward/inverse kinematics problems, it explicitly excludes the inference of the robot mechanical topology.

Indeed, this state of the art of robotics learning research suggests gaps in understanding and methods for constructing body models. Key challenges include balancing data-driven and principle-driven approaches, decoupling body learning from external measurement devices, and providing a concrete interpretation of the robot body schema. This dissertation aims to address these issues, focusing on learning essential properties of the body morphology for tree-like floating base structures. The goal is to integrate advanced incremental learning methods with postulates from embodiment and first-order principles from rigid multibody kinematics and dynamics, creating a unified framework that produces estimates of relevant body structure features. This approach provides a significant step toward advancing robots into more self-sufficient and self-learning systems.

- **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 [26].
  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 [27], [30].
  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 [14] and conventional offline system identification methods performed in controlled spaces (laboratories). [17], [31].
  2. In contrast to the conventional identification processes for fixed-base robots, the procedures for floating base robots are not as standardized [1], [18].
  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 mod-

ern 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 [25]. 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 [13].
  - 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], [11], [12], [20], [23], [29]
  - Some other works require tactile inputs[8], [19], [33]
  - Few efforts explore combinations of these modalities, like the combination of vision and tactile input[7], somatosensation (proprioception and touch)[22], and the consideration of all these modalities [16], [24], [28]
  - As stressed 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.
  - 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. No clear definition of what the robotic schema is and how to construct it
  2. 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.
  3. Identifying crucial research challenges in robotics involves delving into the integration of cutting-edge machine learning techniques with existing prior information and well-established first-order principles from mechanics, aiming to develop more effective and efficient learning algorithms for embodied systems. This area presents numerous opportunities for development, offering potential solutions to address data requirements, improve generalization capabilities, and gain deeper insights into body

structure and properties. Recent contributions, such as the insightful work by Geist et al. [9] and the comprehensive study by Lutter et al. [21], have started to address these challenges in depth, shedding light on promising avenues for advancement in robotics research.

4. Unclear understanding of how object handling extends the robotic body schema

5. Limited exploration of the mechanical arrangement of joints and links (mechanical topology).

6. Leveraging engineering approaches for system identification and modern online learning techniques to provide a first realized robot body schema has not been extensively explored.

7. 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).

8. Despite the general consensus that embodiment plays a crucial role in shaping the relationships among sensorimotor signals, the connections between sensorimotor regularities and body structural knowledge in robotics remain poorly understood [15]. A desired method addressing this gap should not only acknowledge the variability in statistical properties of signals but also demonstrate plasticity to adapt to different motion policies and accurately reflect these effects.

Research Questions and Contributions

Research questions

Q 1 *How can the self-discovery of robot body models be synthesized from relevant embodied sensory modalities by merging incremental learning methods and principled knowledge and obviating the need for external measurement systems?*

Q 2 *Which minimal set of sensorimotor modalities is necessary and sufficient to enable the autonomous learning of fundamental properties of the robot morphology?*

Q 3 *How can the sensorimotor relationships emerging from robot embodiment be exploited to support the gradual understanding and monitoring of the body morphology?*

Contribution 1: Robot body morphology 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 body structure

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: Incremental learning of physically feasible inertial characteristics

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

Chapter: 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

Chapter: Methodology

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

Chapter: Results

Introduction

Conclusion

Conclusion

This section will conclude the study by presenting a concise summary of its content and providing a perspective on the application of learning methods for embodied systems. It will outline the primary research outcomes within the context of the proposed research questions, assess the significance of these findings, revisit the contributions made, examine the study's limitations, and suggest potential avenues for future research.

Summary

This dissertation set out to develop a framework for the acquisition of fundamental properties associated to a robot's body morphology. The focus centered around three essential concepts: model learning, first-order principles, and the robot body schema. Throughout the discussion, emphasis was placed on the crucial role of integrating prior structural information into learning schemes to enhance their performance. The dissertation also highlighted the significance of a robot's ability to construct and maintain a body schema, providing them with heightened bodily awareness and improving capabilities in locomotion, motion planning, and interaction. In summary, the essential ideas in the chapters included the following:

- The *Theoretical Foundations* chapter explored a diverse set of tools employed to construct a robot body schema. These tools were drawn from a broad spectrum of disciplines, encompassing state-of-the-art online learning methods, techniques for network topology inference, and analytical approaches derived from graph theory and information theory, as well as methods from differential geometry.

