Decentralized Grasp Coordination and Kinematic Control for Cooperative Manipulation

Rajkumar Muthusamy
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Rajkumar Muthusamy

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Abstract

Multi-robot systems have shown potential over single robot systems in handling long, large and heavy objects. Manipulation with multiple robots increases task precision and decreases required load capabilities of individual robots while saving cost and space. However, the limitations of multi-robot systems in communication, sensing and knowledge sharing and constraints that occur while performing cooperative manipulation pose challenges for coordination and control. This thesis focuses on multi-robot grasp planning and control of collaborative manipulation.

First, the thesis examines the question how to plan cooperative grasps given a known object for a group of robots that are decentralized and heterogeneous. Decentralized grasp planning approaches which account for incomplete embodiment knowledge and utilize imprecise local information from vision are presented. In addition, to tackle observation constraints, strictly decentralized approaches which only require role assignments are also proposed. Grasp decisions from the approaches are based on evaluation of traditional grasp quality measures under uncertainty. All approaches aim to maximize the quality of cooperative grasp under decentralization and heterogeneity. The approaches are further extended to include task specific information and their usefulness to particular tasks are studied. For experimental study, a complete system pipeline for decentralized grasp coordination is developed and physical metrics to evaluate the success of cooperative grasps are presented. The main contribution of this part is the first extensive investigation of grasp planning for decentralized multi-robot coordination.

Second, given a cooperative manipulation task for heterogeneous multi-robot system, the thesis studies, how to safely coordinate the motions under joint limit constraints. A kinematic controller that employs relative Jacobian for coordination of motions and a control strategy based on task prioritization and smooth activation to ensure safe collaborative manipulation and smooth joint limit avoidance are presented. Behaviour of the controller under different redundancy configurations and applicability in practice for collaborative manipulation are demonstrated.

Keywords  Decentralized systems, Heterogeneous robots, Multi-robot Coordination, Grasp planning, Cooperative manipulation, Kinematic control, Relative Jacobian.
Preface

The work for this dissertation has been started after joining the intelligent robotics Group at Aalto University in 2013. This work has been partly supported by the European Commission (FP7-ICT9) through the RECONFIG project, Academy of Finland through the SEASPIDER project and Aalto ELEC Doctoral school through the Electrical Engineering and Automation Department. Here I gratefully acknowledge the funding provided by the Institution and Agencies.

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<td>CEBOT</td>
<td>Cellular robotic system</td>
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<tr>
<td>CZ</td>
<td>Centralized</td>
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<tr>
<td>CLIK</td>
<td>Closed form inverse kinematics</td>
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<tr>
<td>DOF</td>
<td>Degree of freedom</td>
</tr>
<tr>
<td>DI</td>
<td>Decentralized independent</td>
</tr>
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<td>DIB</td>
<td>Decentralized individual best</td>
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<tr>
<td>DA</td>
<td>Decentralized average</td>
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<td>DE</td>
<td>Decentralized expectation</td>
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<td>DP</td>
<td>Decentralized planners</td>
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<tr>
<td>DSP</td>
<td>Digital signal processor</td>
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<tr>
<td>F/T</td>
<td>Force/Torque</td>
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<td>FWS</td>
<td>Functional wrench space</td>
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<td>FPFH</td>
<td>Fast point feature histogram</td>
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<td>GWS</td>
<td>Grasp wrench space</td>
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<td>GbD</td>
<td>Grasping by demonstration</td>
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<td>GPM</td>
<td>Gradient projection method</td>
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<td>GPU</td>
<td>Graphical processing unit</td>
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<tr>
<td>GO</td>
<td>Globally optimal</td>
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<tr>
<td>HF</td>
<td>Hard finger</td>
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<tr>
<td>ICP</td>
<td>Iterative closest point</td>
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<td>MRS</td>
<td>Multi-robot system</td>
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<td>MRGP</td>
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<td>MAS</td>
<td>Multi-agent system</td>
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<td>NTS</td>
<td>Non task specific</td>
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<td>OWS</td>
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<td>PowF</td>
<td>Frictionless</td>
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<td>PRM</td>
<td>Probabilistic Roadmap</td>
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<td>PPC</td>
<td>Prescribed Performance control</td>
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<td>RGB-D</td>
<td>Red, green, blue plus depth</td>
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<td>RRT</td>
<td>Rapidly Exploring Random Tree</td>
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<td>SNS</td>
<td>Saturation in the null space</td>
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<td>SDI</td>
<td>Strictly decentralized independent</td>
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<td>$a$</td>
<td>Amplitude of contact force</td>
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<td>$y$</td>
<td>Index variable</td>
</tr>
<tr>
<td>$z$</td>
<td>Index variable</td>
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<tr>
<td>$\nabla$</td>
<td>Gradient</td>
</tr>
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**Greek symbols**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>Friction coefficient</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Torque multiplier</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Epsilon quality measure</td>
</tr>
<tr>
<td>$\Omega$</td>
<td>Jacobian transformation matrix</td>
</tr>
<tr>
<td>$\psi$</td>
<td>Wrench transformation matrix</td>
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<tr>
<td>$\phi_R$</td>
<td>End-effector relative orientation</td>
</tr>
<tr>
<td>$\dot{\omega}_e$</td>
<td>Angular velocity</td>
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Part I

Introduction
1. Introduction

A multi-robot system (MRS) is a group of robots under an organizational structure aiming to perform tasks with collective efforts. These systems have recently gained increased popularity in several application domains \cite{1,2} and interest in robotics community due to their increased potential over single robot systems \cite{3}. Building a single sophisticated robot with many capabilities and a high payload capacity is expensive and prone to single point failures. Moreover, an individual robot cannot accomplish a high complexity task alone. Therefore, the use of multiple simple and less expensive robots is preferred in several application domains to accomplish a wide range of tasks. As the robot market is widening and becoming competitive, robots of different brands with specialized abilities and capability will become a part of the multi-robot system and need to coordinate to handle both simple and complex tasks. Even though the diversity of robots is known to increase the flexibility, robustness and cost effectiveness \cite{4}, achieving cooperation among the robots can be difficult due to the limitations in communication, sensing and sharing knowledge. Especially, coordination and control are the key challenges in such systems that motivate this thesis.

Coordination of multiple robots is a fundamental problem for performing cooperative tasks. Most studies consider multi-robot coordination in a centralized setting, where complete knowledge sharing and central decision making are the key attributes \cite{5,6}. In contrast, the coordination of decentralized systems is more challenging due to the limited communication and sensing, incomplete knowledge, heterogeneity of robots and distributed decision making \cite{7}. However, recent works have demonstrated the potential of distributed systems to achieve increased robustness \cite{8}. Moreover, heterogeneity of individual robots allows the collection of robots to join their forces in tasks not achievable to individual robots \cite{9}.

Many of today’s robots are equipped with simple grippers or sophisticated hands
Introduction which allows them to perform tasks from simple pick and place to highly dexterous manipulation in both domestic and professional environments. Manipulation with multiple robots may increase task precision and decrease required load capabilities of individual robots. This thesis mainly considers multiple robotic manipulators equipped with multi-fingered hands for cooperative tasks. Moreover, the challenges are emphasized in cases with heterogeneous robots, that is, when the robots’ physical embodiments differ.

Cooperative manipulation of large and heavy objects has become an important task in several robotic application domains such as construction, forestry, agriculture and service robotics [10, 11, 12, 1]. To perform such tasks, robots in a group need to coordinate to grasp a common object. Then kinematic coordination and movement synchronization need to be maintained to avoid damage since the coordinated multi-robot grasps on the common object form a closed kinematic chain. In simpler terms, multiple robots grasp and move a common object in a tightly coordinated fashion to accomplish such tasks. In this thesis, we consider cooperative manipulation tasks and approach the grasping and kinematic control problem in the multi-robot context.

Grasp planning is a well established research topic in robotics. Unlike caging, grasping allow precise manipulation by immobilizing an object. Determining where and how to grasp a given object is the scope of the grasp planning problem. In the grasping process for a known object, a grasp can be examined by analysing its key properties quantified by grasp quality measures [13]. Disturbance resistance is one key grasp property which can be identified with force and form closures. Figure 1.1 shows two typical failure modes when manipulating large or heavy objects with single robots. Even though the grasp planning has produced force closure grasps that are able to resist some external disturbances, the finger forces may be insufficient for stabilizing the object in hand leaving the object dangling (Fig. 1.1(a)) or the arm torques may be insufficient for lifting the object (Fig. 1.1(b)), typically because of the gravity force. These failures make evident the need for multiple robots and corresponding grasp planning to handle such large and heavy objects successfully.

Grasp planning as a problem gets more complex and difficult when the multi-robot system (MRS) is decentralized (making decisions without global information) or is composed of heterogeneous robots (difference in embodiments and capabilities). In such systems, the robots may have no knowledge about the embodiments of the other robots. In simpler terms, decentralized grasp planning poses the challenge of incomplete embodiment knowledge whereas a typical single robot grasp planning pipeline includes only uncertainties such as object pose and shape. To the best of our
knowledge, only we have explored the possibilities of grasp planning for multi-robot coordination in a decentralized context and with a heterogeneous group of robots [14, 15, 16].

(a) Failure: Object dangle.  (b) Failure: Insufficient force to lift.

(c) Success: Coordinated lift.

Figure 1.1. In (a) and (b), KUKA LWR 4+ and Kinova Jaco robot attempt object manipulation. Coordinated grasping and manipulation of a heavy object with two heterogeneous robots in (c).

To perform a manipulation task, a kinematic controller is generally used to determine a unique joint space solution for a robotic manipulator by solving the inverse kinematics problem in the differential (velocity) level, that is, by mapping the end effector Cartesian velocity to a joint velocity using the inverted Jacobian of the manipulator. In the case of a redundant manipulator, there exist an infinite number of joint space solutions at each location of the end effector. These self motions of the structure do not affect the end effector location but offer the possibility to select better arm configurations. The kinematic redundancy can be exploited to achieve secondary objectives such as the avoidance of joint limits, obstacles, collisions and enhancement of manipulability. To select a solution, several objective functions and performance criteria can be applied in the kinematic control. The handling of joint motion constraints, that is limits on joint position or velocity, has been a main criterion addressed
extensively in the single manipulator case. Several redundancy resolution schemes exist to resolve the redundancy of the manipulator under joint constraints. With multiple robots, cooperation and joint limit avoidance are important issues explored actively by the multi-robot research community.

Multi-arm manipulation can be even more difficult when the system is composed of heterogeneous manipulators, that is, having a different number of redundant motions and physical embodiments. Indeed, when the number of critical joints (the number of joints close to their operational limits) of a cooperating manipulator is higher than its redundant motions, then all joints limits cannot be avoided and the cooperation quality is drastically degraded, even if the other cooperating manipulator has available redundant motions. Coordinated grasping and manipulation allows greatly increased handling capabilities as shown in Fig. 1.1(c).

1.1 Problem statement

The general problem addressed by this dissertation is the grasp planning and coordinated control of multiple robots for cooperative object manipulation tasks. The increase in autonomous and heterogeneous robots in multi-robot systems demands decentralized grasp solutions and safety in coordinated motion while performing such tasks. Two main research questions we tackle in this dissertation and corresponding motivational scenarios are as follows:

**Research Question 1:** Given a known object, how to determine cooperative grasps for a group of robots that are decentralized and heterogeneous.

Motivational scenario: Consider a future setting where two heterogeneous robots equipped with robotic hands collaborate in a household environment to transport a large or heavy object. The robots are of different brands which limits the extent of shared knowledge. The robots then need to solve the grasp coordination problem in a decentralized fashion.

**Research Question 2:** While performing a cooperative manipulation task, how to coordinate motions safely and smoothly between multiple heterogeneous robots (robotic manipulators) under joint position constraints.

Motivational scenario: Consider a future construction site where two heterogeneous robots collaboratively manipulate a common object. These robots may have different number of joints and face physical limitations. The controller then needs to solve the motion coordination problem considering kinematic constraints, joint lim-
its and insufficient redundant motions in individual manipulators. Thus damages and task failures are avoided.

Assumptions: The term embodiment refers to physical shape and size of the robot. In research question 1, the hand geometry of the robot is the only considered embodiment and heterogeneity refers to the difference in hand embodiment of robots. Moreover, for each individual robots in a group, the existence of other robots, execution order of robots and rough hand pose estimate from observation are assumed to be given. In research question 2, both full arm and hand geometry of the robot are considered and heterogeneity refers to the difference in robot’s embodiment and having a different number of redundant motions.

1.2 Contributions

While studying the above problems, a number of contributions have been made in this dissertation which are summarized in the following list:

- A systematic characterization of multi-robot systems relating to the aspects of coordination (Section 2.3).

- A formulation for evaluation of multi-robot grasps based on wrench space quality measures (Section 3.4).

- Grasp coordination approaches for multi-robot systems under three organizational set-ups, centralized, decentralized and strictly decentralized (Section 4.3). The approaches handle the problems of decentralization and heterogeneity of robots in MRS. The approaches include

  - Four decentralized grasp planning approaches for a group of decentralized robots that have incomplete knowledge of each other’s embodiments. The approaches provide coordinated grasping under limited communication and imprecise sensing while not requiring global planning. Among the four approaches, two probabilistic approaches outperformed baseline approaches and demonstrated the ability to compensate the incomplete information especially for heterogeneous robots by performing close to optimal, centralized planning. Simulation experiments reveal that the probabilistic treatment of embodiment uncertainty leads to increased grasp qualities. The considered assumption of embodiment similarity
is sufficiently good to allow handling uncertainties caused by heterogeneity in a
decentralized setting.

– Four strictly decentralized grasping approaches that account for observation con-
straints and incomplete knowledge in decentralized group of robots. The coordi-
nation decision is mainly based on the assigned role for each robot. For a homo-
geneous group of robots, the probabilistic approaches outperformed the baseline
approaches.

• An analysis about the importance of task specific quality measures in cooperative
grasping settings and a performance study by incorporating task specificity in de-
centralized grasping approaches (Section 5.2.4).

• Five experimental metrics that quantify the quality of a cooperative grasp and
an experimental procedure to acquire the physical measures by doing a simple
lift/lower operation (Section 6.2.3).

• A system of two heterogeneous robots that perform autonomous operations to ex-
perimentally study the grasp coordination approaches and analyse robot handling
capabilities (Section 6.1).

• A kinematic controller for cooperative manipulation that ensures safety by provid-
ing coordinated relative motions and joint limit avoidance while following a world
frame trajectory. The hierarchical control approach based on relative Jacobian uses
a smooth activation function that provides gradual activation of joint limit avoid-
ance for both redundant and non redundant manipulators (Section 8.2).

• Implementation of the kinematic controller for a heterogeneous dual-arm system,
which is composed of a redundant 7-DoF manipulator and a 6-DoF non-redundant
manipulator (Section 8.4).
1.3 Author’s contribution

Parts of this dissertation have been previously published or are under review in the following conferences and journals.


The author reviewed the background works on grasping and multi-robot systems and investigated how robotic grasp planning can be performed in a multi-robot system without central coordination. He proposed decentralized grasp planning approaches for multi-robot coordination, performed the relevant software implementations and tests and had the responsibility of analysing results and writing the manuscript. V. Kyrki contributed actively to the development of approaches and the revision of publication.


The author proposed the idea of incorporating task specific information in planning multi-robot grasps. He performed experiments on task specific grasp planning for particular tasks and studied the usefulness of the extended decentralized approaches. The article was written by the author, with cooperation of the co-authors.


The author proposed new physical metrics for cooperative grasps evaluation in experiments. He was responsible for carrying out the experiments both in simulation and experiments. V. Kyrki provided discussion and comments on the manuscript and contributed to writing of the publication.
Introduction


The author together with V. Kyrki formulated the decentralized grasp planning approaches [15] for the heterogeneous robots. The author designed and demonstrated a complete system pipeline for decentralized grasp coordination which includes 3D model reconstruction and pose estimation for grasped objects, decentralized grasp planning, grasp execution and collaborative manipulation. He was responsible for both simulations and real-time experiments and physical evaluation of cooperative grasps. The article was written by the author, with cooperation of the co-author.


The background review on redundancy resolution methods and kinematic control of redundant manipulator under constraints was done by the author. He together with D. Ortenzi proposed a centralized control strategy to safely coordinate motions of multiple robots manipulating a common object under joint limit constraints. The author was mainly responsible for the low level integration of two heterogeneous systems, controller implementation, analysing and reporting the obtained results. He also contributed in writing parts of the article. The co-authors actively provided discussion and comments on the publication and contributed to writing of the publication as well.

In addition to the above, the thesis has unpublished contributions in characterization of multi-robot systems (Ch. 2) and development of strictly decentralized grasp planning approaches (Ch. 4). These contributions are solely author’s.

In addition, during the doctoral study, the author has worked on the following articles which are not included in this dissertation:

6. Todor Stoyanov, Robert Krug, Rajkumar Muthusamy and Ville Kyrki, “Grasp Envelopes: Extracting Constraints on Gripper Postures from Online Reconstructed
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The above summary of publications are accomplished during the course of working towards this dissertation.

1.4 Dissertation outline

The next chapter begins by presenting the necessary background and works related to this thesis. The rest of the thesis is divided in two main parts: Part II addresses the grasp coordination problem in heterogeneous and decentralized MRS and Part III addresses the kinematic control problem for cooperative manipulation under joint limits.

In Part II, Chapter 3 gives the background on grasp analysis and quality measures and presents the multi-robot grasp formulation for quality evaluation. Chapter 4 presents grasping based coordination approaches for different organizational set-ups of a robot group. Next, Chapter 5 studies the proposed approaches in simulation. To evaluate the approach performance in real systems, Chapter 6 first describes a system implementation and then presents experimental metrics, procedure and results.

In Part III, Chapter 7 summarizes the theoretical background about redundancy and their existing resolution methods and presents a compact relative Jacobian formula-
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tion for cooperative heterogeneous robots. Chapter 8 presents the control approach for safety in cooperative manipulation and studies them in simulation and physical environment. Experimental results of the cooperation of KUKA LWR 4+ and Kinova Jaco robots are reported and discussed. Finally, the thesis is concluded and the areas of future work are discussed in Chapter 9.
2. Background and Related Works

2.1 Grasp planning for known objects

"Man is the most intelligent among animals because he has hands"- Anaxagoras

Grasp planning has become an important research topic in the field of robotics, as the robots are increasingly equipped with grippers or multi-fingered hands to accomplish a wide range of tasks. Even though a robotic hand is less complex when compared to the human hand, planning a robotic grasp for a wide variety of objects and tasks is challenging. However, humans can grasp objects spontaneously without much planning. The ability to simplify a huge space of possible grasps is assumed to be gained because of the long time process of learning and gained experience. Studying human grasping is beneficial to robotics, especially learning human hand postures and their adjustment to desired tasks can advance grasping in robots.

Several earlier works focused on understanding the human way of grasping. Napier [19] studied the structural and functional aspects of a human hand and characterized human grasps into two main types: power grip and precision grip. Both types are distinguished based on the final hand posture achieved on the object relating to a task. These grasps became fundamental in realizing robotic grasps. A taxonomy of grasp was presented by Cutkosky [20], who further classified the two main grips in manufacturing tasks by observing the human grasp selection in the presence of hand, task and object constraints. Arbib et al. [21] developed the concept of virtual fingers that considers multiple fingers as a single functional unit and further Iberall [22] presented a concept called ‘oppositions’ based on human grasping that demonstrates basic grasp configuration to exert forces on the opposing sides of the grasped object.

