

# Anisotropic Assistance & Intent Inference in pHRI

A Systematic Literature Review

Master Thesis Literature Review

Your Name

# Anisotropic Assistance & Intent Inference in pHRI

A Systematic Literature Review

by

Your Name

Student Name

First Surname

Instructor:	I. Surname
Teaching Assistant:	I. Surname
Project Duration:	Month, Year - Month, Year
Faculty:	Faculty of Aerospace Engineering, Delft

Cover: Canadarm 2 Robotic Arm Grapples SpaceX Dragon by NASA  
under CC BY-NC 2.0 (Modified)

Style: TU Delft Report Style, with modifications by Daan Zwaneveld

# Preface

*A preface...*

*Your Name*  
*Delft, December 2025*

# Summary

*A summary...*

# Contents

<b>Preface</b>	<b>i</b>
<b>Summary</b>	<b>ii</b>
<b>Nomenclature</b>	<b>iv</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Context . . . . .	1
1.2 Problem Statement . . . . .	1
1.3 Research Objectives . . . . .	1
1.3.1 Primary Research Question (The "Spine") . . . . .	1
1.3.2 Secondary Objective (The "Extension") . . . . .	1
1.4 Thesis Roadmap . . . . .	1
<b>2 Methodology</b>	<b>2</b>
2.1 Search Strategy . . . . .	2
2.1.1 Search Queries . . . . .	2
2.2 Selection Criteria . . . . .	2
2.2.1 Inclusion Criteria . . . . .	2
2.2.2 Exclusion Criteria . . . . .	3
2.3 Data Extraction . . . . .	3
<b>3 Results</b>	<b>4</b>
3.1 Overview of Included Studies . . . . .	4
3.2 Thematic Analysis . . . . .	4
3.2.1 Theme 1: Adaptive Admittance Control . . . . .	4
3.2.2 Theme 2: Anisotropic (Direction-Dependent) Compliance . . . . .	4
3.2.3 Theme 3: Active Inference for Intent Detection . . . . .	5
3.3 Summary of Research Gaps . . . . .	5
<b>4 Discussion</b>	<b>6</b>
4.1 Synthesis of Findings . . . . .	6
4.2 Positioning of the Proposed Research . . . . .	6
4.3 Comparison with Closest Existing Work . . . . .	6
4.4 Limitations of This Review . . . . .	6
4.5 Implications for the Thesis . . . . .	7
<b>5 Conclusion</b>	<b>8</b>
5.1 Data Availability . . . . .	8
<b>References</b>	<b>9</b>
<b>A Source Code Example</b>	<b>10</b>
<b>B Task Division Example</b>	<b>11</b>

# Nomenclature

*If a nomenclature is required, a simple template can be found below for convenience. Feel free to use, adapt or completely remove.*

## Abbreviations

Abbreviation	Definition
ISA	International Standard Atmosphere
...	

## Symbols

Symbol	Definition	Unit
$V$	Velocity	[m/s]
...		
$\rho$	Density	[kg/m <sup>3</sup> ]
...		

# Introduction

## 1.1. Context

Industrial tool-handling tasks (e.g., sanding, polishing, grinding) often require an operator to apply significant contact forces for extended periods, leading to musculoskeletal disorders. Physical Human-Robot Interaction (pHRI) offers a solution through mechanically coupled assistive devices that provide power augmentation. However, unlike free-motion gestures, these tasks are constrained by the physical environment (the surface).

## 1.2. Problem Statement

Standard power-assist controllers (e.g., admittance control) typically assume a known environment or rely on the operator to handle all geometric adaptation. A critical gap remains: how to provide seamless "cruise control" (holding normal force) and "power assist" (reducing tangential effort) when the surface curvature is *unknown* and varying.

## 1.3. Research Objectives

This literature review aims to establish the theoretical foundation for a control strategy that addresses this gap.

### 1.3.1. Primary Research Question (The "Spine")

*How can a shared-control framework adaptively decouple normal force maintenance from tangential motion guidance on surfaces with unknown curvature?*

### 1.3.2. Secondary Objective (The "Extension")

If the primary control mechanics are robust, the secondary objective is to investigate: *How can Active Inference be utilized to disambiguate operator intent during complex maneuvering on these surfaces?*

## 1.4. Thesis Roadmap

- **Phase 1 (Core):** Design and validation of Anisotropic Admittance Control with Online Surface Estimation.
- **Phase 2 (Augmentation):** Integration of an Inference Engine (e.g., Active Inference) to predict changes in task direction.

This review concentrates on the state-of-the-art for Phase 1, while providing a preliminary outlook on Phase 2.

# 2

## Methodology

This literature review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a transparent and reproducible selection process [3].