- The *Methodology* chapter's discussion introduced the reformulation of the robot system identification problem as a sequence of learning problems, guided by proprioceptive robot data and relevant first-order principles. It outlined the close connection between this reformulation and the learning of crucial aspects of a robot's body schema. The chapter covered the presentation of mechanical topology, kinematic characterization, and the learning of physically feasible inertial parameters for both fixed and floating base tree-structured robots.

- The *Results* chapter presented the outcomes of both virtual and physical experiments. It demonstrated the inference of a robot's mechanical topology through the analysis of proprioceptive signals, showcasing the learning of joint axes' locations and orientations as a consequential outcome. The presented results encompassed robot arms, hexapods, and humanoid robots, providing support for the outlined claims. Furthermore, the chapter introduced the online learning of physically feasible inertial parameters, validated through experiments conducted on a real seven-degree-of-freedom manipulator.

- The *Discussion* chapter explored diverse facets, placing particular emphasis on understanding the influence of excitation and sensor noise on learning outcomes. Additionally, the chapter delved into challenges associated with the robot's structure and the types of joints. It examined the intricate interplay between motion policy and mutual information, assessed the sampling efficiency concerning the precision of estimated body properties, deliberated on the observability of parameters, and provided comparisons to end-to-end learning approaches.

Perspective on deep learning for embodied systems

In presenting our findings, this study strategically employed alternative methodologies rooted in deep learning for comparative analysis. The results underscore the efficacy of integrating principled knowledge in addressing challenges associated ~~with sample efficiency and generalization within~~ with end-to-end learning applications for robotic systems. It is imperative to emphasize that our intent is not to diminish the commendable achievements of deep learning frameworks. Rather, the critique concerning the indiscriminate exclusion of principled and model-based knowledge serves as a call to acknowledge the limitations inherent in pure black-box learning. The principal message stress the importance of purposefully incorporating available knowledge to mitigate unnecessary complexities in intricate learning problems.

In fact, the frequently cited challenges in learning paradigms for embodied systems, such as the curse of dimensionality, limited generalization, sample efficiency, and computational demands, appear to signify an inherent intractability gap within these complex systems. This brings out the inevitable necessity to introduce any available principled knowledge to ameliorate the limitations faced by pure black-box learning. The augmentation of representational capabilities in contemporary deep learning methodologies through the integration of structural knowledge lays the foundation for achieving genuine autonomy in robotic systems.

Revisiting the research questions

~~This study has as primary argument the emphasizes on the significance of leveraging principled knowledge to introduce structure into learning frameworks for embodied systems.~~ In answering the research questions introduced Sec. XXX, the development of a robot body schema is proposed as a central element.

A1 **The proposed robot body schema is a fundamental body model.** Unlike conventional input-output black box models within the field of robot model learning, this study shifted its focus to acquiring knowledge about the morphological properties of the robot physical self. This approach emulates the construction of a body schema, yielding benefits associated with enhanced bodily awareness. Importantly, principles from embodiment and the kinematics and dynamics of rigid multibody systems are integrated with identification and incremental learning methods to define a sequence of modules inherently compatible with machine learning methods. Each module contributes to understanding a fundamental property of the robot body, encompassing its mechanical topology, kinematic description, and inertial characterization.

A2 **The proposed robot body schema relies exclusively on proprioception.** Research supports that proprioception is fundamental to building a basic body schema. Parting from this premise, this work utilized joint signals already available in modern robots, providing joint position, velocity, and joint torque. Additionally, the inclusion of body angular velocities and accelerations was motivated to complete the necessary and sufficient set of sensory signals that enable the learning of the topological, kinematic, and dynamic properties of the broad class of floating base tree-structured robots with reasonable accuracy. It was shown that while the body properties inferred from proprioception can indeed be complemented by tactile and visual information, they are inherently independent of them.

A3 **The proposed robot body schema is designed to be adaptable and flexible.** By leveraging the fundamental connection between embodiment and information structure, the underlying body topology can be extracted. Consequently, changes to the sensorimotor relationships promoted by alterations to the embodiment lead to the adaption of the estimated topology. Furthermore, as the estimation of kinematic and dynamic properties of the robot body operates within an incremental learning paradigm, there is a persistent monitoring component inherent to the learning process. This continual adjustment of the currently valid robot body description mirrors the plasticity of a body schema. These monitoring and adaption processes play a crucial role in recalibrating estimated body properties—whether in response to gradual changes or comprehensive adaptations necessitated by sudden, unexpected alterations.

Contributions and limitations

Contributions

C1 Unifies essential proprioceptive signals, including afferent and efferent sensory inputs and commands, to enable robots in autonomously acquiring, monitoring, and adapting knowledge about their body structure, eliminating the dependence on external off-body sensors.