These concepts suggest that human hand control for common grasping tasks takes place in a configuration space of lower dimensionality than the DOF of the human
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hand. To verify this hypothesis, Santello et al. in [23] recorded the joint angle information from human subjects during grasping tasks and the results validated the hypothesis. Later, Ciocarlie et al. [24, 25] coined the term eigengraps by extending this concept to robotic hands. Recently, Feix et al. [26] presented a new taxonomy which summarizes the existing human grasp taxonomies with new additions such as intermediate grasps. A total of 33 different grasp types were identified and arranged under three major categories namely (1) power, precision and intermediate grasps (2) opposition types and (3) virtual fingers. Feix et al. claim any grasp can be classified under these three major concepts.

In the last decade, development of grasp simulators such as Graspit! [27], OpenRave [28], Simox [29] and openGRASP [30] played an important role in the growth of robotic grasping research. Avoiding the necessity of expensive hardware, these simulators allow the user to import different hand and object models and provide a controlled environment to test and tune planning algorithms. Moreover, they require less time and resources to perform experiments that involve exhaustive search and evaluation whereas full scale experiments with real hardware are time consuming and costly.

Given a robot hand, an object and a task to perform, planning an appropriate grasp is a fundamental challenge in robotic grasping. Traditionally two approaches, analytical and empirical are used for robotic grasp planning. The analytical approach aims either to find good contact locations on an object for a grasp or to analyse a grasp to find its appropriateness both at contact and hand level using an analytic formulation whereas empirical approaches aim to mimic grasps demonstrated by humans or otherwise generate grasps for the object being observed. The empirical approaches are more associated to recognition, classification and learning. Sahbani et al. presented a comprehensive summary of techniques based on these approaches in [31].

In the empirical line of grasp planning, data driven approaches gained popularity among the research community since they combine analytical and empirical methods to address the grasp planning problem and complement the conventional practices carried out in the simulator. The data driven approaches divide the grasp planning problem in two sub-problems: grasp generation and grasp evaluation. The former addresses the question on how to generate a set of grasp candidates for an object from the infinite space of possible hand configurations and the latter deals with how to evaluate the generated grasp candidates with quality measures and criteria that are appropriate for the application in hand. Based on the prior knowledge available about the object, the data driven approaches solve the above sub-problems in different
manners. Bohg et al. [32] classified data driven approaches according to known, familiar and unknown object categories.

Our focus is mainly on data driven approaches for known objects. Under this category, a complete geometric model of the objects in the form of a 3D mesh is available for planning grasps. The challenge here is how to generate a finite set of grasp hypotheses by directly processing a 3D object model. Borst et al. [33] randomly generated grasp candidates on a primitive object surface and reduced the number of candidates by filtering them with a simple heuristic. The complexity of the approach is determined by the form of object geometry. Their approach aims to generate grasps that are sufficiently good rather than optimal for the object. Diankov [34] sampled the object surface by casting rays from a bounding primitive to the target object and computed normals at the sampled surface to steer the hand with approach directions such that grasp candidates are generated. The complexity of these approaches is determined by the form of object geometry. Many works focused on object representations and proposed shape approximation techniques to reduce the search space. These works come under grasping by parts paradigm.

Miller et al. [35] used 3D geometric primitives such as box, sphere, cone and cylinder to approximate the shape of an object and generated grasp candidates by defining simple heuristics (e.g. pre-grasps or start positions [20]) on the simplified object. For new objects, the user has to manually decompose the object into a set of primitive shapes. Goldfeder et al. [36] presented a method that automatically decomposes the object into a multi-level tree of superquadrics and generated candidate grasps on superquadric approximations with a simple tree hierarchy. Huebner and Kragic [37] opted for a box representation and proposed a fit-and-split algorithm that decompose an arbitrary object into a set of minimum volume bounding boxes. The above methods simplified the object shape to reduce complexity. Leaving out geometric details of an object can possibly discard valuable candidate grasps. In particular, grasps which might be intuitive for a human can possibly be discarded due to a poor approximation of the object geometry.

Considering this issue, Przybylski et al. [38, 39] used inscribed spheres to approximate the shape of 3D objects and improved the accuracy of geometric representations. They presented two versions to generate candidate grasps based on the shape complexity. First refers to medial axis [38] and is limited to simple shapes and the second version is referred to as medial axis transform [39] that accounts for complicated shapes. The medial axis transform is a complete shape descriptor that holds both structural and symmetry information. This shows its ability to generate poten-
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tial grasp candidates. Aleotti and Caselli [40] presented a topological representation of the shape (skeleton) of the object to generate grasp candidates by parts. From the perspective of human grasping, Ciocarlie et al. [24, 25] presented the concept of eigengraps for generating grasps in a low dimensional hand posture space.

In all of the above mentioned works, the grasps are generated offline and stored in a standardised database for further analysis and use. These grasps are generally examined for their closure properties and ranked with wrench space quality measures. One of the most popular metrics used to quantify the grasp in the simulation is epsilon metric [41] but this analytical metric has been criticized in recent times due to its possible selection of fragile grasps in the ranking process [42]. To filter out these fragile grasps, a suggested approach is to add noise to the grasp parameters and prune grasps that do not support neighbouring grasps yielding a force closure. This approach is followed by Weisz and Allen in [42], where they introduced object pose error in experimental simulations and studied the ability of the epsilon metric to predict a grasp that is stable. A comprehensive review on grasp analysis and quality evaluation is given in Chapter 3. Apart from that, a rich survey on grasp quality metrics can be found in [43].

Another way to generate grasp hypotheses is learning from human grasp demonstrations. The underlying idea of this approach is to imitate the human demonstrated grasp in a robotic system. The imitation process involves recognising the type of grasp placed on the object and mapping the human embodiment to the desired robot embodiment. Romero [44] adopted the approaches used in learning by demonstration [45] for robotic grasping and referred them as grasping by demonstration (GbD). In the GbD paradigm, imitation and demonstration are the two main approaches which are classified according to the directness of embodiment and record mapping. Sensors on Teacher and External observation are the two main types of imitation based approaches that are prominently used in grasping demonstrations.

Ekvall and Kragic [46] presented a method for generating robot grasps based on object primitives and human demonstration. During an object manipulation task, their system estimates the pose of the grasped object and recognises the grasp types using data gloves equipped with magnetic trackers worn by the human demonstrator. Then, the recognised grasp type is mapped to robotic hands. Moreover, when the robot executes their grasp they select the best approach vector from an offline trained experience database. By introducing object pose errors, the authors conducted experiments in the simulation environment and found that grasps are sensitive to position inaccuracies.
Even though the user demonstrates a natural grasp, the gloves with magnetic tracker that are worn by the user cause ambiguity in the grasp and also the mapping is non trivial since the embodiment of the robot hand is not identical to the human hand. Therefore purely vision based grasp learning systems are naturally motivated. To overcome the limitations of data gloves and physical interactive sensors, Romero et al. [47] focused on visual grasp recognition and presented a human-to-robot grasp mapping system, where the human demonstrated grasp posture is first classified according to the taxonomy in [20] and mapped to a particular robot hand. They evaluated this approach in the GraspIt! simulator using 3D object and hand models and also demonstrated the grasp with real hardware such as Barrett hand. However, they report that the grasp strategy is affected by the embodiment difference between human and robotic hand. Recently, Balasubramanian et al. [48] used kinesthetic teaching in human grasp demonstrations and introduced a human guided grasp measure for grasp selection. This metric was used to rank grasps in [39].

Approaches learning from humans facilitate grasp hypothesis generation from an online demonstration process and allow establishing an experience database for robotic grasp planning. However, the mapping between different embodiments and recorded states can introduce imprecision in robotic system and sometimes mapping failure causes complete system failure.

A typical grasping system for known objects comprises of offline and online modules. In the offline module, for every object model a grasp hypothesis set is generated, ranked and stored in a database. In this thesis, we use approaches that generate grasp candidates offline and measures that analytically quantify the grasps.

2.2 Kinematic control of redundant manipulator

To increase flexibility and safety in task execution, many of today’s robots are designed to posses kinematic redundancy, that is, a robotic manipulator may have more degrees of freedom than those needed to accomplish a particular task in the Cartesian workspace. These extra degrees of freedom can be utilized to satisfy specific performance criterion such as kinematic singularities [49], avoidance of joint limits [50], obstacles [51], manipulability enhancement [52], self or workspace collisions [53], besides moving the end-effector to a goal.

Kinematic redundancy enhances the manipulator capability however by increasing the control complexity. Several local and global redundancy resolution techniques
have been proposed to resolve the inverse kinematics problem of the redundant manipulator in the velocity level and select a solution from the infinite possibilities of arm configurations based on a specific performance criterion. The global approach [54] optimizes joint space solution for a desired trajectory or prescribed path with respect to a performance criterion limited to offline objectives (e.g. average kinetic energy). The local approach [55] optimizes instantaneous joint motion that is required to move towards an end-effector goal according to a performance criterion related to real-time objectives. We concentrate on local redundancy resolution schemes [56] for redundant manipulators where the methods adopted can be categorized into three types, namely Jacobian-based, null space projection and task augmentation.

Whitney et al. [57] proposed to use Jacobian pseudo-inverse to locally minimize the norm of joint velocities with respect to a task constraint. However, the avoidance of singularities is not guaranteed during task execution with pseudo-inverse solutions. Moreover, Jacobian based methods [58, 59, 60] block the use of redundant motions for secondary tasks. To execute additional constraints along with the primary task, extended Jacobian [61] and augmented Jacobian [62] within the class of task augmentation approaches were proposed. However algorithmic singularities and conflicts between tasks are known to occur while computing the solutions. To manage the constraints on the joint velocities without task violations, null space methods [63] which correspond to self-motions of the robot are widely adopted to optimize various performance criteria. Especially pseudo-inverse with null space projection is a popular technique to achieve a secondary objective in least-square sense.

A more effective approach to manage multiple tasks was proposed by Nakamura and Hanafusa [64] based on task prioritization. Dubey et al. [65] presented an effective gradient projection scheme where they utilized the pseudo-inverse with null space projection technique along the task prioritization strategy that projects the gradient of the lower priority task into the Jacobian null space of the higher priority task.

Several studies have been performed on single redundant manipulators affected by joint limits, many of which are based on the Gradient Projection Method (GPM) [66]. This method aims to minimize the distance of the joints to their middle range position by projecting the gradient of a quadratic cost function. The main disadvantage of this method is that it uses all available redundant motions for keeping all joint positions in the middle of their range. In order to save some redundant motions, other approaches make use of the potential fields [67], operating only on those joints whose positions are close to their limits. A recent work [68] projects a joint limit avoidance function based on Prescribed Performance Control methodology (PPC) into the Jacobian null
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space of the desired task. However, this method treats joint limit avoidance as a low priority task, hence, avoidance is not guaranteed. A method that ensures joint limit avoidance is described in [69]. It concerns a supervisory controller that permits to switch from the classical projection operator to a new projection operator based on the directional redundancy method proposed in [70]. The method proposed in [71] consists of a hierarchy of controllers, in order to divide the main task into several subtasks. In particular, individual subtasks are progressively interrupted by a supervisory controller to ensure sufficient degrees of motion for joint limit avoidance. Finally, the Saturation in the Null Space (SNS) algorithm [72] considers the projection of the exceeded end-effector velocity into the null space of the main task Jacobian matrix, namely partial Jacobian matrix, composed by the non-saturated joints. This method also includes main task velocity scaling, when the partial Jacobian null space becomes rank deficient.

2.3 Multi-robot systems

MRSs have been studied since 1980’s. Several works have focused on building taxonomies, proposing research topics, presenting surveys and exploring application domains. In the following we capture notable works on coordination and cooperation in MRS.

Dudek et al. [73] presented a taxonomy that classifies a MRS with respect to communication, computational capacity and other capabilities. They emphasized the usefulness of their taxonomy by positioning existing earlier works. At the same time, Cao et al. [10] investigated the underlying mechanism of cooperation in MRS and synthesized five taxonomic axes that were interdependent and broad, namely group architecture, resource conflict, origin of cooperation, learning and geometric problems. Moreover, they surveyed the literature up to mid 1990s within these research axes and discussed constraints arising from technological limitations and identified distributed systems, artificial intelligence and biology to be important disciplines for MRS.

As research progressed in the direction of distributed systems and plenty of works demonstrated physical robot implementations, Arai et al. [5] and Parker [74] focused on distributed robotic systems and identified seven primary research topics within the context of MRS that includes biological inspirations, communication, architectures, localization/mapping/exploration, object transport and manipulation, motion coordi-
nation, and reconfigurable robots. Moreover, they discussed the growing interest and open issues in distributed MRS and pointed out that coordination and communication are the key challenges that drive this field. Many researchers started to focus on these particular aspects of MRS.

Farinelli et al. [6] presented a taxonomy that classifies the coordination approaches in MRS. Focusing on the coordination aspect, first the authors characterized MRS by two groups of dimensions, namely Coordination Dimensions and System Dimensions. The former aim at characterizing the type of coordination that is achieved in the MRS while the latter include the system features that influence team development. Their taxonomy is built within the coordination dimension targeting specific applications. They summarized the literature up to 2000 relating those to their taxonomy and indicated that the problem of coordination will be central to the design of MRS, especially when dealing with complex tasks and large scale systems.

Yan et al. [3] also focused on the problem of multi-robot coordination and in a systematic manner reviewed the existing literature on MRS. They also studied the coordination problem in multi-robot motion and task planning and analysed the methods that allowed conducting such planning in a MRS. More recently, Darmanin et al. [1] reviewed more recent works on MRSs and categorized them according to their application domain. Moreover, they emphasize that limited communication is one of the major challenges that occurs among the team members and needs to be solved in most application domains.

Parker [2] classified MRSs based on the architecture type, heterogeneity in the team, communication issues and task allocation schemes. Apart from that, several application domains were discussed.

In the following, a systematic characterization of MRSs focusing on coordination is presented. The characterization allows to understand the essentials, mechanism, complexity to formulate and tackle the coordination problem. We characterize MRSs with five primary topics, namely group size and composition, sensors, information and knowledge, multi-robot communication, multi-robot planning and coordination protocol, and multi-robot decision making structures.

2.3.1 Group size and composition

By looking at the composition of robots in a group, a MRS can be classified as homogeneous or heterogeneous. In a homogeneous group, each robot has identical embodiment, capabilities and payload capacity which is less complex and simpler to coordi-
nate and control as a group. Even the hardware and software of the robots are exactly same in these groups. One typical hierarchical architecture that targets medium and large scale homogeneous systems with simple robots is CEBOTS [75], which is inspired by the cellular organization of biological entities. Majority of works consider homogeneous groups in applications such as foraging [76], exploration [77], cooperative box pushing [78, 79], multi-arm manipulation [14, 15, 79], area surveillance[80], Robotic soccer [81, 82] and transportation [83].

In a heterogeneous group, the robots are diverse and may have dissimilar embodiments, different capabilities and sometimes each robot is specialized in doing only particular tasks. The diversity in such a group emerges from the difference in hardware components and control software. Even though these groups are known to increase flexibility and robustness [4], the robots require greater ability to tackle the coordination problem. In the literature dedicated architecture such as ALLIANCE were proposed for such groups and research works considering the use of heterogeneous robots in multi-robot applications such as search and rescue [84], surveillance and reconnaissance [85], exploration [86 87], assembly and construction [88] and multi-arm manipulation [16]. In both group types, to avoid any conflicts in operation, the robots are generally prioritized or assigned distinct roles at design-time, or dynamically at run-time [89, 90].

Figure 2.1 illustrates a body/brain evolution chart for MRS where a clear distinct-
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The distinction between multi-agent system (MAS), MRS and swarm robotics is presented in terms of the number of software agents (brains) and physical robots (bodies). Group size varies greatly in swarm robotics where it is usually determined based on time and cost factors and the type of application. However, the robots used in swarms are small, simple and equipped with few sensors and actuators. MRSs with highly capable robots on the other hand stay in the mid range in group size due to the applications concerned with limited workspace and tasks such as object manipulation and transportation in domestic, professional and hazardous environments.

2.3.2 Sensors, information and knowledge

A robot is embedded with sensors to gather information from the environment and to analyse its own condition. Sensors such as cameras, tactile sensors and force/torque transducers are widely applied in robots. For a manipulation task, a vision sensor often enables the robot to plan tasks and tactile and F/T sensors improve the performance task. In MRS, sensors play an important role in coordination and cooperation. For example if a system is heterogeneous and distributed, robots can use vision sensors to perceive and infer actions of other robot to make their own decision. However, the inference of the acquired information is based on the available knowledge.

In MRS, the level of information (global or local) that is available to the robot and the knowledge each robot possesses about others in the group determines the complexity of the coordination problem. A robot group with global information and complete knowledge is able to perform cooperative tasks precisely and effectively by optimally planning coordination. However, robots with local information and incomplete knowledge need to somehow model the other robots in the group while planning coordination. Modelling others’ actions, intentions, states and capabilities with some belief can increase cooperation quality as well as decrease the explicit communication requirements within the group. More often in the literature the modelling is carried out only with the implicit information that is perceived or gathered by the robots from the environment. In the modelling process, most importantly, the robots should have some representation of others to make inferences of this implicit acquired information. In this thesis, robot modelling has been explored most extensively in the context of multi-arm grasping where a common object is used.
2.3.3 Multi-robot communication

Communication between robots supports decision making in individual robots and enables cooperating robots to perform tasks effectively. Here we address how robots in a MRS can exchange information that is crucial for coordination and cooperation. In particular, the ways of inter-robot communication and the underlying mechanism are our primary focus.

Several papers detail communication in multi-robot systems. Dudek et al. [73] addressed the issue of communication by characterizing the communication system in terms of topology, range and bandwidth. Cao et al. [10] studied broadly about the interactions that could possibly occur in a multi-robot scenario. They identified interaction via communication, sensing and environment as the three major types and grouped them under communication structure.

By focusing on the ways of information exchange, Farinelli et al. [6] classified communication to direct or indirect whereas Yan et al. [3] referred to it as explicit or implicit. Both direct and explicit communication refer to a specific act of communication that aims to convey the precise information within the robot group whereas indirect and implicit refer to observing the side effects caused by robot actions or induced changes in the environment which aim to convey information that may be imprecisely observed by other robots.

We categorize communication in three forms based on the way the information is exchanged: communication via messages, communication via environmental changes and communication via physical interactions.

**Communication via messages:** This form of communication is explicit and refers to the direct exchange of information between robots through messages. The robots are bound to have a dedicated communication module to transmit and receive messages. A message can contain any information such as sensor data and command that belong to a particular robot. For example using a wireless network, robots can communicate their positions and task related data to the other robots.