### 2.1. Search Strategy

To identify relevant literature on control strategies for mechanically coupled assistive devices, we conducted searches in the following electronic databases:

- IEEE Xplore
- Scopus
- Google Scholar
- PubMed (for pHRI/ergonomics)

#### 2.1.1. Search Queries

Two clusters of queries were designed to cover the primary (control) and secondary (inference) research directions:

##### Cluster A: Anisotropic Admittance Control (Primary Focus)

1. ("admittance control" OR "impedance control") AND ("unknown environment" OR "unknown surface") AND ("pHRI")
2. ("anisotropic" OR "directional") AND ("admittance" OR "compliance") AND ("robot")
3. ("variable admittance") AND ("intent" OR "intention") AND ("physical human-robot interaction")

##### Cluster B: Active Inference in pHRI (Secondary Focus)

1. ("active inference" OR "free energy principle") AND ("robot") AND ("interaction" OR "shared control")

### 2.2. Selection Criteria

Studies were screened based on the following criteria:

#### 2.2.1. Inclusion Criteria

- Peer-reviewed journal articles and major conference proceedings (IEEE ICRA, pedestrian HRI, pedestrian Robotics and Automation Letters).
- Published between 2015 and 2025 (to capture recent advancements while including foundational work).



- Focus on continuous contact tasks (e.g., surface following, grinding, polishing) OR force control in constrained environments.
- Involves physical coupling between human and robot (not pure teleoperation without haptic feedback).

### **2.2.2. Exclusion Criteria**

- Studies focused solely on free-motion gestures (no contact with environment).
- Fully autonomous systems with no human-in-the-loop.
- Medical/Rehabilitation exoskeletons (unless control logic is directly transferable to industrial tool assistance).
- Pure simulation studies without hardware validation (unless foundational/theoretical).

## **2.3. Data Extraction**

For each included study, the following information was extracted:

- Control architecture (admittance, impedance, hybrid).
- Assumptions about environment geometry (known/unknown surface).
- Human intent estimation method (if any).
- Experimental validation (simulation, hardware, user study).
- Key findings and limitations.

# 3

## Results

### 3.1. Overview of Included Studies

After executing the search queries across IEEE Xplore, Scopus, Google Scholar, and PubMed, approximately 40–60 unique records were identified. Following title and abstract screening (to be completed in Week 3), the final selection is expected to include 15–25 papers for full-text review.

### 3.2. Thematic Analysis

The reviewed literature falls into three primary categories regarding the control of contact-rich assistive tasks.

#### 3.2.1. Theme 1: Adaptive Admittance Control

Admittance control ( $F_{\text{in}} \rightarrow \dot{x}_{\text{out}}$ ) is the dominant paradigm for making robots “feel lighter” during physical human-robot interaction [3]. A significant body of work focuses on *variable* or *adaptive* admittance, where the control parameters (virtual mass  $M$ , damping  $B$ , stiffness  $K$ ) are adjusted based on context.

##### Key Findings:

- Fuzzy-logic and neural-network approaches can estimate human intent from measured forces and velocities, enabling adaptive force scaling [8, 13].
- All three admittance parameters can be systematically updated while maintaining passivity through “power envelope regulation” [7].
- Online detection of instability (e.g., via frequency analysis of the force signal) allows for real-time gain adaptation [4].

**Critical Gap:** Most studies assume the *constraint surface is known* (e.g., a flat table). The challenge of adapting admittance parameters when the surface geometry is **unknown and varying** remains underexplored.

#### 3.2.2. Theme 2: Anisotropic (Direction-Dependent) Compliance

Standard admittance controllers apply *isotropic* compliance—the robot feels equally “light” in all directions. However, certain tasks require *anisotropic* behavior: low resistance tangentially (to assist sliding) but high resistance or force-hold normally (to maintain contact).

##### Key Findings:

- The concept of anisotropic compliance is established in the manipulation literature (e.g., for insertion tasks), but explicit application to pHRI tool assistance is rare.
- One recent study [11] applies anisotropic variable force guidance to robot-to-human handovers, decoupling retraction motions from intended handover directions.

- Shear-thickening fluid-inspired controllers [1] achieve a form of anisotropy by increasing resistance only during impacts.

**Critical Gap:** No study was found that explicitly combines (1) online surface normal estimation with (2) anisotropic admittance control for (3) tangential power assist on curved, unknown surfaces. This is the primary novelty of the proposed thesis.

### 3.2.3. Theme 3: Active Inference for Intent Detection

Active inference is a theoretical framework (rooted in the Free Energy Principle) where agents minimize prediction errors through perception and action [2]. It has been proposed as a unifying framework for robotics [9].