C2 Restructures the processes of robot kinematic calibration and parametric robot system identification into a machine-learning-friendly computational graph. The graph's modular topology, abstracted into a sequential online learning pipeline, integrates streams of proprioceptive signals with first-order principles, derived from the system's embodiment. This facilitates the extraction of fundamental features of the robot body schema.

C3 Examines the fundamental proprioceptive signals to characterize key morphological properties in tree-like floating base structures. The mechanical topology, initially inferred using model-free information-theoretic measures, is simultaneously validated and utilized to establish the kinematic description of the robot's body, independent of external calibration devices.

C4 Augments the robot body schema description by determining the inertial properties of links within the inferred morphology. Introducing a method to learn these properties online, considering their existence on the Riemannian manifold of symmetric positive definite matrices, ensures continuous physical feasibility.

Limitations

The assumptions, methods, and claims articulated in this dissertation are specifically tailored for the broad category of tree-like robotic structures featuring revolute joints and either fixed or floating bases. It is crucial to highlight that the scope of this study deliberately excludes parallel mechanisms and soft robots, leaving the applicability of the introduced framework explicitly for future exploration.

Within the robot body schema learning pipeline, as depicted in Fig. XXX, one aspect that remains unaddressed is the online generation of excitation motions in line with the learning context—a challenge known as the exploration problem in the literature. This intricately links to the motion policy adopted by the robot for achieving estimation, akin to reinforcement learning. Unlike conventional excitation trajectory design for inertial parameter estimation, challenges arise when learning the robot's mechanical topology and kinematic description. Here, not only do appropriate excitation motions need to be defined, but alternative methods must also be explored to determine control strategies enabling the execution of such motions.

Ensuring self-safety is a critical consideration during the process of learning the physical self. While safety is often discussed in the context of human-robot interaction, for a robot in the phase of discovering its morphology, it is paramount to ensure physical integrity. It's worth noting that the methodology presented in this dissertation does not address self-safety. Indeed, the risks of environmental and self-contacts during virtual experiments were disregarded. However, the joint trajectories employed in real robot experiments were meticulously designed to prevent contacts. Certainly, especially for floating base robots, (environmental) contacts are not only unavoidable but also necessary. In general, without contingent strategies ensuring self-safety, there is a possibility that exploratory motions during learning may result in self-damage. This underscores why the early stages of many learning frameworks are primarily executed in virtual environments. In general, developing contingent strategies to ensure safe bodily exploration remains an open question.

Future work

Currently, robots predominantly exist as rather rigid structures and offer a considerably limited yet well defined range of sensory signals in comparison to biological bodies. It follows logically that aligning the robot body schema with models and methods derived from rigid multibody dynamics and system identification is a natural choice. However, as robots progress, incorporating more sensing modalities and advanced actuation mechanisms—such as elastic joints with multiple degrees of freedom and bodies allowing for a tolerable amount of deformation—the spectrum of validity of rigid body assumptions decreases. This amplifies the need for an enhanced robot body schema that is able to compensate for the deviations in the model assumptions directly from the relationships in the sensorimotor signals.

As highlighted in the dissertation's introduction, proprioception, touch, and vision stand out as essential modalities for establishing and maintaining a body schema. This work exclusively concentrated on leveraging proprioception to gain a fundamental understanding of the robot's body morphology. Future endeavors should naturally aspire to seamlessly integrate touch and vision into the process of learning an internal representation of the body. Vision, in particular, has been a focal point in numerous research efforts addressing the body schema.

The maturation of touch, facilitated by more advanced torque and wrench sensing devices and diverse artificial tactile skins, allows for its application in calibration and contact detection. Coupled with technological advancements in elastic joints, these features could open up new avenues for safe exploratory motions. Further technological developments mirroring the finesse of tactile receptors in human skin could offer myriad possibilities to extract more information about the robot body, resembling the formation of sensoritopic maps REF. The integration of touch and vision with proprioception could provide opportunities to model the shape of the robot—on could say, the space it occupies. This, in turn, would offer immediate advantages to vision, acting as a source of redundant information or compensating for missing data in scenarios with poor visibility or total occlusion.

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.

- Lastly, this research outlines a direction to unify previous research endeavors encompassing body schema learning and system identification in robotics into a coherent unified robot body learning framework for any robot. Additionally, this research lays a foundation to provide robots with the capability of autonomous life-long learning (building, maintenance, and adaption) of the robot body schema.

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