Explicit communication can be used for performing loosely coupled [91] and tightly coupled [11] cooperative tasks in MRS. Even though this form of communication is precise, it is limited and complex when it comes to large number of robots and harsh environments. To handle and enhance explicit inter-robot communications, several frameworks, methods, techniques, schemes and languages have been proposed [2, 73, 6, 81, 92]. In the literature, most of the coordination approaches have used this form of communication.
Balch and Arkin in [93] studied the importance of communication and concluded that even though explicit communication significantly improves the performance in robot groups, it is not essential when an implicit form of communication is available. Moreover, they claim that complex communication strategies offer little or no benefit over simple ones. Vail and Veloso in [90] proposed an approach to coordinate a robotic soccer team where only crucial and minimal information is exchanged via messages and rest of the information is gathered or inferred via sensing the interactions.

**Communication via environmental changes:** This form of communication is implicit and refers to an indirect way of information exchange between robots (e.g. through visual changes). In simple terms, a robot observes the changes in the environment produced by another robot’s action, pose, gesture and interaction with objects and infer the changes to respond to others in a similar fashion such that the information is exchanged in a non-physical manner. This form of communication is possible only when robots in the multi-robot system are equipped with appropriate sensors (e.g. vision sensors) to observe the changes.

In this form of communication, the robots require the ability to distinguish other robots in a group and objects in the environment. Moreover, the way each robot perceives the robot induced changes involves modelling of other robots. For example, if robot A needs to infer the perceived changes of robot B such as position and orientation, first the robot A has to model robot B with its available representations and reason the change and vice versa so that both are able to cooperate with the changes. Vaughan et al. in [94] demonstrated a foraging task performed by mobile robots that communicate by leaving landmarks in the environment. This form of communication has recently been utilized in coordination approaches and has gained momentum in the multi-robot research community.

**Communication via physical interaction:** This form of communication is implicit and refers to an indirect way of information exchange between robots through physical interactions. In simple words, a robot observes the physical forces induced by other robots using appropriate sensors and infer the intent to respond others in similar fashion such that the information exchange occurs in terms of physical means.

The inter-robot communication is thus achieved through the interaction forces sensed by the cooperating robots. This form of communication also demonstrated by Khatib et al. in [95] for cooperative manipulation task. This form of communication is widely adopted and beneficial in cooperative manipulation due to the continuous requirement of information exchange.
2.3.4 Multi-robot planning and coordination protocol

In MRS, planning is essential to coordinate a group of robots in order to accomplish overall system goals. Task planning and motion planning are the two main aspects considered in multi-robot planning. Recently, grasp planning has also gained popularity due to the increasing number of robots with grippers and demand of cooperative manipulation tasks in several application domains. In the following we detail these planning aspects.

In multi-robot context, task planning has been studied from two perspectives, namely task decomposition and task allocation. On one side, the problem on how to decompose an overall system goal or complex task [96] into sub tasks has been studied. The problem of task decomposition has been addressed in a soccer robotic system [97, 98] and heterogeneous MRS [99]. On the other hand, the problem on how to allocate tasks to robots to maximise system performance has been the main focus and has been considered as an instance of the optimal assignment problem. Several authors proposed taxonomies [100, 101] and reviewed [102] the state of the art in multi-robot task allocation MRS. Several task allocation approaches are presented in the literature such as auction based [78], market based [103] and trade based [104]. Wawerla and Vaughan [83] presented two task allocation strategies for a multi-robot transportation system.

Motion planning [105] is the problem of generating a continuous robot motion for a known or unknown path while avoiding collisions with obstacles. In addition, multi-robot motion planning considers possible interference between robots. This problem has been studied mainly on mobile multi-robot systems [106] and to an extent in multi-arm systems [107, 108, 109]. In the multi-robot context, motion planning falls under two main categories; that is deliberative and reactive [93]. Pure reactive methods offer real time response by using only local information. For example, the potential field approach falls under this category. Deliberative methods use prior knowledge to plan a path and pre-calculate robot motions, where cell decomposition [110, 111], potential field [112, 113] and roadmaps are the three major approaches in application domains such as area coverage, exploration and industrial manipulation. The roadmaps can be further divided into Voronai diagram [114, 115], probabilistic [107, 109] and sampling based (RRTs [116] & PRMs [108]). In these approaches, only for cell decomposition map of two dimensional workspace in order to cut down the computation complexity and high dimensional space. Moreover, the problem of continuous motion planning is reduced to a discrete graph search problem.
in the workspace. The development of these approaches follows ones for single robot systems.

Multi-robot grasp planning (MRGP) is the problem of determining grasps for a set of robots in such a way it is cooperatively optimal with respect to external disturbances or specific tasks. In this thesis, we explore this problem for robots in a group that are decentralized in nature and heterogeneous in composition.

As a coordination protocol, a MRS can adopt either a sequential protocol where each robot acts in a sequence based on assigned priorities or a simultaneous protocol where all the robots in a group act simultaneously based on the assigned roles. The selection of a coordination protocol in MRS is also mainly dependent on the decision making structure.

2.3.5 Multi-robot decision-making structures

Decision making structures in MRS can be classified to centralized and decentralized. For a group of robots, a decision making structure can be adopted by analysing the physical ability and capability of individual robot, limitations on communication, availability of sensors, constraint on environment, cooperative task and the type of multi-robot coordination problem to be solved. In the following we detail these structures and point out related works.

Centralized decision making: In centralized structures, a central unit that may be leader has complete knowledge of cooperating robots and global information about the state of robots and environment. Thus, for a given task, the central unit can generate an optimal team plan and directly communicate the decision to the individual robots. At the same time, cooperating robots convey relevant state information to the central unit in order to update decisions. This structure is effective for small group sizes with reliable communication and operations in static environments.

In GOFER project, Caloud et al. [117] presented a sense-model-plan-act architecture for indoor automation which was aimed to perform tasks such as maintenance, cleaning, hazard detection and object transportation with multiple mobile robots. They demonstrated simple tasks such as pushing a box with three identical robots. Chaimowicz et al. [118] developed an architecture for tightly coupled multi-robot coordination that offers flexibility in leadership change and role assignment. A leader-follower approach with role assignment mechanism was demonstrated while performing manipulation and transportation of objects in an unstructured environment with heterogeneous teams. Several examples of centralized approaches for
Background and Related Works

Multi-robot coordination can be found in [119, 120] related to cooperative manipulation and transportation and in [121, 122, 123] for multi-robot exploration applications. MRS with such a structure can be considered to be a single robotic system having multiple degrees of freedom. Centralized structures are vulnerable since they heavily rely on communication and central unit for decision making, and any delays in communication can lead to task failure and any malfunctions of central unit can cause a system failure.

Decentralized decision making: Under a decentralized structure, each robot plans and decides on its own using local information available through its sensors to accomplish a common goal. There is no central unit to share global information or to make decisions on behalf of other robots. In a decentralized system, robots often gather or infer local information from physical interaction or visual observation such that explicit communication requirement is minimized. This enables faster and better response of robots to dynamic changes in the environment. In MRS, decentralized strategies are mainly based on sequential decision making such that each robot gets a chance to observe and reason its own decision towards the common goal. However, there are approaches that purely rely on assigned roles of the robots in a group.

A decentralized architecture has several advantages over a centralized one [3, 124, 125, 126, 127, 128]. Usually this architecture: 1) does not suffer from single point failures (reliable); 2) is more robust since all robots operate independently (robustness); 3) lowers the computational complexity of the system since each robot computes and optimize its own plans and decisions; 4) has the potential to accommodate a large number of robots (scalable); 5) allows the robots to adapt and better respond to local changes in the environment. However, the main drawback of this architecture is that the solutions are often sub optimal. Decentralized multi-robot systems such as ACTRESS [129] and M+ [130] have been proposed for loosely coupled tasks such as box pushing. Dedicated distributed architectures such as ALLIANCE [124] offer solutions to multi-robot cooperation. Based on this architecture Parker also demonstrated foraging, box pushing and target tracking. Recently proposed MURDOCH [131] is a task allocation system that is based on a distributed negotiation mechanism, the system demonstrated its handling capacity for tightly and loosely coupled tasks for both homogeneous and heterogeneous teams.
Background and Related Works
Part II

Multi-Robot Grasp Planning Under Heterogeneity and Decentralization
3. Grasp Quality Evaluation

A primary goal of a robotic grasp is to immobilize an object to allow precise manipulation. The ability to resist external disturbances is the key grasp property for robotic applications and it can be determined by quantifying the quality with an appropriate quality measure. The concept of wrench space that is composed of forces and torques is considered elegant and useful in grasp evaluation.

In this chapter, we focus on wrench space measures to evaluate grasp quality. In particular, measures that associate geometric location of the contacts and consider limitations on finger forces [43] are considered for evaluation. First, a necessary background on grasp analysis is given. Then, we categorize wrench space measures into non task specific (NTS) and task specific (TS). The NTS measures quantify a grasp by examining how well the grasp can withstand external wrenches from any direction. TS measures quantify a grasp based on the ability to resist disturbances from a task that is to be performed. Finally, a formulation to evaluate multi-robot grasps based on the wrench space measures is presented. When planning cooperative grasps, this allows a team of robots to determine a globally optimal solution and rank other grasp combinations.

3.1 Background

Given an established grasp, two questions arise: on what basis the grasp should be evaluated and how to compute its effectiveness. These key questions are typically addressed by grasp quality measures. The basis for evaluation can be determined by identifying the properties of a grasp without prior knowledge of a task.

In general, four properties are looked for in a grasp: Disturbance resistance, dexterity, equilibrium and stability [43]. Among them, disturbance resistance is crucial for a grasp that ensures the immobilization of an object even under external disturbances.
Form and force closure are the well known conditions to maintain object immobility. Form closure analysis considers the grasp geometry whereas force closure is about the finger contacts and their friction constrained force components. Force closure is an well established criterion for a grasp which ensures to withstand external wrenches applied on the object from any direction. In the early literature, Salisbury [132], presented an analytical procedure for testing the form and force closure and later Nguyen [133] defined force closure condition for a grasp. Trinkle [134] developed a measure to evaluate 'how far a grasp is from losing form closure' and a method to examine strong force closure. Nowadays force closure criterion is considered to be a minimal requirement in grasping applications.

Two approaches, analytical and empirical, can be traditionally followed to find force closure grasps for 3D objects. The analytical approach is concerned with finding contact locations on the object surface for a grasp to be force closure which come under the grasp synthesis problem and the algorithms associated to this approach rely heavily on optimization theory which takes significant amount of computational time in providing solution. Moreover, finding the hand configuration and pose is another problem to be solved for given force closure contacts. These factors limit the applicability in online planning. A survey on grasp synthesis algorithms can be found in [31]. The empirical approach is concerned on analysing a set of available candidate grasps such that each grasp is checked whether they are force closure and ranked according to a quality measure. This approach finds optimal force closure grasp among the candidates corresponding to the quality criterion. For known objects, various methodologies for sampling and ranking grasps are presented by Bohg et al. in [135] under the hood of data driven grasp synthesis.

Mishra in [136] compared various quality metrics and addressed their computational complexity. A rich survey on grasp quality metrics is presented by Roa and Suarez in [43], where they associate measures with respect to contact location and hand configuration. In particular, the contact location associated measures are divided into three groups: algebraic, geometric and limit on the magnitude of force. Wrench space metrics are popular among the metrics since they represent forces and torques which gives a physical meaning in grasp quality evaluation. In this thesis, we consider wrench space quality measures that associate geometric location of the grasp contacts and considers the limitations of the finger force that can be applied on the object.
3.2 Grasp analysis

To analyse a grasp, first the type of contact that occurs between two bodies and their associated model is chosen. Second, to capture all contacts of a grasp and to examine the total force and torque acting on the object, a compact grasp expression which maps the applied contact force to a single frame of reference is formulated. Third, to facilitate grasp evaluation, the space of wrenches (force and torques) that belongs to a grasp, object and task is constructed and considered.

3.2.1 Contact model and friction

Choosing the contact type between finger and an object is fundamental to grasp analysis. A contact is modelled by selecting particular force or/and moment components that need to be transmitted to the object via point or region. Three types of point contact models are widely used to analyse the multi-fingered robot grasp:

![Contact Models]

<table>
<thead>
<tr>
<th>Contact Models</th>
<th>Transmitted Components</th>
<th>Frictional constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>PwoF</td>
<td>$[f_n]^T$</td>
<td>$f_n \geq 0$</td>
</tr>
<tr>
<td>HF</td>
<td>$[f_n, f_o, f_t]^T$</td>
<td>$\sqrt{f_o^2 + f_t^2} \leq \mu f_n, f_n \geq 0$</td>
</tr>
<tr>
<td>SF</td>
<td>$[f_n, f_o, f_t, m_n]^T$</td>
<td>$\sqrt{f_o^2 + f_t^2} \leq \mu f_n, f_n \geq 0, m_n \leq \mu_2 f_n$</td>
</tr>
</tbody>
</table>

Table 3.1. Contact models and their corresponding wrench intensity vectors.

A Frictionless model is used when a contact takes place in a frictionless point. It only transmits the force applied at the contact in normal direction. This model
Grasp Quality Evaluation

is useful in theory and not applied in practice. A Hard finger model is used when a contact takes place in a frictional point. Under the Coulomb friction constraint, it transmits force in both tangential and normal direction at the contact point. Soft finger model is used when a contact takes place in a frictional region. It allows not only forces in all directions but also moment about the normal direction.

Fig. 3.1 illustrates the three contact models and their corresponding wrench intensity vector and frictional constraints are presented in Table 3.1 A complete review on types of contact between two bodies can be found in [137] (e.g. line and planar contacts). In this thesis, we use the hard finger model to analyse the contacts from established robot grasps. A grasp which makes use of frictional forces to avoid slippage between object and robot hand is the preferred characterization in our study.

Friction is a useful phenomenon in robotic grasping and static friction is a resisting force that prevents slipping between two bodies in contact. When friction occurs at a point contact, knowing the range of tangential frictional force \( f_o, f_t \) corresponding to the exerted normal force \( f_n \) is the point of interest. Coulomb friction model is one way to represent the static friction. To ensure non-slippage, a contact force \( \vec{f} = [f_n, f_o, f_t]^T \) at a point \( j \) must satisfy the frictional constraint

\[
FC_j = \{ \vec{f}_j \in \mathbb{R}^3 | \sqrt{f_o^2 + f_t^2} \leq \mu f_n \} 
\]

where \( \mu \) is the empirically determined coefficient of friction that bounds the tangential components \( f_o, f_t \) with respect to the applied normal component \( f_n \) at the contact point. \( FC_j \) is then called as a friction cone. In short, all admissible forces by a contact normal are constrained to the friction cone. Generally, the non-linear problem in constraint (3.1) is solved by linear approximation. For simplicity and convenience, the friction cone is linearised by an \( n \)-sided polyhedral convex cone shown in Fig 3.2 and a edge vector on the boundary of the cone at contact point \( j \) is represented as

\[
\vec{v}_{jk} = \begin{bmatrix} f_{nj} \\ \mu \cos \left( \frac{2\pi k}{m} \right) f_{o_j} \\ \mu \sin \left( \frac{2\pi k}{m} \right) f_{t_j} \end{bmatrix}
\]

Under this approximation, the contact force can be represented as

\[
\vec{f}_j \approx \sum_{k=1}^{m} a_{jk} \vec{v}_{jk}; \quad a_{jk} \geq 0,
\]

where coefficient \( a_{jk} \geq 0 \), amplitude of contact force, can be bounded to one by setting constraint \( \sum_{k=1}^{m} a_{jk} \leq 1 \) because the edge vectors are unitary forces. This
simple constraint and assumption is useful to analyse grasp with multiple contacts because the constrained contact force is upper bounded by applying unit force in the normal direction.

\[ \vec{w}_j = B_j \vec{f}_j \]

where \( \vec{f}_j \) is the force applied at the contact point and \( B_j \) is the wrench basis matrix that captures the wrench intensity vector transmitted through that contact. For example, a hard finger model has the following:

\[
B_j = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

\[
\vec{f}_j = [f_n, f_r, f_o]^T \sqrt{f_o^2 + f_r^2} \leq \mu f_n
\]

Let us consider an n-fingered robot hand grasping an object and our goal is to compute the net wrench acting on the object. First we need to express the contact force at different locations in a common reference frame. By having the centre of mass...
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of an object as a reference frame one can also capture the moment induced by each contact force on the object. A single contact wrench in the object coordinate frame is expressed as

\[
\vec{w}_j^o = T_j^o B_j \vec{f}_j,
\]

\[
T_j^o = \begin{bmatrix}
R & 0 \\
\vec{c} \times R & R
\end{bmatrix}
\]

(3.6)

where \( T_j^o \) is the fixed transform between contact frame and object frame for a particular contact. A grasp matrix \( G \) collects each transformed wrench basis that maps the applied force at each contact point to a single frame of reference, preferably the grasped object’s centre of mass. Finally the net resultant wrench acting on the object can be computed from

\[
\vec{W}_o = G \vec{F}, \quad G = [T_1^o B_1, \ldots, T_n^o B_n], \quad \vec{F} = [\vec{f}_1, \ldots, \vec{f}_n]
\]

(3.7)

To study and optimize the grasp forces, the expressions in (3.6) and (3.7) is useful. However, our objective is to evaluate a grasp and quantify them under a unit wrench space.

3.2.3 Wrench space

The space spanned by force and torque vectors is called a wrench space. One can analyse the properties of a grasp by examining the wrench space constructed from grasp contact wrenches. In our case, the force closure property is the minimal criterion expected from a grasp to withstand an arbitrary disturbance. Moreover, a wrench space constructed from object or task wrenches also facilitates grasp quality evaluation. In particular, to quantify a grasp, several existing quality measures utilize a wrench space that belongs to an object or task.

Generally, a grasp is modelled with contacts that occur between the robot hand and object. A grasp wrench space (GWS) is spanned by contact wrenches applied through a grasp. For frictional contacts, the force applied at each contact points is constrained to a friction cone. A contact wrench modelled with discretized friction cone \( \mathcal{F}_j \) and torque multiplier \( \lambda \) for scale invariance that complies with the unit space is expressed as

\[
\vec{w}_j = \left( \frac{\vec{f}_j}{(\vec{c}_j \times \vec{f}_j)/\lambda} \right) = \sum_{k=1}^{a_{jk}} a_{jk} \vec{w}_{jk}
\]

where,

\[
\vec{w}_{jk} = \left( \frac{\vec{v}_{jk}}{(\vec{c}_j \times \vec{v}_{jk})/\lambda} \right)
\]

(3.8)
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at the contact point \( j \), \( \mathbf{w}_{jk} \) is the primitive wrench produced by the exerted primitive force (edge vector) along each edge of the linearised friction cone that spans through the wrench space. The contact force is upper bounded since the normal components are under the frictional constraint. Ferrari and Canny showed how to build a unit grasp wrench space in [138] for two optimality criterion’s. Without setting a quality criterion, a grasp wrench space by computing convex hull over the set of primitive wrenches can be built as:

\[
GWS \triangleq \text{CH}(\bigcup_{j=1}^{n_j} \{\mathbf{w}_{j1}, \ldots, \mathbf{w}_{jn_k}\})
\] (3.9)

Several works demonstrated the use of contact locations to evaluate grasp quality [139, 138].

A task-oriented grasp is expected to resist task induced disturbance wrenches and maintain force equilibrium throughout the task. The wrench space spanned by the expected task disturbance for a given task is known as the task wrench space (TWS). By measuring how well the TWS can fit inside the GWS, one can determine the task oriented grasp quality. However, incorporating the task criteria in evaluation is challenging due to the difficulty in modelling a task. Only few works have addressed the problem of task modelling while the rest have focused on incorporating task specifications directly in grasp planning.

