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# 1 INTRODUCTION

## 1.1 Motivation

## 1.2 Problem Statement

## 1.3 Research Questions and Contribution

## 1.4 Overview of content

# 2 RELATED WORK

## 2.1 Model learning in robotics

### 2.1.1 System identification

### 2.1.2 Local and global models

### 2.1.3 End-to-end learning (black box models)

## 2.2 Data-driven learning with structure information

## 2.3 Model learning and the body schema

### 2.3.1 Internal representations

### 2.3.2 Sensorimotor maps

# 3 THEORETICAL FOUNDATIONS

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### 3.1.1 Forward and inverse dynamics

### 3.1.2 The Newton-Euler formulation of the inverse dynamics

### 3.1.3 Composition of the kinematics and dynamics

## 3.2 Robot proprioception

### 3.2.1 Definition

### 3.2.2 Human and robot proprioception

### 3.2.3 A sensor suite for robot proprioception

## 3.3 State-of-the-art Gradient Descent

### 3.3.1 Fundamentals

### 3.3.2 Momentum gradient descent

### 3.3.3 ADAM gradient descent

### 3.3.4 AMS gradient descent

## 3.4 Fundamentals of graph<sup>4</sup> theory

### 3.4.1 Definition of a graph

### 3.4.2 Graph representation, the adjacency matrix

### 3.4.3 Metrics for graph comparison

## 3.5 Network topology inference (better names for subsections needed)

### 3.5.1 Detecting linear dependencies with covariance

### 3.5.2 Based on graph signal processing

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