



# Some Placeholder Title

**A Master Thesis**

written by

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The code for this project is available at  
[https://github.com/vmstavens/in\\_hand\\_pose\\_estimation](https://github.com/vmstavens/in_hand_pose_estimation)

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## **Abstract**

Some abstract text explaining the goal, methods and conclusion of the project.

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## **Acknowledgements**

My acknowledgements

## Acronyms

**acronym-abbr** acronym-description.

**CP** correspondence problem.

**CV** computer vision.

**DL** deep learning.

**DOF** degrees of freedom.

**PE** pose estimation.

**ROS** Robot Operating System.

## Terms

**computer vision (CV)** is a scientific field which deals with how computers can gain a high-level understanding from digital inputs in the form of images or videos.

**correspondence problem (CP)** the problem within computer vision (CV) to localize the projection of the same object in 3D space in 2 or more images.

**deep learning (DL)** is a technique for data driven pattern recognition.

**docker container** , a docker container is a standard unit of software that packages up code and all its dependencies so the application runs quickly and reliably from one computing environment to another[1].

**glossary term** glossary term description.

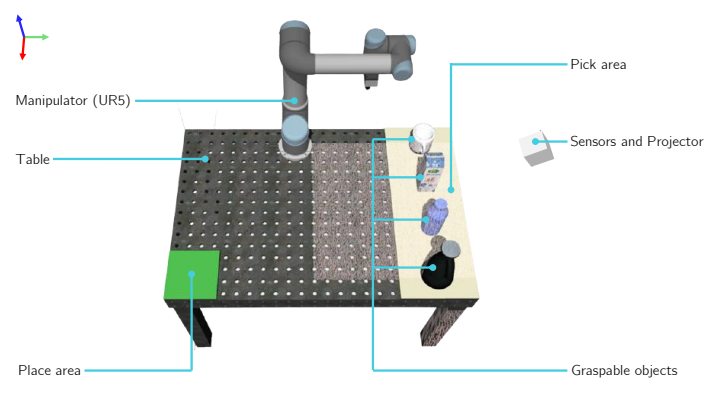
**pose estimation (PE)** is a scientific pipeline which deals with how computers can gain a high-level understanding from digital inputs in the form of images or videos.

**Robot Operating System (ROS)** some description.

## Chapter 1

# Example section

This document demonstrate the use of figures, references, SI units, glossary, math notation, lists, and otherwise relevant formatting specifications. Paragraphs are typically separated using `\medskip`.



**Fig. 1:** An example image using actorym-description.

To exemplify math notation, consider the mapping between the joint configuration of a robot

$$\mathbf{q} = [q_1 \quad q_2 \quad \dots \quad q_n]^\top, \quad (1)$$

and glossary term, given as a homogeneous transformation

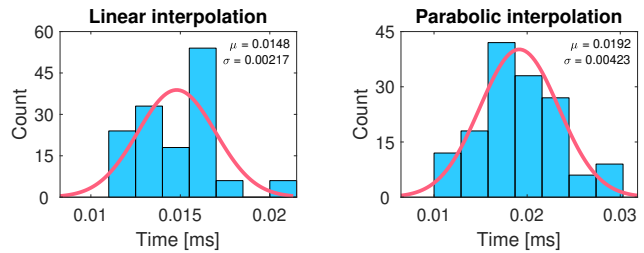
$$\mathbf{T}_B^A = \begin{bmatrix} \mathbf{R}_B^A & \mathbf{t}_B^A \\ \mathbf{0}^{1 \times 3} & 1 \end{bmatrix}, \quad (2)$$

where  $\mathbf{R}_B^A$  and  $\mathbf{t}_B^A$  is the rotation and translation, respectively, from frame  $\{A\}$  to frame  $\{B\}$ , denoted using a homogeneous transformation matrix  $\mathbf{T}(\mathbf{q}) \in \mathbb{R}^{4 \times 4}$  as a function of the joint configuration in (1), as described in [robotics-book].

Complex table/figure hybrids with aligned captions and functioning labels can be implemented using `minipage`, as shown in Table 1 and Fig. 2. Use `\cite` as a placeholder for citations.

Pose \ Method	1	2	3
Linear	18.97 s	20.35 s	22.85 s
Parabolic	13.66 s	14.93 s	17.33 s

**Table 1:** Trajectory durations of the interpolation-based trajectory generation methods.



**Fig. 2:** Average planning time for each of the interpolation-based trajectory generation methods.

For numbers, units and ranges, the `siunitx` package is used, which allows to express a number 10, a range of 5 s to 6 s, or a SI unit of  $5.73 \pm 1.09$  s. Inline row-vectors (with the transpose symbol) can be written as  $\mathbf{a} = [\mathbf{a}_p \quad \mathbf{a}_o]^\top$ , where as parentheses can be automatically written using  $(a, b)$  or  $\left\{\frac{a}{b}, c\right\}$ . Also, shorthands for  $\mathbf{A}^{-1}$ ,  $\mathbf{A}^\dagger$  and  $\mathbf{A}^\top$ .