A task can be modelled either by sensor measurements from human demonstration or a heuristic approximation based on experience. The sensor measures vary with objects, tasks, tools and environment which is challenging in task generalization and requires a lot of human effort to capture. Therefore, instead of measuring, most works adopt the method of approximating the task wrench space. Getting inspiration from manipulability ellipsoids Yoshikawa [140], Li and Sastry [141] approximated the task by a wrench space ellipsoid and computed a task oriented grasp quality measure. They modeled the task with object trajectory which was planned according to the specific task and object geometry.

Incorporation of the geometry of object in the wrench space is useful in grasp quality evaluation. Pollard [142] introduced object wrench space (OWS) that accounts for all possible task disturbance wrenches by incorporating the object geometry in the wrench space. In simpler terms, any disturbance wrench that acts on the surface of the object is captured in the OWS. An elementary wrench generated by a unit length disturbance force \( \mathbf{f}_j \) acting on any point \( j \) on the surface of the object can be
Grasp Quality Evaluation

expressed as

\[ w_j = \begin{bmatrix} f_j \\ (e_j \times f_j)/\lambda \end{bmatrix}, \quad f_j \in FC_j, \quad ||f_j|| = 1, \quad j = 1, \ldots, \infty \] (3.10)

OWS is the union of elementary wrenches that is exerted on the surface of the object by the unit force disturbances constrained with set \( O_c \)

\[ OWS \triangleq \mathbb{C}(\bigcup_{j=1}^{n_j} \{ w_j \}) \] (3.11)

which can also be considered to be the wrench space that belongs to all potential grasps. Similar to the idea in [141], Borst et al. [143] approximated the OWS with an ellipsoid and measured the quality by fitting the OWS ellipsoid in GWS. Even though the object wrench space has to be computed for one single time, the measures associated have no physical meaning when it comes to specific task but it is useful when the task is unknown. Haschke et al. [144] proposed a metric that evaluates a grasp for a specific task which accounts for wrenches in a particular direction. In particular, they evaluated a grasp based on the task wrench along single direction built upon an optimization problem which has application in pushing and lifting and rotating objects. However, an optimal grasp based on the metric does not guarantee robustness towards disturbances while performing the manipulation task since the grasps are not necessarily force closures.

Zhu and Wang [145] presented the notion of Q distance and proposed the idea for designing a convex set (Q set) in the wrench space instead of the traditional unit ball. When any constructed convex set contains the given point (origin) with at least a minimum scale factor they guarantee the force closure property of a grasp and the scale is considered as a Q measure. Then, Boutselis et al. [146] incorporated task specific information in the Q set containing the origin and evaluated the grasp quality by fitting them within the GWS. The optimal grasp determined from the task oriented criteria is expected to withstand disturbances in particular direction, that is heuristically approximated from the task specifications.

Focusing on task specificity, some recent works considered using haptic devices to gain grasp experience and gather actual manipulation measurements from human demonstration. Aleotti and Caselli [147] used a data glove to demonstrate a sequence of task oriented exemplary grasps in a virtual reality environment and formulated a functional wrench space (FWS) by mapping the demonstrated human hand grasp to the robot hand grasp. The FWS spanned with the task specific wrench set is used
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to evaluate the set of candidate grasps for determining an appropriate task oriented grasp. However, they are unable to capture the wrench exerted throughout the task. Moreover, the correspondence problem in kinematic and configuration space between robot and human hands is an open issue. In the same line earlier Li and Pollard [148] searched for candidate grasps by a shape-matching algorithm and evaluated the grasps by a task-oriented criterion.

Lin and Sun [149] used a Phantom Omni device to collect task related disturbances from the human task specific demonstration carried out in virtual reality environment. Rather than simple pick and place task they aim to model interactive tasks (e.g. writing with a pencil) and proposed a task-oriented metric based on distribution of task disturbances. In particular, the scaling factor between unit grasp wrench space (UGWS) and the TWS is taken as the quality measure. This quality measure checks the candidate grasps ability to withstand impulses and periodic disturbance that occurs during an interactive task. The approach and quality metric complements each other well. However, the applicability of the approach is limited due to constraints enforced such as thumb placement area and grasp types.

Moreover, the wrenches that occur on the fly varies. Therefore, the selected grasp is guaranteed to succeed only if the manipulator mimics the human demonstration exactly. Task specificity in grasping is still an open problem.

3.3 Wrench space metrics

Once an object is grasped by a robot hand two main question arises: how effective is the grasp against disturbances and is the grasp good enough for a particular task. By evaluating the quality of the grasp one can determine the grasp.

Metrics that evaluate grasp quality by analysing the 6-D wrench space spanning contact wrenches is our primary focus. In particular, we are interested in metrics that consider a limit on the magnitude of the force applied by the fingers at the contacts. Several metrics evaluate grasps without setting limits on finger forces which causes ambiguity while applying forces that is needed to resist small or large magnitude of disturbance wrenches, even though they are force closure. These algebraic and geometric quality measures do not characterize force and torque which are crucial to grasps with few contacts.

The following wrench space metrics evaluate the quality of a grasp with the limits enforced in finger forces such that a chosen grasp can resist any magnitude of
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disturbance wrenches from all or particular direction with minimal effort.

3.3.1 Non task specific metrics

Kirkpatrick et al. [139] proposed a non task specific quality measure for an n-fingered robot grasp. By fitting a largest ball in the unit grasp wrench space they quantified the quality of a grasp. This measure (radius of the fitted ball) reflects the ability of a grasp applying unit force at each contact point to withstand external disturbance (forces and torques) from any direction. Ferrari and Canny [138] improved this work by presenting two optimality criteria that emphasize the arrangements of grasp force. The two criteria are formulated by imposing constraint on the finger forces and normalizing the normal force component applied by each finger. In the following they are briefly discussed

**Criterion 1:**
The magnitude of the force applied by each finger is independent and individually bounded by setting \( \| \mathbf{f}_n \| \leq 1 \) where the normal component for each finger is assumed to be similar and normalised to one. The primitive wrenches from a grasp are generated by following the same procedure as in criterion 1. Under the \( L_\infty \) norm, the resultant wrench produced by n-fingered robot grasp is given by

\[
W_{L_\infty} = \sum_{j=1}^{n} \sum_{k=1}^{m_j} a_{jk} \mathbf{w}_{jk} \quad a_{jk} \geq 0, \sum_{k=1}^{m_j} a_{jk} \leq 1 \quad (3.12)
\]

The convex hull of the Minkowski sum of the individual convex sets of primitive wrenches applied at each contact point under the \( L_\infty \) unit grasp wrench space is expressed as

\[
UGWS_{L_\infty} = \bigcap_{j=1}^{n} \left\{ \bigoplus_{j=1}^{m_j} \mathbf{w}_{jk} \right\} \quad (3.13)
\]

**Criterion 2:**
The sum magnitude of forces applied by the fingers at the contact points is upper bounded by setting \( \sum_{j=1}^{n} \| \mathbf{f}_n \| \leq 1 \) where the normal component \( \mathbf{f}_n \) is normalized and assumed to be unit in magnitude. If all contacts that occur from a grasp have friction, then the contact force applied at a point can be expressed as a set of primitive forces \( \mathbf{v}_{j1}, ..., \mathbf{v}_{jm} \) which corresponds to the unitary edge vectors on the boundary of the discretized friction cone (see (3.1)). These primitive forces then produce a set of primitive wrenches \( \mathbf{w}_{j1}, ..., \mathbf{w}_{jm} \) at each contact point for which a compact expression is given in (3.8). The resultant wrench produced by the robot grasp on the object is
given by
\[ W_{L_1} = \sum_{j=1}^{n_j} \sum_{k=1}^{n_k} a_{jk} \vec{w}_{jk} \quad a_{jk} \geq 0, \sum_{j=1}^{n_j} \sum_{k=1}^{n_k} a_{jk} \leq 1 \] (3.14)

The convex hull of the primitive wrenches \( w_{jk} \) under a L1 norm with respect to a unit grasp wrench space
\[ UGW_{S_{L_1}} = \text{CH}(\bigcup_{j=1}^{n_j} \{ \vec{w}_{j1}, \ldots, \vec{w}_{jn_k} \}) \] (3.15)

For grasp evaluation, we use the widely accepted non task specific measure known as epsilon metric which is a gauge (0–1) for force closure grasps. \( \varepsilon \) is computed using a unit grasp wrench space defined under \( L_1 \) norm. In other words, we adopt Criterion 2 to built a unit grasp wrench space for grasp evaluation. The measure corresponds to the radius \( r \) of the largest ball \( B_r = \{ b \in \mathbb{R}^6 \mid \| b \|_2 \leq r \} \) fitting inside the convex hull of the contact wrenches \( W^i \). The grasp quality is then
\[ \varepsilon_{\text{metric}} = \max_r \{ B_r \subseteq (UGW_{S_{L_1}}) \}. \] (3.16)

### 3.3.2 Task specific metric

As opposed to the Euclidean grasp quality metrics that employ symmetric norms (i.e., \( L_i, i = 1, \ldots, \infty \)), herein, we consider a task specific measure that is based on the concept of \( Q \)-distance, originally proposed in [145] for curved objects. Let us first denote \( \text{int}(\ast) \) as interior of a set and \( \mathbf{0} \) as origin of the wrench space. Given a compact, polyhedral convex set \( Q \subset \mathbb{R}^m \) that contains the origin (i.e., \( 0 \in \text{int}(Q) \)), the \( Q \)-distance from a point \( \vec{c} \in \mathbb{R}^m \) to a convex polyhedron \( A \subset \mathbb{R}^m \) (i.e., \( d_Q(\vec{c},A) \)) can be defined as [145], as follows:

<table>
<thead>
<tr>
<th>If ( \vec{c} \notin \text{int}(A) )</th>
<th>If ( \vec{c} \in \text{int}(A) )</th>
</tr>
</thead>
</table>
| \[ d_+^Q(\vec{c},A) = \min \sum_{k=1}^{K} \rho_k \] \[ s.t. \] \[ \sum_{k=1}^{K} \rho_k \vec{u}_k = \sum_{i=1}^{N} \alpha_i \vec{a}_i - \vec{c} \] \[ \sum_{i=1}^{N} \alpha_i = 1 \] \[ \rho_k, \alpha_i \geq 0 \] | \[ d_Q^-(\vec{c},A) = \max_{k=1,\ldots,K} d_Q^-(k) \] \[ \text{where} \] \[ d_Q^-(k) = \min(-\rho) \] \[ \rho \vec{u}_k = \sum_{i=1}^{N} \alpha_i \vec{a}_i - \vec{c} \] \[ s.t. \] \[ \sum_{i=1}^{N} \alpha_i = 1 \] \[ \alpha_i, \rho \geq 0 \]
where $\vec{u}_k, k = 1, \ldots, K$ and $\vec{a}_i, i = 1, \ldots, N$ denote the vertices of $Q$ and $A$ respectively. Notice that the aforementioned linear programs can be easily solved using the simplex method.

Assuming that $\{\vec{w}_j, \ldots, \vec{w}_{jn}\}$ are the primitive wrenches of the grasp configuration, the inequality $d_Q^-(0, \text{CH}(\{\vec{w}_j, \ldots, \vec{w}_{jn}\})) < 0$ is equivalent to a set containing the origin denoted as $0 \in \text{int}(\text{CH}(\{\vec{w}_j, \ldots, \vec{w}_{jn}\}))$ and can be considered as a sufficient condition for force closure. The task specific metric can be expressed as

$$Q_{\text{metric}} = \left| d_Q^-(0, \text{CH}(\{\vec{w}_j, \ldots, \vec{w}_{jn}\})) \right|$$

which can be geometrically interpreted as the largest radius of the $Q$-set contained in $\text{CH}(\vec{w}_j, \ldots, \vec{w}_{jn})$. Therefore, larger $\left| d_Q^-(0, \text{CH}(\{\vec{w}_j, \ldots, \vec{w}_{jn}\})) \right|$ leads to a grasp configuration with larger radius of the $Q$-set that fits within the convex hull of the primitive wrenches. Notice that the utilized quality measure is tightly connected to the $Q$-set; thus, the optimal configuration (i.e., the configuration that maximizes $\left| d_Q^-(0, \text{CH}(\{\vec{w}_j, \ldots, \vec{w}_{jn}\})) \right|$) is directly related to $Q$. Hence, from the aforementioned statement and aiming at formulating a task oriented metric [146], the $Q$-set should contain the origin as well as those wrenches that need to be applied in order to balance the task disturbances. Therefore, instead of just guaranteeing the force closure property as in [145], the obtained configuration will be able to compensate disturbances in particular directions corresponding to the task specifications.

![Figure 3.3](image-url)  

**Figure 3.3.** A hypothetical example illustrating the advantage of the $Q$-distance over the $L_2$ norm in evaluating the task specificity of grasp configurations.

To illustrate the aforementioned, let us consider Fig. 3.3. In these images two hypothetical convex hulls are depicted, for two grasp configurations. The quality
Grasp Quality Evaluation

The metric used in the first case is the $L_2$ norm, while in the second case, the adopted $Q$-set differs significantly from the $L_2$ sphere. It is obvious that the convenient $L_2$ norm evaluates equally these two cases. In contrast, the $Q$-distance discriminates the two configurations according to the task specifications imposed by the $Q$-set.

3.4 Multi-robot grasp evaluation

Assume $N$ robots, $R^1, R^2, \ldots, R^N$ grasping an object. Let $\mathcal{C}^i$ be the contact point set of robot $i$ such that $\mathcal{C}^i = \{ \mathbf{c}^i_1, \ldots, \mathbf{c}^i_{n_{pi}} \}$ are the contact points. The contact forces must then satisfy the friction constraint

$$\sqrt{(f_{n_j})^2 + (f_{t_j})^2} \leq \mu f_{f_{n_j}}; \quad i = 1, \ldots, N, \; j = 1, \ldots, n_{pi} \quad (3.18)$$

where $f_{n}$ and $f_{o}, f_{t}$ denote normal and tangential force components.

In other words, each contact force $f_j = [f_n, f_o, f_t]^T$ must lie within the corresponding friction cone. In a multi-robot scenario, the static coefficients of friction $\mu$ may vary according to the materials of object and robot hand. Following the standard approach, the friction cones are linearised as $n_k$-sided polyhedral convex cones. Thus, the force applied at the $j^{th}$ contact of robot $i$ can be approximated as

$$\mathbf{f}_j^i \approx \sum_{k=1}^{n_k} a_{jk} \mathbf{v}_{jk} \quad a_{jk} \geq 0 \quad (3.19)$$

where $\mathbf{e}_{jk}$ denote the edge direction vectors of the linearization. The magnitude of the grasp contact forces is determined by limiting the sum magnitude of the contact normal forces to one, $\sum_{j=1}^{n_{pi}} \sum_{k=1}^{n_k} a_{jk} \leq 1$. The wrench set produced by contacts of robot $i$ can then be written $W^i = \{ \mathbf{w}^i_1, \ldots, \mathbf{w}^i_{n_{pi}} \}$ where wrench of the $j^{th}$ contact is

$$\mathbf{w}^i_j = \left( \frac{\mathbf{f}_j^i}{\lambda} \right) \cdot \left( \mathbf{e}_j^i \times \frac{\mathbf{f}_j^i}{\lambda} \right), \quad \lambda = \max_{j \in \{1 \ldots n_{pi}\}} \| \mathbf{e}_j^i \| \quad (3.20)$$

As forces and torques do not share a common metric, the torque component of the wrench is scaled by $\lambda$, the distance from object centroid to the furthest contact, to ensure scale invariance. We also limit the magnitude of the multi-robot grasp contact forces by $\sum_{i=1}^{N} \sum_{j=1}^{n_{pi}} \sum_{k=1}^{n_k} a_{jk} \leq 1$ such that the wrench space formed by the grasps of all $N$ robots is defined under an $L_1$ norm as

$$\text{MGWS} = \text{ConvexHull} \left( \bigcup_{j=1}^{N} \{ \mathbf{w}^i_{j1}, \ldots, \mathbf{w}^i_{j_{n_{pi}}} \} \right). \quad (3.21)$$

Any grasp that contains the origin of the wrench space is a force closure. We define that a cooperative grasp is valid only if $0 \in \text{int(ConvexHull}\{ \mathbf{w}^i_{j1}, \ldots, \mathbf{w}^i_{j_{n_{pi}}} \}) \forall i$, that is,
the grasp of each robot is independently a force closure. This condition is needed in
the decentralized setting since robots do not accurately know each others’ grasps. It
should be noted that (3.21) models the forces as dependent on each other.

To define a quality metric for the multi-robot grasp, we use the epsilon metric in
(3.16) which is a gauge (0–1) for force closure grasps. ε is computed using a unit grasp
wrench space defined under $L_1$ norm. The measure corresponds to the radius $r$ of the
largest ball $B_r = \{ b \in \mathbb{R}^6 \mid \| b \|_2 \leq r \}$ fitting inside the convex hull of the multi-robot
contact wrench space (MGWS). The cooperative grasp quality is then

$$C_\varepsilon = \max_r \{ B_r \subseteq (MGWS)_{L_1} \}. \quad (3.22)$$

The task specific wrench space quality measure in (3.23) quantifies the grasp quality
corresponding to a task specification at the same time checking the force closure
property of a grasp. The task specific cooperative grasp quality is then

$$CQ_{\text{metric}} = \left| d_0^C(0, \mathbb{CH}(\{w_{j1}, ..., w_{jn} \})) \right| \quad (3.23)$$

### 3.5 Discussion

In this chapter we presented the necessary background to analyse robotic grasps and
a formulation to quantify the quality of multi-robot grasps based on the task specific
and non-task specific wrench space grasp quality measures. Computing the maxi-
mum disturbance wrench in a unit wrench space that can be resisted by the contacts
is one of the most popular ways to evaluate the quality of a grasp, and this met-
ric has been used in many grasp analysis tools [27]. In this thesis we use criterion
one (Sum magnitude version) which models the forces as dependent on each other.
This version was chosen over criterion two (Minkowski sum version) which consid-
ers independent forces for computational efficiency since the Minkowski sum has
exponential complexity in number of contact points.
Grasp Quality Evaluation
4. Grasp Planing for Multi-Robot Coordination

In this chapter, we present multi-robot grasp planning (MRGP) approaches for a group of robots under three different decision making structures, namely centralized, decentralized and strictly decentralized. The approaches evaluate wrench space measures for making grasp coordination decisions. In particular, we evaluate these measures in probabilistic context for decentralized systems to compensate for the incomplete information.

4.1 Related Works

There are two major lines of research in multi-robot systems. On one hand, several multi-robot system architectures have been proposed to build, negotiate and execute plans \([150, 124, 9, 118]\) in centralized and distributed fashions. On the other hand, control schemes for cooperative robots have received wide attention. In particular, achieving precise motion coordination in manipulation is in constant development \([151, 8]\). These are motivated by applications in field, service and space robotics such as building construction, cargo handling and object transportation which involve multi-robot cooperative handling of large, complex and heavy objects. We are interested in developing coordination approaches for decentralized robots with minimal communication and sensing requirements.