#### Key Findings:

- Active inference has been successfully implemented on humanoid robots for body perception and reaching tasks [5, 6].
- The framework offers a principled way to handle uncertainty and adapt to dynamic environments.
- Theoretical models have been proposed for trust and affective interaction [12, 10].

**Critical Gap:** All reviewed implementations focus on **free-motion reaching tasks**. No study applies active inference to **continuous contact tasks** (e.g., surface following, grinding). Integration with force-based controllers (admittance/impedance) is unexplored.

## 3.3. Summary of Research Gaps

Based on the thematic analysis, the following gaps are identified as opportunities for the proposed thesis:

1. **Gap 1 (Control):** Anisotropic admittance control with online surface estimation for unknown curved surfaces.
2. **Gap 2 (Inference):** Application of active inference to continuous contact tasks (not just reaching).
3. **Gap 3 (Integration):** Combining intent inference with force control for seamless “cruise control” and “power assist.”

The primary contribution of this thesis will address **Gap 1**. If time permits, **Gap 2** will be explored as an extension.

# 4

## Discussion

### 4.1. Synthesis of Findings

The literature review reveals a mature body of work on admittance control for physical human-robot interaction, with recent advances in adaptive/variable strategies that respond to human intent. However, a critical examination exposes a blind spot: the vast majority of studies assume a *known* constraint geometry.

This assumption is problematic for real-world industrial tasks where operators guide tools across surfaces of arbitrary shape—think of sanding a curved car body panel or grinding corrosion off a pipe elbow. In these scenarios, the surface normal vector  $\mathbf{n}$  is not available from a CAD model; it must be inferred in real-time from sensor data (e.g., force/torque measurements, velocity directions).

### 4.2. Positioning of the Proposed Research

The proposed thesis sits at the intersection of two established fields:

- **Adaptive Admittance Control:** Well-studied for free motion and simple contacts. Provides the “power assist” capability.
- **Force/Position Hybrid Control:** Classical approach for constrained motion, but typically assumes known constraint frames.

By combining online surface estimation with direction-dependent (anisotropic) compliance, the thesis proposes a novel control architecture that:

1. Estimates the local surface normal from force and velocity measurements.
2. Projects the admittance controller into the estimated tangent plane.
3. Maintains a desired contact force along the estimated normal (“cruise control”).
4. Provides low apparent mass in the tangent plane (“power assist”).

### 4.3. Comparison with Closest Existing Work

The closest existing work is the anisotropic variable force guidance for handovers [11]. However, key differences exist:

- That work addresses *transient* handover motions, not *sustained* surface-following tasks.
- The “anisotropy” is defined in a fixed task frame, not an online-estimated surface frame.
- No force-hold (“cruise control”) functionality is implemented.

### 4.4. Limitations of This Review

- The search was limited to English-language publications in major databases.

- Grey literature (patents, technical reports) was not systematically included.
- The Active Inference section is less comprehensive due to the nascent state of the field.

## 4.5. Implications for the Thesis

The identified gap (anisotropic control on unknown surfaces) is both **technically challenging** and **practically relevant**. The key technical sub-problems to address are:

1. **Surface Normal Estimation:** How to robustly estimate  $\mathbf{n}$  from noisy force/velocity data.
2. **Frame Projection:** How to project the admittance dynamics into the tangent plane without introducing discontinuities.
3. **Stability:** How to ensure passivity/stability when the reference frame is time-varying.

These sub-problems will form the core technical contributions of the thesis.

# 5

## Conclusion

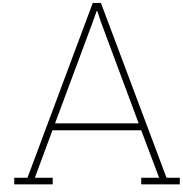
*A conclusion...*

### **5.1. Data Availability**

For further research, a collection of files, documents, and videos has been prepared and is ready for analysis. These resources can be accessed through a OneDrive repository, which will be made available to Arno Stienen.