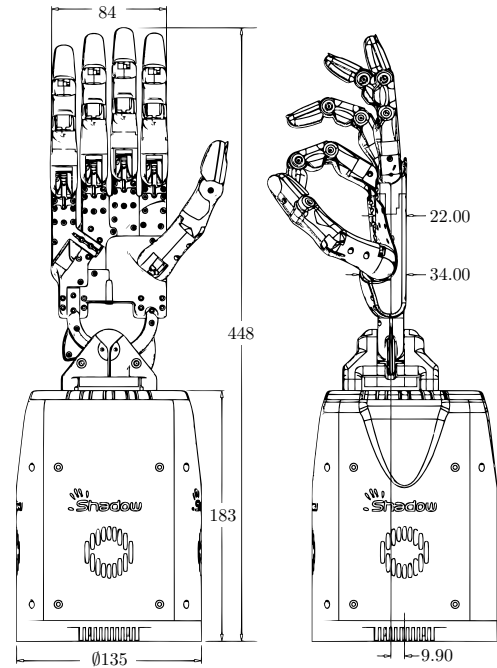
## Chapter 2

# Introduction

The developments in robotics as a field has over the past years provided automation solutions to execute repetitive manual tasks with high efficiency and reliability [\[1\]](#). One of the most common tasks being pick and place tasks which involves picking up an object from one position and placing it in another. This can be parted into the following subparts: Object localization, pose estimation, grasping and placing. In the solutions currently present for industrial use computer vision (CV) is used for object localization and pose estimation (PE) due to the low cost of cameras and the field's maturity. However, while these solutions may be sufficient for certain tasks they fundamentally suffer from the weaknesses introduced by vision techniques. These include a great number of outliers caused by occlusions, reflecting, transparent or homogeneous surfaces, and repetitive structures when solving the correspondence problem (CP). These problems as of the writing of this project have yet to be completely solved. Promising results have been found with the rise of deep learning (DL) which in present time has proven its versatility and provides proof of concept solutions for narrow cases in pose estimation of transparent [\[2\]](#) and reflective objects [\[3\]](#). This is relevant since industrial settings often contain transparent and especially reflecting objects as metallic parts tend to appear frequently and have high reflectances.

To solve these problems this project aims to perform in-hand pose estimation through only the use of tactile sensors. Specifically this will be done on a Shadow Dexterous Hand [\[4\]](#) with 20 degrees of freedom (DOF). Using tactile inputs rather than visual, eliminates the weaknesses mentioned above. A schematic showing the hand can be seen in Fig. 1. Using this approach, the overall problem can be partitioned into 3 sub-problems labeled problem 1, 2 and 3. Problem 1 involves modeling the contact between the gripper's fingers and the object, also referred to as tactile perception. Problem 2 is to convert the collected data from problem 1 to meaningful surface data, treat these data as features and use them to estimate pose candidates. Finally problem 3 involves in-hand manipulation, such that further information is gained by probing the object. Here new desired surface points are found such that strong surface features are found to better identify the object's correct pose. The development of this project is done in the docker container provided by Shadow Robotics for simulation, control and development of the hand [\[5\]](#). Here a hardware-simulation agnostic Robot Operating System (ROS) [\[6\]](#) control [\[7\]](#) interface is provided, which provides fundamental tools to interact with the robot hand.

The dynamic simulation environment Gazebo [\[8\]](#) is provided as part of the



**Fig. 1:** Schematic of Shadow Dexterous Hand from Shadow Robots, based on [\[6\]](#). The measurements are in mm.

hello there

- work will be done in simulation provided by shadow robotics **cite**. ROS, Gazebo, docker.
- The project will be implemented as a meta-package with sub packages for each of the problems.
- state of the art will be presented in chapter x

o Related work - During your literature search what did you find? - Your own or the research group's prior work if any? o Project aim or Hypothesis - How did you derive your project aim (engineering design process) or hypothesis which you are testing (scientific method) and how it connects to related work?



## Chapter 3

# State of the Art

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### 3.1 Problem 1 - Tactile Perception

What is tactile perception? Why is it relevant?

How is a tactile sensor constructed [7] what different types exist and which one is present in the model provided.

*"Representations of tactile data are commonly either inspired by machine vision feature descriptors"*

often used in computer vision context, where each tactile image

Addressing the problem

### 3.2 Problem 2

### 3.3 Problem 3

## Chapter 4

# Problem 1

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### 4.1 Introduction

Here we write the introduction for problem 1.

### 4.2 Related Work

Here we cite the related work by `\cite{source-label}` like this [7]

## Chapter 5

### **Problem 2**

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## Chapter 6

# Discussion

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Chapter 7

## **Conclusion**

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# Bibliography

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- [1] docker. *What is a container*. URL: <https://www.docker.com/resources/what-container/>.
- [2] Xu, Chi et al. “6DoF Pose Estimation of Transparent Object from a Single RGB-D Image”. In: *Sensors* 20.23 (2020). ISSN: 1424-8220. DOI: 10.3390/s20236790. URL: <https://www.mdpi.com/1424-8220/20/23/6790>.
- [3] He, Zaixing et al. “6D Pose Estimation of Objects: Recent Technologies and Challenges”. In: *Applied Sciences* 11.1 (2021). ISSN: 2076-3417. DOI: 10.3390/app11010228. URL: <https://www.mdpi.com/2076-3417/11/1/228>.
- [4] Straszheim, Troy et al. *Shadow Robot*. URL: <https://www.shadowrobot.com/dexterous-hand-series/>.
- [5] Robot, Shadow. *The Shadow Robot Company*. URL: <https://github.com/shadow-robot>.
- [6] Components, ROS. *The Shadow Dexterous Hand*. URL: <https://www.roscomponents.com/en/robotic-hands/117-shadow-dexterous-robotic-hand.html>.
- [7] Chi, Cheng et al. “Recent Progress in Technologies for Tactile Sensors”. In: *Sensors* 18.4 (2018). ISSN: 1424-8220. DOI: 10.3390/s18040948. URL: <https://www.mdpi.com/1424-8220/18/4/948>.

Appendix A

## **Appendix A Title**

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