Coordination problems are traditionally often modelled using game theory \([152]\). However, our problem is different from the standard coordination game where the agents need to make simultaneous decisions without knowing each others choice being made but sharing the information about each others’ dynamics. In contrast, in our case the “rules” of the game are not shared as the agents are not aware of the actions available to other agents. Instead, the agents are able to (inaccurately) observe each others’ actions, so that the decisions are made sequentially.
There are two primary ways for realizing multi-robot manipulation: caging and grasping. Caging \cite{153, 154, 155} bounds the mobility of an object to prevent it escaping. Several papers address coordinated manipulation based on caging. Sudsang and Ponce\cite{155} presented a centralized algorithm for three disc-shaped robots that maintains the object closure during pushing. Also decentralized approaches for controlling a team of mobile robots transporting a planar object have been presented \cite{156, 157}. To cope with a large number of robots and complicated objects, \cite{158} considered object closure in configuration space. Robust caging was proposed in \cite{159} that aimed to reduce the number of caging robots. Multi-robot caging is a well known strategy for loosely-coupled tasks that allows imprecise manipulation.

In contrast to caging which allows imprecise manipulation, grasping using for example force \cite{160} and form \cite{161} closures allows moving objects precisely. Even if robot hands with multiple fingers are often preferred \cite{162}, the smaller number of required contacts makes force closure attractive and widely studied. Various grasp planners \cite{32, 163} and quality metrics \cite{13, 41} have been proposed even if the correlation between simulated metrics and real performance is not very high \cite{164}. Most of the planners were developed for single handed or bi-manual \cite{162, 165} robots.

Planning is an inseparable part of multi-robot coordinated manipulation where most works focus on task \cite{130} and motion planning. To handle large components such as structures and beams in a space environment, a prototype system for multi-robot cooperative transport and assembly was reported in \cite{166}. In \cite{167}, an automated assembly system was presented, where a team of heterogeneous robots executed cooperative manipulation actions using a geometric pre-planner and a symbolic planner to assemble a furniture kit. The assembly planning was based on task allocation. Recently, to realize an assembly plan, grasp planning was addressed in \cite{168}, where the multi-robot grasp planning was formulated as a constraint satisfaction problem for a sequential assembly operation. In particular, the algorithm considered collision and transfer constraints in a sequential and multi-robot context and determined the set of feasible robot configurations. Unlike the above, we concentrate on the decentralized coordination problem.

### 4.2 Multi-robot grasp planning

Grasp planning is a well addressed problem for known objects in single and bi-manual robotic systems. Data driven methods are popular and widely accepted due
to the systematic way of solving the grasping problem. In the line of data driven methods for a known object, the grasp planning problem involves grasp hypothesis generation for the given object and evaluation of those generated hypotheses using wrench space quality measures such that good grasp solutions are produced.

So far, task and motion planning has been mainly considered for planning coordination in multi-robot systems. Grasp planning can be useful and important in providing effective grasp coordination solutions for multi-robot manipulation. We mean effective in terms of the ability of the grasp to withstand external disturbances.

Multi-robot grasp planning (MRGP) is the problem of determining grasps for a set of robots that is cooperatively optimal subject to external disturbances or specific tasks. The complexity of MRGP problem increases for robot groups that are decentralized in nature and heterogeneous in composition. In this case, grasp planning of each individual robot in the group needs to account for and approximate the cooperating robots while planning cooperative grasps.

### 4.3 Grasp coordination

Let \( \mathcal{G}' = \{ \mathcal{g}_1', \ldots, \mathcal{g}_n' \} \) denote a set of grasp hypotheses for robot \( i \) where each element \( \mathcal{g}_k' \) corresponds to a relative hand pose of the robot w.r.t. the target and \( |\mathcal{G}'| \) is the number of hypotheses for robot \( R_i \). Some hypotheses do not necessarily satisfy the force closure property, that is, there may exist \( \mathcal{g}_k' \) such that \( 0 \notin \text{ConvexHull}\{\mathcal{g}_k': \mathcal{W}'\} \).

Any existing pre grasp planners can be used in the grasp hypothesis generation. For simplicity of description, in the following we consider two robots \( R_1 \) and \( R_2 \) grasping an object based on hypothesis sets \( \mathcal{G}'_1 \) and \( \mathcal{G}'_2 \). Let \( Q_{R_i}(x)|x \in \mathcal{G}'_i \) denote the quality measure value for \( R_i \) executing grasp hypothesis \( x \) from the set \( \mathcal{G}'_i \), and \( Q_{R_1,R_2}(x,y)|x \in \mathcal{G}'_1, y \in \mathcal{G}'_2 \) denote the quality measure of robots \( R_1 \) and \( R_2 \) executing grasps \( x \) and \( y \) respectively. Any wrench space quality measures from Chapter. 3 can be used. For decentralized and strictly decentralized approaches we also define \( Q_{R_1,R_2}(x,y) \equiv Q_{R_1,R_2}(x,y)|x,y \in \mathcal{G}'_1 \) to denote the joint quality measure of executing both grasps \( x \) and \( y \) simultaneously using the embodiment of robot \( 1 \). This last term is used in decentralized approaches to approximate \( Q_{R_1,R_2}(x,y)|x \in \mathcal{G}'_1, y \in \mathcal{G}'_2 \) without the knowledge of the embodiment of the other robot. The approximation is good if both cooperating robots have similar embodiment.
4.3.1 Centralized multi-robot system

In a centralized MRS, a central unit performs grasp planning on behalf of the group and communicates the corresponding grasp decisions to the individual robots. The availability of complete knowledge about the robots, objects and tasks as well as the global state information in the central unit allows it to produce optimal grasp coordination solutions for the group. The centralized decision structure is preferable in the case of small groups in structured operations and ideal environments because of the optimal solutions.

Centralized settings: Centralized grasp coordination problem denotes a setting where (1) the communication is explicit between the central agent and coordinating robots through dedicated hardware (e.g. communication via messages); (2) the central unit has access to object models and robot embodiment information which is crucial for grasp planning and decision making.

4.3.2 Centralized approach

The centralized approach determines an optimal grasp combination over all grasps made by the robots by optimizing over the joint quality measure $Q_{R^1,R^2}(x,y)|x \in \tilde{G}^1, y \in \tilde{G}^2$. Thus, the optimal quality $Q_c$ is

$$Q_c = \max_{x \in \tilde{G}^1, y \in \tilde{G}^2} [Q_{R^1,R^2}(x,y)]$$

(4.1)

which is obtained by grasps $C_1, C_2$ for robots $R^1$ and $R^2$ respectively

$$(C_1, C_2) = \arg \max_{x \in \tilde{G}^1, y \in \tilde{G}^2} [Q_{R^1,R^2}(x,y)].$$

(4.2)

The centralized approach thus provides the global optimum over the grasp hypotheses. However, this approach requires the knowledge of the quality measure $Q_{R^1,R^2}$ which is not available in decentralized decision making.

4.3.3 Decentralized multi-robot system

In a decentralized MRS, each robot is autonomous in making its own grasp plans and coordination decisions. However, the robots in such a system lack global knowledge about the environment and complete information about the cooperating robots in the group. Moreover, limitations in communication and sensing often lead to sub-optimal coordination solutions. We formulate MRGP approaches that utilize imprecise local
information gained through sensors or produce estimates based on the role assigned to overcome the limitations of decentralized system.

In the following, we consider two settings that impose decentralized and strictly decentralized decision making structure in the decentralized MRS. These setting gives a infrastructure to formulate decentralized approaches with respect to to multi-robot grasp planning.

### 4.3.4 Decentralized settings

Decentralized grasp coordination problem denotes a setting where (1) the explicit communication between the coordinating robots is restricted and the robots are aware of the existence of others; (2) the individual robots are only aware of their own embodiments. The incomplete knowledge adds up as uncertainty in the decentralized grasp planning problem. We formulate decentralized solutions to multi-robot grasp planning in the above setting.

In the proposed decentralized setting, each robot plans their own grasp by imprecisely observing the other robot’s action and the perceived information of approximate hand location is the only available observation. In particular, we adopt a sequential approach where the robots plan and act in turn so that each robot is able to observe the previous robot’s actions before planning its own. Moreover, robots do not have physical embodiment information of cooperating robots. To account for this, each robot uses their own model as a model for all robots. This is an approximation that is handled in a probabilistic framework to account for the inaccuracy of the assumption. The probabilistic approaches then aim to maximize the expected grasp quality over the embodiment uncertainty.

### 4.3.5 Decentralized Approaches

For the planning to benefit from knowing the fact that there are several decentralized robots, each robot assumes that the physical capabilities of other robots are equal to their own, that is, the other robots are able to grasp the target object in the same fashion as the robot itself. As this might not be the case in reality, we also assume that the assumption of equal capabilities has only a limited degree of belief. Moreover, the following decentralized approaches neither precisely observe the grasps of the cooperating robot nor share information by explicit communication.
Grasp Planing for Multi-Robot Coordination

**Decentralized Individual Best (DIB)**

As a first baseline approach, we propose an approach called decentralized individual best planner where both robots greedily optimises their own individual grasps without taking into account the other robot. In the two robot case, $R_1$ maximizes its own grasp quality

$$DIB_1 = \arg \max_{x \in \mathcal{G}_i} [Q_{R_1}(x)]$$

(4.3)

and then $R_2$ maximise its own grasp quality avoiding collisions with $R_1$

$$DIB_2 = \arg \max_{y \in \mathcal{G}_i} [Q_{R_2}(y)].$$

(4.4)

This approach serves as a baseline for decentralized multi-robot grasp planning.

**Decentralized Independent (DI)**

As a second baseline approach, we propose an approach called decentralized independent planner which greedily optimizes the grasp quality while considering also the possible earlier grasps that other robots have already executed. In a two robot case, $R_1$ thus maximizes only its own grasp quality

$$DI_1 = \arg \max_{x \in \mathcal{G}_i} [Q_{R_1}(x)]$$

(4.5)

while $R_2$ observes the location of the grasp made by $R_1$ and uses the closest grasp in its own set to model that. That is,

$$DI_2 = \arg \max_{y \in \mathcal{G}_i} [Q_{R_2}(\hat{DI}_1, y)], \quad \hat{DI}_1 = \arg \min_{z \in \mathcal{G}_i} \|z - DI_1\|.$$  

(4.6)

This approach also serves as a baseline for decentralized grasp planning.

**Decentralized Average (DA)**

To benefit from the knowledge that multiple robots will be grasping under incomplete knowledge of other robot’s capabilities, we propose to maximize the expectation of the quality of the multi-robot grasp configuration. Considering a two robot case, $R_1$ thus aims to choose a grasp that maximizes the expected quality over the unknown grasp of $R_2$

$$\arg \max_{x \in \mathcal{G}_i} \mathbb{E}_{y \in \mathcal{G}_2} [Q_{R_1}(x, y)].$$

(4.7)

Note that this function can be evaluated on $R_1$ without any knowledge about $R_2$ but that it assumes that the joint quality $Q_{R_1, R_2}(x, y)$ can be approximated by $Q_{R_1}(x, y)$ which approximation is good when the embodiments of the robots are similar.
It should be reiterated now that \( R^1 \) uses its own grasp hypotheses as hypotheses also for \( R^2 \) and thus both \( \vec{G}^1 \) and \( \vec{G}^2 \) are evaluated over the same set of hypotheses. To evaluate the expectation, we need to make an assumption about the grasp taken by \( R^2 \). We now propose two approaches based on different baseline assumptions. In the first approach, we assume that each grasp in the hypothesis set is equally likely, that is, \( P(\vec{G}^2 = x) = \frac{1}{|\vec{G}^1|} \) for all \( x \). Using this assumption, (4.7) becomes

\[
DA_1 = \arg \max_{x \in \vec{G}^1} \frac{1}{N} \sum_{y} Q_{R^1}(x, y) 
\]

This approach is termed the decentralized average approach due to the average quality appearing in (4.8). \( R^2 \) plans its grasp similarly to the decentralized independent approach, that is,

\[
DA_2 = \arg \max_{y \in \vec{G}^2} Q_{R^2}(\hat{DA}_1, y), \text{ where } \\
\hat{DA}_1 = \arg \min_{z \in \vec{G}} \|z - DA_1\|.
\]

We hypothesize that even this approach should give an improvement over the decentralized independent planning approach as it explicitly models the situation that there will be more robots grasping after the first robot. The extension to more robots is straightforward: The expectation is taken over all robots who have not yet executed their grasps (i.e. the incomplete knowledge).

**Decentralized Expectation (DE)**

While the equal probabilities model is simple and likely to outperform the baseline sequential planning, the approach fails to use the information that also the further robots are trying to choose optimal grasps from their perspective. Thus, we propose a second model, where the likelihoods of the grasps are not equal but where the higher quality grasps are more likely to be chosen. Again, let us consider the two robot case for simplicity of description. The underlying idea is that \( R^2 \) will choose the best grasp that it is able to execute. However, we assume that the grasps produced by \( R^1 \) have a limited probability of success for \( R^2 \) (for example, they might not be force closure grasps for \( R^2 \)). Let us denote \( P_S \) the probability of success that a grasp of a \( R^1 \) can be executed by \( R^2 \). Assuming Robot 2 will execute the best executable grasp, the probability that the \( j \)th best grasp (considering both executable and not-executable grasps) will be executed is \( P_S(1 - P_S)^{j-1} \). Let \( w_j \) denote the permutation of grasps for \( R^2 \) so that the joint quality \( Q_{R^1}(x, y) \) is ordered in a decreasing order,
that is, $Q_{R_1}(x, w_j) > Q_{R_1}(x, w_{j+1})$. Under these assumptions, the expected quality will be maximized with

$$DE_1 = \arg \max_{x \in \mathcal{G}_1} \sum_j P_S (1 - P_s)^{j-1} Q_{R_1}(x, w_j)$$  \hspace{1cm} (4.10)$$

$R_2$ plans it grasp again similarly to the two previous approaches,

$$DE_2 = \arg \max_{y \in \mathcal{G}_2} [Q_{R_2}(\hat{DE}_1, y)] \text{, where}$$

$$\hat{DE}_1 = \arg \min_{z \in \mathcal{G}_1} \|z - DE_1\|.$$  \hspace{1cm} (4.11)$$

Larger $P_S$ means that the approximation of $Q_{R_1, R_2}$ by $Q_{R_1}$ is trusted more. In the limiting case $P_S = 1$ the approximation is expected to be fully correct and

$$DE_1 = \arg \max_{x \in \mathcal{G}_1} [\max_{y \in \mathcal{G}_1} Q_{R_1}(x, y)],$$

which corresponds to the globally optimal solution if the embodiments are identical. If $P_S \to 0$ this approach becomes equal to the decentralized average approach. In this paper, $P_S = 0.5$ was chosen empirically as a compromise between these.

4.3.6 Strictly Decentralized settings

Strictly decentralized grasp coordination problem denotes a setting where (1) both implicit and explicit communication between cooperating robots is restricted and each robot is only aware of the existence of others; (2) an individual agent is aware of its own physical embodiment and assume the other agents as itself; (3) a role is assigned to each robot in the group.

In the proposed strictly decentralized setting, each robot predicts the possible grasp executed by the other robots by using their own model as a model for other agents and plans their own grasp based on the assigned role. We simplify the roles by describing them as a priority of grasp execution. Agents are unable to gather any grasp information of other agents due to the limitations in observation. The availability of the priority based roles and object knowledge enabled them to make their own grasp plan and act simultaneously. The incomplete knowledge and unavailable local information pose great challenge to multi-robot grasp planning. We propose baseline and probabilistic approaches to examine their ability to overcome the uncertainty in homogeneous and heterogeneous groups for coordination.
4.3.7 Strictly Decentralized Approaches

Apart from the fact that there are several decentralized robots, the assumption of equal physical capabilities between robots is still considered with limited degree of belief in the following strictly decentralized approaches. Moreover, the approaches neither observe the grasps of the cooperating robot nor share information by communication. Due to the observation constraint, even though the robots perform decentralized grasp planning, the coordination decision is mainly based on the assigned role for each robot. For the two robot case, we assign one robot a leader, the other a follower. The leader is responsible for the first grasp. The follower predicts the grasp executed by the leader to plan its own grasp. In the following formulations, $R^1$ is assigned a leader role and $R^2$ assigned a follower role.

Strictly Decentralized Individual Best (SDIB)

As a first baseline approach, we propose an approach called strictly decentralized individual best planner where both leader and follower robots greedily optimise their own individual grasps. However, the follower robot prunes its own optimal grasp from the grasp set to account for the grasp by the leader and optimizes the grasp quality again with the available set. The follower thus assumes that its own optimal grasp is executed by the leader robot which is true in the homogeneous case.

In the two robot case, $R^1$ maximizes its own grasp quality

$$SDIB_{11} = \arg\max_{x \in \mathcal{G}^1} [Q_{R^1}(x)]$$
(4.12)

while $R^2$ first estimates its own optimal candidate grasp $SDIB_{21} = \arg\max_{x \in \mathcal{G}^2} [Q_{R^2}(x)]$ then prune the candidate from the grasp set $\mathcal{G}^2$ to maximise its own grasp quality

$$SDIB_{22} = \arg\max_{y \in \mathcal{G}^2 - \{SDIB_{21}\}} [Q_{R^2}(y)]$$
(4.13)

This approach serves as a baseline for strictly decentralized planning.

Strictly Decentralized Independent (SDI)

We propose an approach called strictly decentralized independent planner where the leader robot greedily optimizes the grasp quality without taking into account of the other while the follower robot considers a possible executed grasp by the leader robot while planning and chooses a grasp that maximizes the joint grasp quality. In a two robot case, $R^1$ thus maximizes only its own grasp quality

$$SDI_{11} = \arg\max_{x \in \mathcal{G}^1} [Q_{R^1}(x)]$$
(4.14)
while $R_2$ uses its own optimal grasp as the estimate of $R_1$ grasp and maximizes the joint grasp quality

$$SDI_{22} = \arg\max_{y \in \mathcal{G}^2} [Q_{R_2}(SDI_{21}, y)],$$

where

$$SDI_{21} = \arg\max_{x \in \mathcal{G}^2} [Q_{R_2}(x)].$$

This approach also serves as a baseline for strictly decentralized planning in MRS.