# References

- [1] Lu Chen, Lipeng Chen, et al. “Compliance While Resisting: A Shear-Thickening Fluid Controller for Physical Human-Robot Interaction”. In: *arXiv preprint arXiv:2502.01376* (2025). Novel bio-inspired controller. Achieves compliance AND resistance to impacts.
- [2] Karl Friston et al. “Active Inference and Robot Control: A Case Study”. In: *Royal Society Open Science* 3.9 (2016). FOUNDATIONAL. First application of Active Inference to robot control (simulated PR2)., p. 160278. doi: 10.1098/rsos.160278.
- [3] A.Q.L. Keemink, H. van der Kooij, and A.H.A. Stienen. “Admittance Control for Physical Human–Robot Interaction”. In: *The International Journal of Robotics Research* 37.11 (2018). FOUNDATIONAL. TU Delft. Comprehensive overview with 7 design guidelines. Must-cite., pp. 1421–1444. doi: 10.1177/0278364918768950.
- [4] K. Kronander and A. Billard. “Online Stability in Human-Robot Cooperation with Admittance Control”. In: *IEEE Transactions on Haptics* 9.4 (2016). Addresses instability detection and online gain adaptation. Highly relevant for stability analysis., pp. 519–530. doi: 10.1109/TOH.2016.2530162.
- [5] Pablo Lanillos et al. “Active Inference Body Perception and Action for Humanoid Robots”. In: *arXiv preprint arXiv:1906.03022* (2019). Implementation on iCub. Reaching tasks. Does NOT address continuous contact.
- [6] Pablo Lanillos et al. “End-to-End Pixel-Based Deep Active Inference for Body Perception and Action”. In: *arXiv preprint arXiv:2001.05847* (2020). Deep learning version. Still focused on reaching/perception, not force control.
- [7] Mingjing Li et al. “Human Intention-Oriented Variable Admittance Control with Power Envelope Regulation in Physical Human-Robot Interaction”. In: *Mechatronics* 83 (2022). Systematic adaptation of ALL THREE admittance parameters. Power envelope for passivity., p. 102746. doi: 10.1016/j.mechatronics.2022.102746.
- [8] Yanling Li et al. “Adaptive Human Force Scaling via Admittance Control for Physical Human-Robot Interaction”. In: *IEEE Robotics and Automation Letters* (2021). Fuzzy logic for intent estimation. Shows adaptive scaling improves performance. doi: 10.1109/LRA.2021.3067293.
- [9] Noor Sajid et al. “How Active Inference Could Help Revolutionise Robotics”. In: *Entropy* 24.3 (2022). Comprehensive overview of Active Inference potential in robotics. Good for background., p. 361. doi: 10.3390/e24030361.
- [10] Various. “Active Inference Through Energy Minimization in Multimodal Affective Human-Robot Interaction”. In: *Frontiers in Robotics and AI* (2021). Emotion estimation, not physical interaction.
- [11] Various. “Overcoming the Cognition-Reality Gap in Robot-to-Human Handovers with Anisotropic Variable Force Guidance”. In: *IEEE Robotics and Automation Letters* (2024). ANISOTROPIC control for handovers. Decouples retraction motions. Very close to thesis concept.
- [12] Various. “Trust as Extended Control: Human-Machine Interactions as Active Inference”. In: *Frontiers in Human Neuroscience* (2021). Theoretical model of trust in HRI via Active Inference. Conceptual, not implemented.
- [13] Xuefeng Zhang et al. “Variable Admittance Control Based on Trajectory Prediction of Human Hand Motion for Physical Human-Robot Interaction”. In: *Applied Sciences* 11.12 (2021). Uses LSTM neural network for trajectory prediction. Smoother interaction., p. 5651. doi: 10.3390/app11125651.



## Source Code Example

*Adding source code to your report/thesis is supported with the package listings. An example can be found below. Files can be added using \lstinputlisting[language=<language>]{<filename>}.*

```
1 """
2 ISA Calculator: import the function, specify the height and it will return a
3 list in the following format: [Temperature,Density,Pressure,Speed of Sound].
4 Note that there is no check to see if the maximum altitude is reached.
5 """
6
7 import math
8 g0 = 9.80665
9 R = 287.0
10 layer1 = [0, 288.15, 101325.0]
11 alt = [0,11000,20000,32000,47000,51000,71000,86000]
12 a = [-.0065,0,.0010,.0028,0,-.0028,-.0020]
13
14 def atmosphere(h):
15     for i in range(0,len(alt)-1):
16         if h >= alt[i]:
17             layer0 = layer1[:]
18             layer1[0] = min(h,alt[i+1])
19             if a[i] != 0:
20                 layer1[1] = layer0[1] + a[i]*(layer1[0]-layer0[0])
21                 layer1[2] = layer0[2] * (layer1[1]/layer0[1])**(-g0/(a[i]*R))
22             else:
23                 layer1[2] = layer0[2]*math.exp((-g0/(R*layer1[1]))*(layer1[0]-layer0[0]))
24     return [layer1[1],layer1[2]/(R*layer1[1]),layer1[2],math.sqrt(1.4*R*layer1[1])]
```



# B

## Task Division Example

*If a task division is required, a simple template can be found below for convenience. Feel free to use, adapt or completely remove.*

**Table B.1:** Distribution of the workload

Task		Student Name(s)
	Summary	
Chapter 1	Introduction	
Chapter 2		
Chapter 3		
Chapter *		
Chapter *	Conclusion	
Editors		
CAD and Figures		
Document Design and Layout		