**Strictly Decentralized Average (SDA)**

The function presented in equation (4.7) determines $R_1$ grasp that maximizes the expected quality over the unknown grasp of $R_2$ while assuming the joint quality $Q_{R_1,R_2}(x,y)$ can be approximated by $Q_{R_1}(x,y)$. In the following approach formulations, we evaluate (4.7) on both leader and follower robot to overcome the observation constraint. Moreover, the role assigned decentralized robots use their own hypothesis sets to evaluate joint quality. The different baseline assumptions in decentralized approaches are again considered to devise our probabilistic approaches. In the first approach, we assume that each grasp in the hypothesis set is equally likely, that is, $P(\mathcal{G}^2 = x) = 1/|\mathcal{G}^1|$ for all $x$ and $P(\mathcal{G}^1 = y) = 1/|\mathcal{G}^2|$ for all $y$. Using this assumption in (4.7), the leader robot $R_1$ determines its grasp based on average quality, represented as

$$SDA_{11} = \arg\max_{x \in \mathcal{G}^1} \frac{1}{N} \sum_y Q_{R_1}(x,y)$$

(4.16)

then the follower $R_2$ uses its own hypothesis set to estimate a grasp that is possibly executed by the leader robot and plan a grasp that maximizes the joint quality and cooperation. In particular, the estimation approach is similar to (4.16).

$$SDA_{22} = \arg\max_{y \in \mathcal{G}^2} [Q_{R_2}(SDA_{21}, y)],$$

where

$$SDA_{21} = \arg\max_{x \in \mathcal{G}^2} \frac{1}{N} \sum_y Q_{R_2}(x,y).$$

(4.17)

We hypothesize that even this approach should give an improvement over the strictly decentralized independent planning approach as it explicitly models the situation that there will be more robots grasping after the leader robot. The extension to more robots is straightforward since the expectation is taken over all robots based on the assigned roles.
**Strictly Decentralized Expectation (SDE):**

In this approach, each robot assumes the other robots try to choose optimal grasps from their perspective. Thus, the higher quality grasps of the corresponding robots are valued more in the joint quality evaluation. Let us consider the grasps produced by leader have a limited probability of success for the follower and vice versa. The modelling of probability of success and permutation of grasps are explained in the DE approach section. We use the assumptions and modelling for leader in determining its own grasp as well as the follower in the estimations. First, the expected quality of the leader robot will be maximized with

\[
DE_{11} = \arg \max_{x \in \mathcal{G}^1} \sum_y P_y (1 - P_s) \cdot \left( Q_{R^1}(x, w_j) \right).
\]

(4.18)

then the follower \( R^2 \) uses its own hypothesis set to estimate a grasp similar to \( 4.18 \) and plan a grasp that maximizes the joint quality and cooperation,

\[
SDE_{22} = \arg \max_{y \in \mathcal{G}^2} [Q_{R^2}(\overline{SDE_{21}}, y)], \quad \text{where} \quad \overline{SDE_{21}} = \arg \max_{x \in \mathcal{G}^2} \sum_y P_y (1 - P_s) \cdot \left( Q_{R^1}(x, w_j) \right).
\]

(4.19)

**4.4 Discussion**

In this chapter, the main objective was to develop approaches that allow to effectively coordinate a decentralized group of robots with grasps to perform cooperative manipulation tasks on large and heavy objects. We presented multi-robot grasp planning approaches for a group of robots under three different decision making structures. The centralized approach was formulated to determine global coordination solutions using the complete knowledge of robots, objects and tasks. For decentralized settings, we devised baseline (DIB,DI) and probabilistic (DA,DE) approaches to produce cooperative grasping solutions not requiring global planning under incomplete knowledge of embodiments, since the setting allowed the robots to possess information only about their own embodiment and capabilities. The decentralized approaches evaluated traditional grasp quality measures in a probabilistic context which compensated for the incomplete information. To improve the cooperative grasp decisions, the approaches allowed the decentralized robots to imprecisely observe the cooperating robots. To compensate for the incomplete information, the approaches evaluated traditional grasp quality measures in probabilistic context.
We also formulated four approaches (SDIB, SDI, SDA, SDE) for the strictly decentralized setting that imposed observation constraint and roles on the decentralized group of robots. The corresponding approaches allowed each robot to estimate other robot grasps with its own model and grasp hypothesis sets. Even though the approaches facilitated the traditional grasp evaluation, the cooperative decisions are mainly based on the role assigned to each independent robot.

Any existing wrench space quality measures can be incorporated in the MRGP approaches to evaluate multi-robot grasps. The presented TS and NTS measures in chapter 3 are used in the coordination experiments in the following Chapters 5 and 6.
5. Multi-Robot Coordination Experiments

In this chapter, we study the grasp coordination approaches presented in Chapter 4 by conducting experiments in a simulation environment. First, we study the performance of the decentralized approaches compared to optimal, centralized planning. Second, we study the importance of incorporating task specific information in grasp planning and examine its usefulness in decentralized approaches. Third, we examine how a heterogeneous group and a homogeneous group perform by adopting the decentralized approaches. Our main focus is on how the probabilistic approaches tackle the embodiment uncertainty in heterogeneous groups. Fourth, scalability is examined by increasing the group size to three robots. Finally, we evaluate the performance of strictly decentralized approaches.

5.1 Simulation environment

Multi-robot experiments are conducted in simulation with GraspIt! simulator [27] simulating the kinematics of the hands, detecting contacts and providing visualization, while the multi-robot grasp planning and grasp evaluation are performed by our software. The simulation experiments consider the grasp quality measures without reachability and environment collision constraints and provide an evaluation in a fully controllable environment.

A functional flowchart of a multi-robot grasping simulation system is depicted in Fig. 5.1. To conduct grasp coordination experiments with known objects, first, the 3D object and hand models required for experiments are collected in a model database. Then a pre planner processes the selected object model to generate grasp candidates. Using information of participating agents and object grasp candidates, a post planner generates multi-robot grasp plans based on the approaches described in Chapter 4. The GraspIt! simulator loaded with object and hand models allows the imple-
Multi-Robot Coordination Experiments

Figure 5.1. Functional flowchart of a multi-robot grasping simulation system for known objects

Representation of the grasp plans and sends contact points for evaluation. Grasp quality measures are used to evaluate the contact points and the quality measure is supplied to the post planner for ranking the grasps. Finally, the post planner determines the optimal grasps and the corresponding object, agent and approach information is stored in the grasp database to compare and study the performance of different approaches.

In the simulations, we use Kinova Jaco and Barrett hand models as agents shown in Fig. 5.2 with the corresponding real robot hands. The physical embodiments of Jaco and Barrett are clearly distinct from each other. Three embodiment combinations were used: (1) two Jaco’s (2) two Barrett hands and (3) one Jaco and one Barrett hand. The former two are homogeneous and the last is heterogeneous. In our experiments, coefficients of friction were set to 1.0 for Jaco and 0.4 for Barrett, according to the materials of contact surfaces. The values were determined empirically based on the guidelines provided in [169]. The hand embodiments and friction coefficients are the major factors that affect the grasp solutions. We use precise CAD object models shown in Fig. 5.3 and imprecise real household object models shown in Fig. 5.4 for our experiments. The procedure for modelling the household objects is explained in the next Chapter.

Two types of sampling based heuristic grasp planners were used to generate grasp hypotheses for the object models. The first type, called the simple planner, samples grasp hypotheses from a given selective path. The other type called the primitive based planner, requires manual decomposition of objects with primitives and uses a set of grasp pre-shapes for each primitive to generate grasp hypotheses. Figure 5.5 (b)-(d) illustrate approach directions (long arrows) and thumb directions (short arrows) for the agents.
5.2 Decision making in decentralized multi-robot systems

5.2.1 Experiment 1: Centralized vs decentralised approaches

In this section, we carry out experiments to compare the performance of the decentralized approaches to the optimal solutions from centralized planning. For our experiments, we selected two Barrett hand model as agents and object models shown in Fig. 5.3 as test objects. Selective path and primitive based pre grasp planner were employed to generate grasp hypotheses for the object models. For box object, we assigned a selective path to the agents and sampled grasp hypotheses based on the path shown in Fig. 5.5(a). For the rest of the objects, we manually decomposed the objects with primitives and generated grasp hypotheses accordingly. The search space of primitive grasp planner is shown in Fig. 5.5 for cylinder(b), sphere (c), aeroplane (d) objects. For our experimental study, we selected grasp hypotheses that satisfied the force closure criterion. Moreover, we use $\epsilon_{metric}$ from 3.16 which is a non task specific measure to evaluate and quantify multi-robot grasps.

5.2.2 Results

We begin by illustrating the results of the different planners. Figure 5.5 shows two agent grasps planned for the objects by MRGP approaches. Subfigures (a)-(d) illu-
Multi-Robot Coordination Experiments

Figure 5.4. Real Household Objects (a-e) and their corresponding 3D models (f-j) used in simulation experiments.

trate the grasp search space produced by sampling based heuristic grasp planners. The second column of subfigures illustrates the globally optimal cooperative grasp which is determined by a centralized planner. Columns three to five illustrate the cooperative grasp results from decentralized approaches (DI, DA, DE). The grasps planned by different approaches vary and the DE approach manages to plan globally optimal grasps in three out of four cases, subfigures (q)-(t).

The availability of complete information of embodiments and objects enabled the centralized planner to produce globally optimal solutions. We access the global plan and information available in the centralized planner and generate joint grasp quality map to further analyse the quality landscape and examine the pre planner grasp search space solution.

Figure 5.6(a)-(d) illustrate the joint quality map of two agents for objects used in the experiments. The joint quality information of two agents are represented in the colour context, where the blue colour indicates collision between agent 1 and 2, the light blue indicates non force closure grasps, the dark red indicates best grasps and other light red variations indicates cooperative grasp of lower quality. The quality map grid can be expressed as $Q(G_1, G_2) \in \mathbb{R}_{44 \times 44}$ for box object where the low quality grasps, non force closure and collisions are concentrated at particular regions and $Q(G_1, G_2) \in \mathbb{R}_{30 \times 30}$ for rest of the objects. Even though we used the same type of planner for aeroplane, cylinder and sphere models, the multiple agent grasp perspective varies. In Fig. 5.6(d), the best grasps are easily spotted and good grasps are distributed well in the joint quality landscape for aeroplane model. This implies that
Figure 5.5. Grasp Search space produced by pre grasp planners on experimental objects (a-d) and Optimal grasps of post grasp planers: centralized (e-h) and decentralized approaches (e-t).
other than collision most of the cooperative grasp are good candidates for further operations.

![Box Object](image1)
![Sphere Object](image2)
![Cylinder Object](image3)
![Aeroplane Object](image4)

**Figure 5.6.** Centralized planning: Joint Quality Map of Two Agent Grasps for Object models

The pattern of joint quality measures for simple objects Fig. 5.6(a)-(c) is quite surprising. In (c), three layers of joint quality measures is exhibited in the joint quality landscape of cylinder object model. In Fig. 5.6(b), best and good grasp are in an assorted pattern. (a) shows a pattern for a defined search space.

For simple objects, determining optimal cooperative grasp in the search space can be challenging for decentralized approaches. For objects with simple geometric shape the pre grasp planner generates a set of grasps that is sufficient to obtain cooperative grasps of high quality. Several pre grasp planner methods that allows to determine good grasp sets for complex objects were discussed in the background chapter. The joint quality map of object models have no correlation with each other to support any generalized decision making patterns, since for each individual object the cooperative grasp patterns are specific.

Effective single agent grasps are most likely to occur near the center of mass of the object. However, multiple agents with their increased disturbance handling abilities differs from the above likeliness. For example in the case of box model, the optimal cooperative grasps in Fig. 5.5(e) are away from the center of mass of the object. To analyze the performance quantitatively, Table. 5.1 presents the grasp quality metrics
Multi-Robot Coordination Experiments

for the best grasps for each planner and object model. The DI approach can be effective for some application when the first robot is constrained to grasp in a particular region and the second agent maximizes the cooperation. However, this baseline approach was inferior to the probabilistic approaches such as DA and DE in general. The shape of the object had effect on the decentralized approaches. For instance, for the cylinder model, the decentralized planners produced optimal results simply because of the object geometry. The sphere model is an interesting case, neither DI nor DA were able to converge to optimal.

<table>
<thead>
<tr>
<th>Objects</th>
<th>Box</th>
<th>Aeroplane</th>
<th>Cylinder</th>
<th>Sphere</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approaches</td>
<td>ε</td>
<td>Grasp Config.</td>
<td>ε</td>
<td>Grasp Config.</td>
</tr>
<tr>
<td>CZ</td>
<td>0.2394</td>
<td>Fig.5.5e</td>
<td>0.1438</td>
<td>Fig.5.5f</td>
</tr>
<tr>
<td>DI</td>
<td>0.1559</td>
<td>Fig.5.5i</td>
<td>0.0541</td>
<td>Fig.5.5j</td>
</tr>
<tr>
<td>DA</td>
<td>0.2262</td>
<td>Fig.5.5m</td>
<td>0.1438</td>
<td>Fig.5.5n</td>
</tr>
<tr>
<td>DE</td>
<td>0.2394</td>
<td>Fig.5.5q</td>
<td>0.1438</td>
<td>Fig.5.5r</td>
</tr>
</tbody>
</table>

Table 5.1. Numerical quantitative comparisons between centralized (CZ) vs decentralized (DI,DA,DE) approaches

For all objects, DE outperformed the other decentralized approaches and converged to optimal. For DA and DI, the average qualities were 97% and 73% respectively. The ranking of approaches (DE > DA > DI) was consistent for all cases. Overall, in simulation DA performance was very close to DE and the approach seemed preferable over the DI. This is to be expected as the assumption that embodiments are similar is perfectly true in this case. Moreover, the probabilistic approaches DA and DE outperformed DI significantly which demonstrates the potential for being better approaches for precise object models.

5.2.3 Experiment 2: Task specific vs non task specific grasping

In this section, experiments are conducted (i) to examine the need and importance of task specific quality metrics in cooperative grasp planning strategies and (ii) to verify the effectiveness of the decentralized approaches with task specific measures in multi-robot systems of decentralized nature.

For all experiments, two Barrett hands were used as agents. Two target objects of differing complexity in shape, a box and an aeroplane, were used. Six manipulation
tasks were considered, named T1–T6. Each contains a requirement of force along positive Y axis corresponding to compensation of gravity acting on the object. In addition, T1, T2 and T3 have a task requirement of torque about a single axis (X, Y, Z, correspondingly). T4, T5 and T6 each require torque about two torque axes, X-Y for T4, X-Z for T5, and Y-Z for T6, in addition to gravity compensation. As a non task specific (NTS) grasp quality metric we used the epsilon $\varepsilon$ (3.16) which is identical to GraspIt!. As a task specific (TS) metric, the $Q_{\text{metric}}$ (3.23) is used.

5.2.4 Results

We first study the importance of task specific grasp quality metrics in planning cooperative grasps. This is done by comparing the task specific quality of grasps planned using task specific versus non task specific metrics. The comparison is made in a centralized planning setting, resulting in globally optimal grasp pairs (from the subset of grasp hypotheses proposed by pre-planners), so that the effect of decentralized planning can be removed from the comparison.

Sampling based heuristic grasp planners (see Fig. 5.5 (a) and (b)) for simple (box) and complex (aeroplane) objects are utilized to generate grasp hypotheses in the pre-grasp planning stage. However, only the top thirty grasp quality candidates are chosen in the post-grasp planning stage for the testing of our approaches. The TS and NTS metrics are then computed for each pair of grasp hypotheses. The grasp pair with largest NTS metric was chosen as the non task specific best grasp. These are illustrated in Figs. 5.7 (a) and 5.7 (b). Similarly, the grasp pair with largest TS metric for a particular task is chosen as the globally optimal one for that task.

The task specific quality of the grasps planned without a task specific metric was then compared to the globally optimal quality. The results of this comparison are shown in Table 5.2 which shows the percentual increase in quality when the task specific metric was used. In 9 out of 12 cases the increase in quality was significant (>10%), with the average improvement being 31% and highest improvements being over 70%. A paired samples sign test was used to study the statistical significance of the result. The null hypothesis that there is no statistically significant difference between the cases was rejected at $p < 0.001$, indicating that the task specific metrics should be used in planning when the task is known.

To focus the study on the most interesting cases, we next look into largest and smallest improvements. T3 (for box, Fig. 5.7e) and T1 (for aeroplane, Fig. 5.7f) show the largest improvements and T5 (for box, Fig. 5.7g) and T6 (for aeroplane,
Figure 5.7. Simulated global optimal and decentralized approaches (DI, DA, DE) for grasping objects (box, aeroplane) by two Barrett hand with regards to trajectory Fig. 5.5 (a) and primitive Fig. 5.5 (b) based heuristic pre planners. (a)-(d) global optimal- Non Task Specific (NTS). (e)-(t) Task Specific (TS) [(e)-(h) Global Optimal, (i)-(l) Decentralized Independent (DI), (m)-(p) Decentralized Average (DA), (q)-(t) Decentralized Expected (DE)]. *First two rows (refer to Table 5.3 (a)) and last two rows (refer to Table 5.3 (b)) emphasize more and less improvements of task specific grasping.
Table 5.2. Increase in global optimal quality of Task Specific (TS) over Non Task Specific (NTS) measures

<table>
<thead>
<tr>
<th>Global Optimal (CZ) Approach</th>
<th>Box Object</th>
<th>Aeroplane Object</th>
<th>Tasks</th>
<th>TS over NTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task 1</td>
<td>17.50%</td>
<td>72.97%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task 2</td>
<td>38.50%</td>
<td>38.70%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task 3</td>
<td>40.58%</td>
<td>36.38%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task 4</td>
<td>14.78%</td>
<td>72.97%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task 5</td>
<td>2.40%</td>
<td>4.70%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task 6</td>
<td>38.50%</td>
<td>0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg</td>
<td>25%</td>
<td>37.62%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 5.7h) the smallest ones. It can be seen in the figure that in the large improvement cases the grasp configurations are entirely different, for example, grasping the airplane’s wings instead of front and aft, while in the small improvement cases the non task specific optimal cases are similar to the optimal task specific configurations. Corresponding numerical results are shown in Tables 5.3 (a) and (b), with CZ denoting results in globally optimal (centralized) setting and lightly shaded cells showing the task specific quality for task specific (TS) and non task specific (NTS) planners.

In Fig. 5.8 (a–d), the task specific joint quality information of two agents is illustrated with colour information for these tasks. The colour bar indicates the worst (blue) and best (Red) task specific grasp quality of two agents, where blue colour indicates collision between agent 1 and 2, the light green indicates non force closure grasps, yellow and light orange variation indicate lower quality grasps, and dark red indicates the best grasps.

T5 for box has small improvement when using TS metric but at the same time many grasp combinations are good overall, as illustrated by the overall red colour in Fig. 5.8. On the other hand, T3 for the same object has much larger improvement while the quality landscape is much more varying (see Fig. 5.8i), corresponding to a more challenging multi-robot grasp planning problem. For the aeroplane (T1 in Fig. 5.8b and T6 in 5.8d), only few close to optimal grasp configurations (dark red) exist in either case. Overall the results are thus inconclusive if the quality landscape correlates to the importance of using a task specific quality measure.
Figure 5.8. Centralized planning: Task specific quality measures for all two agent grasps for particular manipulation tasks.

Decentralized Approaches

The decentralized approaches allow the agents to plan task specific cooperative grasps without precise information about each other. The decentralized approaches formulated in Sec. 4.3.3 are studied to analyse how they perform relative to the centralized globally optimal approach.

On the basis of Table 5.2, the cases with largest and smallest improvements were again picked out for visualization and detailed numerical results. In Fig. 5.7 (i)-(l), (m)-(p) and (q)-(t) correspond to optimal grasp configurations with DI, DA and DE approaches, correspondingly. The graphical illustration gives a good intuition of appropriate grasp contact position by two agents for the proposed approaches. Numerical results for the same tasks in Tables 5.3 (a) and 5.3 (b) use the globally optimal approach as a benchmark for the decentralised approaches.

In particular, we are considering only task based decentralized approach for further analysis, where we expect these approaches to converge towards the globally optimal solution. In Table 5.4 one can see the performance of the decentralized approaches for various manipulation tasks conducted by two agents on box and aeroplane object, where the performance is calculated by percentage decrease of task specific quality with respect to the global optimal quality. The improvement in terms of decrease in
percentage is calculated \((\rho_{DI} - \rho_{GO})/\rho_{GO}\), where \(\rho_{DI}\) and \(\rho_{GO}\) represent grasp quality of DI and the globally optimal (centralized) solution, correspondingly.

From analysing decentralized approaches based on TS for box object corresponding to Table 5.4 Task 3 gives a 31% and 13% decrease in quality for DI and DA approaches depicted in Fig. 5.7(i) and (m), which no worst performing over all ma-
Manipulation tasks for the box object. In Task 5 all decentralized approaches show good performance by getting close to the global optimum (Fig. 5.7 (k), (o) and (s)). Some results in 5.2 and 5.4 are contrary to each other. In particular, for small percentage improvements of in Table 5.2 Tasks (Task 5) gives a grasp configuration closer to global optimal in 5.4 and for large % improvements (Task 3) gives a grasp configuration far away to achieve global quality. In similar fashion, analysing decentralized approaches for aeroplane object, in Task 1 the quality decreased by 79% and 39% for DI and DA approaches depicted in Fig. 5.7 (j) and (n), which are worst performing in the overall manipulation tasks of aeroplane object. On the other side, decentralizes perform worst in Task 6 shown in Fig. 5.7 (l), (p) and (t). For complex object, no convergence conclusion can be drawn, based on the percentage improvements from Table 5.2. Overall from Table 5.2 for complex objects, DI approach has an average of 64% decrease in task specific quality over CZ, meaning that it is far from optimum for most manipulation tasks. The DE approach performs well for both objects and manipulation tasks considered to obtain global optimal configuration.

DA and DE approaches evaluate $n^2$ grasp pairs to find the best grasp configuration while the DI approach which uses $n$ grasp pairs. Therefore, there is no significant complexity issues between the proposed approaches while execution. However, the computational burden persists due to the grasp metric evaluation for the contact points of multiple robots in all approaches.

The performance between DI, DA and DE was compared using paired samples sign tests. According to the test, DA and DE outperform DI as the null hypothesis of no difference was rejected with $p < 0.001$. Finally, DE was compared against the CZ to see if the results show significant difference. The null hypothesis of no difference between CZ and DE could not be rejected ($p = 0.125$), indicating that the experiments did not provide statistical evidence that DE would be worse than the globally optimal solution.

5.2.5 Experiment 3: Homogeneous vs heterogeneous group performance

Heterogeneity in robots adds more uncertainty to the decentralized grasp planning problem. In our study, the heterogeneity and homogeneity in robot group refers to the differences physical embodiment of robot hands but not their dynamic capabilities. In Experiment 1, we only studied the decentralized approaches performance with precise object models and identical hand embodiments (homogeneous group).

For our experiments in this section, we selected Barrett and Kinova Jaco hand
models as agents and imprecise models of household objects as test objects. The five household objects and their models are shown in Fig. 5.4. The sampling-based primitive grasp planner was used to generate grasp candidates for the objects. All candidate grasps were used without pruning. The multi-robot grasps were quantified by the $Q_{\text{metric}}$ (3.23) which also ensures the force closure criterion.

We conducted experiments to study the performance of decentralized approaches with two different homogeneous (Jaco-Jaco, Barrett-Barrett) and one heterogeneous (Jaco-Barrett) robot group. We also exchanged the rules of robots in the heterogeneous group to examine how the sequential planning with particular embodiment affects the approach performance.

### 5.2.6 Results

We begin by illustrating the results of the different planners. Figure 5.9 shows grasps planned for Object 5 by different approaches proposed in this paper. Subfigures (a) and (b) illustrate the individual best grasps by Barrett and Jaco while (c) shows them executed simultaneously (DIB approach). The search space for grasps is depicted in subfigure (d). The second column of subfigures illustrates the optimal cooperative grasp that can be determined by a centralized planner. The four rows correspond to different combinations of robots (Barrett-Barrett, Jaco-Jaco, Barrett-Jaco, Jaco-Barrett). The order of robots has no effect on planning results for the centralized approach. This is unlike the decentralized approaches in columns three to five, where

<table>
<thead>
<tr>
<th>Object</th>
<th>Box</th>
<th>Aeroplane</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DI Approach</td>
<td>DA Approach</td>
</tr>
<tr>
<td>Task 1</td>
<td>-13%</td>
<td>-4.90%</td>
</tr>
<tr>
<td>Task 2</td>
<td>-23.40%</td>
<td>-4.63%</td>
</tr>
<tr>
<td>Task 3</td>
<td>-31.33%</td>
<td>-13.62%</td>
</tr>
<tr>
<td>Task 4</td>
<td>-25.16%</td>
<td>-12.08%</td>
</tr>
<tr>
<td>Task 5</td>
<td>-1.24%</td>
<td>-1.62%</td>
</tr>
<tr>
<td>Task 6</td>
<td>-23.40%</td>
<td>-4.63%</td>
</tr>
<tr>
<td>Avg</td>
<td>-19.60%</td>
<td>-6.90%</td>
</tr>
</tbody>
</table>

Table 5.4. Decrease in task specific quality of decentralized approaches w.r.t. globally optimal solution.
the grasp of the second robot depends on the one executed by the first one. The grasps planned by different approaches vary and the DE approach manages to plan globally optimal grasps in two out of four cases, subfigures (q) and (r). The planning results for DE are further illustrated in Fig. 5.10 which depicts the best grasps for the other four objects.

To analyze the performance, Table 5.5 presents the grasp quality metrics for the best grasps for each planner, object and hand combination for identical (a) and het-

Figure 5.9. Optimal grasps using centralized (CZ) and decentralized approaches (DIB, DI, DA, DE) over different combinations of Barrett (B) and Jaco (J) hands for Object 5.
Figure 5.10. Primitive grasps and optimal joint grasps using DE approach for Objects 1 to 4.

erogeneous (b) embodiments. The results are shown separately to examine the effect of heterogeneity. Each row corresponds to a particular object-hand pair combination. The third column denoted by CZ presents the quality metric values for centralized planning, that is, the globally optimal values. The four subsequent columns present the quality metric values corresponding to the decentralized approaches. The shading color represents the performance with respect to optimal.

For identical embodiments, DE outperforms the other decentralized approaches with average quality 99.9% of the optimal. For DA, DI and DIB, the average qualities are 85.4%, 79% and 61.9% respectively. The ranking of approaches (DE > DA > DI > DIB) is consistent over most cases. Overall, in simulation DE performance is very close to optimal and the approach seems preferable over the other two. This is
Multi-Robot Coordination Experiments

(a) Identical robot decentralized coordination results

(b) Heterogeneous robot decentralized coordination results

Table 5.5. Simulated grasp qualities over different objects, hand configurations and approaches.

to be expected as the assumption that embodiments are similar is perfectly true in this case.

For heterogeneous embodiments, DE outperforms the other decentralized approaches with average quality 84.1% of the optimal. For DA, DI and DIB, the average qualities are 76.1%, 66.8% and 57.6% respectively. The ranking of approaches (DE > DA > DI > DIB) is consistent over most cases. This indicates that the assumption of embodiment similarity is sufficiently good to allow handling uncertainties caused by heterogeneity in a decentralized setting.

The probabilistic approaches DA and DE outperform DI and DIB significantly, also in the case of mixed hardware where one embodiment’s capabilities are used to model another. Thus, at least in simulation considering even incomplete knowledge of the collaboration increases the quality of the collaborative grasps. In other words, the simulation confirms our initial hypothesis that with sufficiently similar robots the projection of a robot’s own model can be used to model another robot in order to
enable collaboration.

Sometimes the globally optimal grasp combinations are not centered around the object center of mass shown by the origin, for example, in Fig. 5.9(f). This is because the object shape has been recovered using visual 3-D reconstruction and thus the model will not be exactly symmetric due to measurement noise. While the overall shape of the object is quite accurate, a central factor affecting the quality measure is the direction of the surface normal at the contacts. Thus, small random variations in the model affect the location of the optimum. In the following, we study the effect of friction differences.

*Effects of friction coefficients*

The optimal quality metric values vary between the hand combinations, with two Jaco hands resulting in highest and two Barrett hands in lowest quality values. This reflects primarily the difference in friction coefficients (contact material) rather than differences in the kinematics of the hands and resulting contact locations. We verified this by conducting experiments with Object 5 by exchanging the friction coefficient between the hands and the corresponding joint quality results are given in Table 5.6. The results indicate that the hand with higher friction coefficients has higher grasp quality and is consistent for all approaches. Nevertheless, other factors such as hand kinematics also affect the quality.

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>Exchanged</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BB</td>
<td>JJ</td>
</tr>
<tr>
<td>CZ</td>
<td>0.0556</td>
<td>0.0815</td>
</tr>
<tr>
<td>DIB</td>
<td>0.0243</td>
<td>0.0405</td>
</tr>
<tr>
<td>DI</td>
<td>0.0467</td>
<td>0.0607</td>
</tr>
<tr>
<td>DA</td>
<td>0.0526</td>
<td>0.0797</td>
</tr>
<tr>
<td>DE</td>
<td>0.0556</td>
<td>0.0815</td>
</tr>
</tbody>
</table>

*Table 5.6. Grasp qualities for original and exchanged friction coefficients. Original Barrett 0.4, Jaco 1.0. Exchanged Barrett 1.0, Jaco 0.4.*
Multi-Robot Coordination Experiments

Figure 5.11. Illustrated Optimal grasps for BBJ combination using different planners.

Table 5.7. Simulated grasp qualities for Object 5 for three robots. ‘B’ indicates Barrett hand, ‘J’ Jaco hand.

<table>
<thead>
<tr>
<th>Hands</th>
<th>CZ</th>
<th>DIB</th>
<th>DI</th>
<th>DA</th>
<th>DE</th>
</tr>
</thead>
<tbody>
<tr>
<td>BBB</td>
<td>0.1894</td>
<td>0.0263</td>
<td>0.1586</td>
<td>0.1672</td>
<td>0.1894</td>
</tr>
<tr>
<td>JJJ</td>
<td>0.3122</td>
<td>0.2377</td>
<td>0.2686</td>
<td>0.2954</td>
<td>0.3122</td>
</tr>
<tr>
<td>BBJ</td>
<td>0.2369</td>
<td>0.0457</td>
<td>0.1864</td>
<td>0.1988</td>
<td>0.2033</td>
</tr>
<tr>
<td>BJB</td>
<td>0.2369</td>
<td>0.0457</td>
<td>0.1579</td>
<td>0.1788</td>
<td>0.2141</td>
</tr>
<tr>
<td>JBB</td>
<td>0.2369</td>
<td>0.0457</td>
<td>0.1294</td>
<td>0.2028</td>
<td>0.2136</td>
</tr>
<tr>
<td>JJB</td>
<td>0.2749</td>
<td>0.0582</td>
<td>0.2283</td>
<td>0.2346</td>
<td>0.2494</td>
</tr>
<tr>
<td>JBJ</td>
<td>0.2749</td>
<td>0.0582</td>
<td>0.1498</td>
<td>0.235</td>
<td>0.2282</td>
</tr>
<tr>
<td>BJJ</td>
<td>0.2749</td>
<td>0.0582</td>
<td>0.1294</td>
<td>0.2376</td>
<td>0.2549</td>
</tr>
</tbody>
</table>

5.2.7 Experiment 4: Scalability

To demonstrate the approaches for more than two robots, we performed simulation experiments with three robots (with total eight different embodiment combinations). Illustration and results of these for Object 5 are presented in Fig. 5.11 and Table 5.7. Consistently to earlier results, DE outperformed the other decentralized approaches with average quality 92% of the optimal. For DA, DI and DIB, the average qualities were 86%, 69% and 26% respectively. The ranking of approaches ($DE > DA > DI > DIB$) was consistent in most cases and the conclusions then agree with the two-robot case.

5.2.8 Experiment 5: Centralized vs strictly decentralized approaches

In this section, we carry out experiments with homogeneous and heterogeneous group of agents to compare the performance of strictly decentralized approaches to the optimal solutions from centralized planning.

For our experiments, we selected household object models, agents combinations, pre grasp planner and quality metric exactly as in Experiment 3. The main difference
is that the groups are under the strictly decentralized decision making structure which does not allow observation of already executed grasps. According to the structure, the formulated approaches allow the robots to make grasps decisions simultaneously based on assigned roles without local information about the cooperating agents. We also exchange the roles of agents in heterogeneous group to examine how it affects the approach performance.
Multi-Robot Coordination Experiments

Table 5.8. Simulated grasp qualities over different objects, hand configurations and approaches.

<table>
<thead>
<tr>
<th>Hands</th>
<th>Objects</th>
<th>CZ</th>
<th>SDIB</th>
<th>SDI</th>
<th>SDA</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>BJ</td>
<td>Obj. 5</td>
<td>0.068</td>
<td>0.039</td>
<td>0.024</td>
<td>0.048</td>
<td>0.062</td>
</tr>
<tr>
<td>JB</td>
<td>Obj. 5</td>
<td>0.068</td>
<td>0.039</td>
<td>0.043</td>
<td>0.060</td>
<td>0.019</td>
</tr>
<tr>
<td>BJ</td>
<td>Obj. 4</td>
<td>0.082</td>
<td>0.045</td>
<td>0.047</td>
<td>0.058</td>
<td>0.074</td>
</tr>
<tr>
<td>JB</td>
<td>Obj. 4</td>
<td>0.082</td>
<td>0.045</td>
<td>0.072</td>
<td>0.070</td>
<td>0.082</td>
</tr>
<tr>
<td>BJ</td>
<td>Obj. 3</td>
<td>0.123</td>
<td>0.071</td>
<td>0.061</td>
<td>0.063</td>
<td>0.029</td>
</tr>
<tr>
<td>JB</td>
<td>Obj. 3</td>
<td>0.123</td>
<td>0.071</td>
<td>0.090</td>
<td>0.090</td>
<td>0.097</td>
</tr>
<tr>
<td>BJ</td>
<td>Obj. 2</td>
<td>0.212</td>
<td>0.108</td>
<td>0.141</td>
<td>0.074</td>
<td>0.121</td>
</tr>
<tr>
<td>JB</td>
<td>Obj. 2</td>
<td>0.212</td>
<td>0.108</td>
<td>0.100</td>
<td>0.101</td>
<td>0.113</td>
</tr>
<tr>
<td>BJ</td>
<td>Obj. 1</td>
<td>0.111</td>
<td>0.075</td>
<td>0.101</td>
<td>0.064</td>
<td>0.060</td>
</tr>
<tr>
<td>JB</td>
<td>Obj. 1</td>
<td>0.111</td>
<td>0.075</td>
<td>0.066</td>
<td>0.077</td>
<td>0.052</td>
</tr>
</tbody>
</table>

5.2.9 Results

For the homogeneous case, we observed that the cooperative grasp results of the strictly decentralized planners (SDP) are identical to the decentralized planners (DP) in Experiment 3. Therefore, to avoid repetitions we refer to Table in 5.5 and their corresponding illustrations in Fig. 5.9 and Fig. 5.10 which show also the outcomes of SDP. We next describe the main results of strictly decentralized approaches for homogeneous group of two agents. Overall, decentralization in homogeneous group has been dealt effectively by both DP and SDP in their corresponding settings with no difference in performance since the assumption that embodiments are similar is perfectly true.

The SDP and DP are clearly distinct when it comes to decision making approach. For heterogeneous case the performance of the strictly decentralized approach varies since the embodiment approximation and estimations for role based decisions are not any more true in this case. Figure 5.12 shows grasps planned with heterogeneous agents for household objects using centralized and strictly decentralized planners. Subfigures (a)-(e) illustrate the optimal grasps determined by centralized planner for different objects. The second and third column of sub-figures illustrates the optimal grasp results of probabilistic approaches (SDA and SDE) that corresponds to the assigned (Barrett (leader)-Jaco (follower)) roles in the group. The last two column of subfigures illustrates the probabilistic approach results that corresponds to the switched roles between the two agent.

The role of agents in heterogeneous group has effect on the planning results for the strictly decentralized approaches due to the imposed observation constraint and
heterogeneity in robots. In simpler terms, the agent that plays the follower role does not observe the actual grasp of the leader robot. The grasps planned by strictly decentralized approaches varies randomly. In particular, the probabilistic approaches failed to plan optimal grasp in 19 out of 20 cases, only one case in subfigure (k) to global optimal.

To analyze the performance, Table 5.8 presents the grasp quality metrics for the best grasps for each planner, object and assignment role. Each row corresponds to a particular object-hand pair combination. The third column denoted by CZ presents the quality metric values for centralized planning, that is, the globally optimal values. The four subsequent columns present the quality metric values corresponding to the strictly decentralized approaches. The shading color represents the performance with respect to optimal.

SDE, SDA, SDI and SDIB showed similar decrease in performance compared to the optimal, the average qualities were 68%, 69%, 66% and 61% respectively. The ranking of approaches has no significance with the average qualities since the difference are less than 10% between the approaches. This indicates that the assumption of embodiment similarity is not sufficiently good to allow handling uncertainties caused by heterogeneity in a strictly decentralized setting.

Using paired samples sign tests, we compared SDE, SDA, SDI, SDIB against the global optimal (CZ) to see if the results show significant difference. The null hypothesis of no difference between CZ and strictly decentralized approaches was rejected with \( p < 0.008 \), indicating that the experiments could provide statistical evidence that SDE, SDA, SDI and SDIB would be worse than the globally optimal solution. This shows both baseline and probabilistic approaches fail to find close to optimal solutions for heterogeneous groups in a strictly decentralized settings. The poor performance of strictly decentralized approaches can be blamed either on the strong restrictions on gathering or inferring local grasp information of the cooperating robots or the inability of the approaches to overcome the heterogeneity in robot groups. The performance issues warrant better approaches and future study in strictly decentralized settings.

### 5.3 Discussion

In this chapter, we showed five experiments and studied grasp coordination approaches in three different multi-robot settings. The centralized approach results were consid-
Multi-Robot Coordination Experiments

Experiments considered globally optimal and used as a benchmark for the decentralized and strictly decentralized approaches. The importance of the task specific cooperative grasping was justified and verified by the qualitative analysis. The task specific decentralized approaches revealed even more benefits for simple objects. The performance results of Experiments 1–4 validated that the probabilistic approaches DE and DA outperformed the baseline approaches DI and DIB. This indicates that the assumption of embodiment similarity is sufficiently good to allow handling uncertainties caused by heterogeneity and decentralization. Moreover, the probabilistic treatment of incomplete knowledge by DA and DE allowed the improvements in performance over DI and DIB approaches that exhibit greedy behaviour. Overall, DE outperformed the other approaches while staying close to the globally optimal for both homogeneous and heterogeneous group under the decentralized setting.

Knowing the existence of other robots is significant information that increases performance in approaches DA and DE. In homogeneous environments, using a high value of $P_S$ which corresponds to just assuming the existence of another robot, is suitable. In the DE approach, if probability of success $P_S = 1$ is considered then the assumption of identical embodiments is true which is similar to maximizing $Q_{R^1}(x, y)$. However, in heterogeneous environments, the identical embodiment assumption is inaccurate. Thus the approaches are empowered to maximize the expected grasp quality over the embodiment uncertainty. Limited experiments with the value of $P_S = 1$ in heterogeneous environments showed multiple failures. Thus, the probabilistic treatment of embodiment difference (heterogeneity) is helpful. In summary, both the knowledge of existence of another robot and the probabilistic treatment are useful in planning grasps in heterogeneous environments.

We compared the strictly decentralized approaches to the globally optimal for heterogeneous and homogeneous groups in Experiment 5. For a homogeneous group, the strictly decentralized approaches maintained their rank order which is $SDE > SDA > SDI > SDIB$. This indicates that the embodiment approximation and estimations in role based decision making process are valid because of the identical embodiments. Even though the strictly decentralized setting allowed simultaneous planning and execution, the observation constraint posed a great challenge for decentralized planning in a heterogeneous group of robots. For heterogeneous groups, strictly decentralized approaches showed decreased performance compared to the global optimum and the performances of different approaches were similar without consistencies. This shows that the probabilistic approaches are not able to provide effective solutions for the heterogeneous case under strictly decentralized settings.
The simulation results using a standard quality measure are limited in the sense that they do not capture all factors of the grasping process. Nevertheless, simulation experiments are valuable for two reasons: Firstly, they make possible repeated experiments where the effect of different factors can be independently studied. Secondly, using also simulations follows the established standard in most grasp planning works, and thus allows hopefully easier interpretation compared to often binary success/failure measures used in many works for real-world experiments. Finally, we aim to correlate the findings of the physical and simulation experiments by providing for the physical experiments simulation quality values besides the physical metrics.

The simulation experiments did not consider the effects of constraints such as reachability and collision avoidance, and uncertainties in grasping process. Moreover, the simulation study assumes that the wrench space grasp quality metrics correspond to good grasps for physical hardware, a hypothesis that can be disputed. These issues are addressed by physical experiments in the next chapter.
Multi-Robot Coordination Experiments
6. Multi-Robot System and Physical Coordination Evaluation

In Chapter 4, simulation experiments demonstrated that the decentralized approaches reach close to globally optimal solutions for homogeneous groups of agents and somewhat worse solutions for heterogeneous groups of agents. Clearly, heterogeneity and decentralization are two main factors that affect the solutions in simulations. In physical systems, reachability constraints and system uncertainties can possibly affect the performance and cooperative grasp success. Thus, physical experiments are needed to study the performance. However, coordinating robotic systems in real time requires solving many problems that are not always apparent in simulations.

In this chapter, we first present a complete modular system which allows physical robots in a group to perform autonomous operations to experimentally study the grasp coordination approaches. The system demonstrates a full grasping pipeline, including 3D model reconstruction and pose estimation for grasped objects, decentralized grasp planning, grasp execution and object manipulation. Then, we carry out physical experiments with a heterogeneous two robot system to study the performance of decentralized approaches under reachability constraints. To evaluate cooperative grasps obtained from the MRGP approaches on real hardware systems, we formulate five novel experimental metrics which allow analysis of grasp quality during and after coordinated manipulation. We also investigate how the wrench space metrics correlate with actual grasp success.

6.1 System architecture and implementation

The developed system facilitates the heterogeneous robots shown in Fig. 1.1(c) to carry out decentralized grasp coordination on real objects. The physical experiments allow to validate the applicability and compare the effectiveness of the decentralized approaches to the optimal. In addition, coordinated manipulation experiments are
carried out to further analyse the cooperative grasps against various uncertainties. The system architecture shown in Fig. 6.1 consists of five functional modules that do perception, planning and control for multiple robots. The off-line part consists of model construction and grasp simulation. The model construction module supplies 3D object models to other modules. The simulation module generates and analyses multi-robot grasp plans and stores the grasps and their qualities in a database. On the online side, the registration module estimates the pose of the real objects. Then, the coordination execution module uses the decentralized grasp planning approaches to plan the final grasp, separately for each robot. Once the grasps are executed, the task execution module then facilitates tightly-coupled manipulation actions. A detailed description of each module follows below.

![Figure 6.1. Function based Architecture for Multi-Robot Coordination in real-time](image)

**Model Construction Module**

We use the KinectFusion GPU pipeline to create a 3D model of the scene by rotating the kinect around the object of interest. This reconstructs a detailed 3D model of a static scene and returns a 3D point cloud or a mesh. The GPU-based pipeline and capabilities of KinectFusion are comprehensively explained in [170]. The obtained 3D model, as shown in Fig. 6.2 (b), then undergoes various filtering/data processing steps based on the object of interest. Finally, the refined object model in (c) is passed to the simulation and registration module. In our experiments, 3D models of household objects shown in Fig. 5.4 (f)–(j) were obtained using this approach.

**Registration Module**

In the online side, determining the object pose for known objects is crucial for reliable grasping and manipulation. We present a model based pose estimation pipeline that allows to register the 3D object models by recognising objects in the scene. The registration pipeline is briefly explained in the following: First, an RGB-D scene depicted in Fig. 6.3 (a) was captured with the help of a Kinect sensor. Then, we applied several filters (passthrough, voxel grid, statistical outliers removal) to remove
unwanted points from the scene as shown in Fig.6.3(b). We then used FPFH (Fast Point Feature Histogram)\cite{171} descriptor to estimate feature points of both object model (c) and filtered scene (b). Once sufficient key points were obtained, SAC-IA (SampleConsensusInitialAlignment) algorithm\cite{171} finds an initial alignment of the imprecise object model in the filtered scene. Finally, the initial alignment is refined and registered using the Iterative Closest Point (ICP) algorithm\cite{172}. Outlier rejection and correspondence settings are tuned to reduce the computational load in real time operation.

Our objective was to find close fits of the model to the real object in the scene, so that the robots can perform stable and realistic operations on the object. The registration pipeline gives a decent object pose estimation result (Fig. 6.3(d)) for a given imprecise object model and scene. In particular, the SAC-IA algorithm gives a good initial fit of the 3D model with the scene and helps ICP to converge faster. Overall, the registration module plays an important role by providing a pose estimate of the given object from the real environment to the decentralized robots in the execution module.
Simulation Module

In the offline side, the simulation module illustrated in Fig. 6.4 is used for grasp plan generation and quality evaluation. The purpose of the module is to generate multi-robot grasp datasets using identical agents to allow efficient real-time execution. In the following, a grasp plan refers to a set of grasp hypotheses generated for an object.

First, a sampling based primitive grasp planner [163] (pre planner) uses the 3D object and robot (hand) models to generate grasp hypotheses. The primitive planner uses a set of grasp pre-shapes for simplified object models as illustrated in Fig. 6.1 (d), where the long and short arrows represent the approach and thumb directions. The candidate grasps are then executed in the simulation environment by the assigned robot and the grasp contacts are determined. The grasp quality is then evaluated using the $\epsilon_{\text{metric}}$ which corresponds to the largest ball fitting inside the convex hull of the contact induced wrenches. Once the grasps are evaluated, the corresponding grasp qualities and hypotheses with simulation info are stored in the multi-robot grasp database. The grasps are simulated using identical robots at a time so that each robot gets access only to a grasp database with its own embodiment. It should be noted that any existing grasp planner and quality measure could be used in the simulation module to produce and evaluate grasp hypotheses for object models.
Effective grasp coordination between robots is required to carry out cooperative manipulation tasks precisely. To conduct decentralized grasp coordination experiments, we develop a framework as shown in Fig. 6.5. The registration and simulation modules provide the estimated object pose and grasp datasets to the individual robots, allowing decentralized decision making on where and how to grasp. Even though the robots have grasp knowledge of the object, the success is determined in the implementation level. In real-time multi-robot coordination, the decentralized approaches allow the robots to plan their own grasp without precise information of each other and execute grasps in a sequential manner. In particular, imprecise observation (rough hand location) from the vision sensor helps the robots in making a grasp decision. The coordination execution module also assist the decentralized robots in making a motion plan and do reachability and collision checks.

In the following we explain how the robots do coordination in decentralized settings. First, the robots access real object pose information from the registration module and grasp information from the multi-robot grasp database. Once the grasp planner has sufficient grasp datasets, the robots makes decision based on the approaches presented in 4.3 and execute their grasp in a sequential manner in the priority order. Then, the success of the executed grasp is further analysed by doing cooperative manipulation tasks.
Cooperative Task Execution Module

Supplying a synchronous motion plan for the coordinated manipulation is the key role of this module. After decentralized coordination, a simple task planner gives a lift/lower task plan to the motion planner. To enable robots to perform such tasks, a motion planner based on Rapidly exploring random trees (RRT) generates trajectories considering kinematic constraints between the manipulators. Thus, the cooperative grasp success can be evaluated by doing simple coordinated co-manipulation.

6.2 Multi-robot experiments using physical hardware

In this section, we present two experiments using physical hardware. First, we study the effect of reachability and collision avoidance on the wrench space metrics. Second, we study the performance of the planned grasps using lift/lower tasks, proposing new experimental measures to analyze the quality of the collaborative grasp.

6.2.1 Set-up

The set-up consists of a Kinova Jaco [173] and a KUKA LWR4+ [174]. The Jaco has an integrated under-actuated three-finger gripper and a rated payload capacity of
A Barrett BH-282 hand [175] with also three under-actuated fingers is mounted on the KUKA arm. The arm has the rated payload capacity of 7 kg and the hand 6 kg. In addition, a Microsoft Kinect was mounted to a fixed location to perform pose estimation of the target objects.

Two objects, a light weight plastic table (Object 3, 1.9 kg) and a heavier chair (Object 5, 4 kg), were chosen so that they have different weights, corresponding to different difficulties for the collaborative grasping. The robots were stationed roughly opposite to each other as depicted in Fig. [17](c). The object was placed between the robots.

6.2.2 Experiment 1: Effect of constraints

To study the effect of constraints, the objects were placed in eight poses separated by 45 degree rotation, as illustrated in Fig. [6.6]. First, the pose of the object is estimated using a vision sensor. Then, the reachability and collision checks are performed in a centralized manner to determine a suitable pose for the object to conduct experiments as well as to filter out the unreachable or colliding grasps for the object pose. Collision at the arm links and object were taken into account while planning motions using a Rapidly Exploring Random Tree planner. If a pose had less than two reachable grasps, the pose was discarded for the experiment as it would provide little useful information. This resulted in four valid poses for Object 3 and five for Object 5.

The wrench space quality measures for the decentralized approaches are reported in Table [6.1]. The table reports the $\epsilon_{\text{metric}}$ values for top three cooperative grasps for each approach to provide more evidence. The values are reported as averages over the reachable poses for each object.

The results are consistent with the unconstrained simulation in that the ranking of the decentralized methods with respect to performance is $\text{DI} < \text{DA} < \text{DE}$. With a more constrained set of grasps in this experiment, the performance differences between the methods are somewhat greater. Also, the performance of DE is slightly worse compared to the global optimum. Nevertheless, the probabilistic treatment of DE shows significant increase in performance compared to the baseline DI approach.

6.2.3 Experimental measures for collaborative grasps

To evaluate the quality of collaborative grasps, we propose five experimental metrics.

**Metric 1 (M1):** Once the cooperative grasp is made, the object is lifted up 10
Table 6.1. Grasp quality averages over reachable poses for top three grasps. Quality shown as percentage of the maximum for each object

<table>
<thead>
<tr>
<th>Grasp</th>
<th>Object 3</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Object 5</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CZ</td>
<td>DI</td>
<td>DA</td>
<td>DE</td>
<td>CZ</td>
<td>DI</td>
<td>DA</td>
<td>DE</td>
<td>DE</td>
</tr>
<tr>
<td>1st</td>
<td>1.00</td>
<td>0.86</td>
<td>0.92</td>
<td>0.98</td>
<td>1.00</td>
<td>0.78</td>
<td>0.83</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>2nd</td>
<td>0.98</td>
<td>0.84</td>
<td>0.90</td>
<td>0.96</td>
<td>0.96</td>
<td>0.72</td>
<td>0.74</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>3rd</td>
<td>0.96</td>
<td>0.80</td>
<td>0.88</td>
<td>0.92</td>
<td>0.88</td>
<td>0.74</td>
<td>0.72</td>
<td>0.80</td>
<td></td>
</tr>
</tbody>
</table>

Figure 6.6. Objects were oriented in eight poses for analyzing the effects of reachability.

Metric 2 (M2): After the lift, a 200 g weight is placed in the center of mass of the object and the tilt measurement is repeated. Again, smaller tilt corresponds to better performance. The center of mass was found by hanging the object from several points with a string attached to the hanging point and the center of mass was found as the intersection of these.

Metric 3 (M3): A 350 g weight is placed farthest to the center of mass of the lifted object and the tilt measure is repeated. This metric measures the effect of an external disturbance shown in Fig. 6.7(f). In particular, the weight was placed at the farthest point from center of mass with the largest displacement due to tilt to avoid experiment bias.

Metric 4 (M4): 5 N of force is applied using a fish scale on the lifted object. The force disturbance is applied 3 times in different farthest locations from the center of mass of the object by hooking down the fish scale as shown in Fig. 6.8(g)-(i). While the disturbance is applied, the robot and object motions are observed visually and the
trial is scored as 0 for a grasp or lifting failure, 0.5 for object slip/pose deviation in both robot hands, 0.75 for object slip/pose deviation in one robot hand, and 1 for no slip/success in withstanding disturbances. The force exertion locations and directions were documented for experiment repeatability.

**Metric 5 (M5):** After all of the above steps, the object is lowered back on the table and the deviation in the object alignment is measured as shown in Fig. 6.8 (j). The deviations are measured from the center of each leg in centimetres and averaged to determine overall deviation. M5 provides a good overall insight on the effects of disturbances.

### 6.2.4 Experimental procedure

The performance of the proposed approach depends on the validity of the assumption that the wrench space grasp quality metric correlates with the performance of the physical system, even in the presence of significant modeling uncertainties. To study the performance, top three collaborative grasps were executed for the two objects with the different methods, and the real time quality metrics were recorded. A single pose with good reachability was chosen for each object. The set-ups for the two objects are shown in Fig. 6.9 (a) and Fig. 6.10 (e).

The step by step procedure for conducting the experiment is illustrated in Figs. 6.7 and 6.8. In Step 0 shown in Fig. 6.7 (a), the object was registered using vision and its pose was recorded manually. In Step 1, planned paths were executed to pre-grasp positions. In Step 2 depicted in Fig. 6.7 (c), the fingers of each hand were closed until a force threshold was reached for each finger. In Step 3, the robots were controlled to execute a synchronized lifting motion shown in (d) and, in Step 4, the tilt of the object (M1) was measured in (e). Next, effect of disturbances was measured by adding a weight as shown in (f) and measuring inclination metrics M2 and M3. Force disturbances in directions other than the gravity were applied with a fish scale in the three places shown in Fig. 6.8 (g)-(i) and M4 was recorded. Finally, robots were controlled to lower the object synchronously and open the grippers as shown in (j) and M5 (position deviation) was recorded.

### 6.2.5 Experiment 2: Cooperative grasps and results

Typical successful and unsuccessful lifts are illustrated in Fig. 6.9. Sub-figures (b)-(d) show Object 3 and Fig. 6.10 (b-d) show Object 5. Subfigures (b) and (f) show successful lifts executed using the best grasp according to the DE approach. Figure 6.9 (c) and (d) show typical partial successes where the object lifted off the supporting
surface but its alignment changed shown by its tilt. Figure 6.10 (g) and (h) show failed lifts for the heavier Object 5 planned using the baseline DI approach. These failures leave some part of the object on the supporting surface.

Tables 6.2 and 6.3 show the experimental results for Object 3 and Object 5 respec-

Figure 6.7. Step by step experimental procedure.
The tables present the experimental and wrench space metrics for top three cooperative grasps for each approach so that CZ-1 denotes the best grasp for the centralized approach, CZ-2 the second best, and CZ-3 the third best.

For the lighter-weight, easier Object 3 (Table 6.2) the results are consistent with earlier simulations as the wrench space metric values correlate quite well with the experimental metrics. This can be seen in that the grasps that failed under disturbances (DI-2, DA-2) have lower wrench space metric values. Furthermore, the best approaches according to simulation, CZ and DE, exhibited again clearly superior performance over the two other approaches. Moreover, grasp ranking within an approach correlates well with the performance according to the proposed experimental metrics. This is true especially for the best performing approaches CZ and DE.

For the heavier Object 5 (Table 6.3), the correlation between the success of the physical system and the simulation results was significantly weaker. Thus, the wrench space metric value did not predict the success of the physical system particularly well.
This results in the surprisingly poor performance of the supposedly globally optimal CZ approach as one of the top three grasps (CZ-2) fails under disturbance. Thus, there are modeling inaccuracies in the system.

The probabilistic approaches DA and DE provided superior physical metric results over CZ and especially DI, failing under disturbance in all top three grasps. Two of the failure cases are illustrated in Fig. 6.10(g)-(h). The great superiority over DI shows that the probabilistic treatment of embodiment uncertainties offers significant advantage for decentralized planning. Moreover, the improvement over CZ seems to indicate that the probabilistic treatment is able to reduce the effect of modeling inaccuracies as an unintended but valuable side-effect. The good performance of DA was slightly unexpected compared to the earlier results but further study would be required to draw more detailed conclusions.

The finding that the ranking of grasps for centralized planning (CZ) differs between wrench space and experimental metrics provides additional evidence to the finding
that the traditional wrench space metrics do not correlate very well with actual grasp success. This calls for further studies, in particular, task specific quality measures will be useful in grasp planning for heavy weight objects since forces and torques need to be applied to counteract the gravity.

Analyzing the proposed experimental metrics, the inclination metrics (M1-M3) correlate well with the overall success under disturbances (M4) while the alignment metric (M5) does not exhibit such a clear correlation. The reason for the smaller correlation of the alignment metric seems to be that the alignment error is caused by a series of uncertainties stemming from the entire system including pose estimation and kinematic control uncertainties. The practical importance of the alignment metric depends on application; in applications such as assembly high precision is required while other object transport applications can often tolerate lower precision.
6.3 Computational complexity

The proposed method can be implemented with an off-line part that generates grasp hypotheses and evaluates their quality metric values (separately for each embodiment), and an on-line part that coordinates the choice of grasps. Assuming sequential operation, the computational complexity of both parts is \( \mathcal{O}(N|G|^N) \) where \(|G|\) is the number of grasp hypotheses and \(N\) the number of robots. This results directly from the number of possible grasp combinations being \(|G|^N\). The off-line part can also be executed in parallel for each robot, resulting in off-line complexity \( \mathcal{O}(|G|^N) \). In practice, the number of possible grasp hypotheses is quite low due to reachability and collision constraints. This indicates that the approach is viable for imagined domestic robot setting with relatively few robots but not for swarms of many robots.

The computation time for the off-line part (generation, simulation and evaluation of grasps) was in the order of a few hours per object without optimization. This is in line with most other current data-driven grasping approaches. For the on-line decision making, Object 3 had the most grasp candidates (395) and the computation times taken for decision making were negligible (between 2ms and 20ms) compared to the time taken by physical actions.
6.4 Discussion

We presented a complete system for performing simple collaborative manipulation starting from point cloud perception. The system was used to experimentally demonstrate and study the cooperative grasping. Simulation experiments in Chapter 5 showed that the proposed probabilistic treatment of incomplete knowledge increases performance over baseline decentralized approaches and shows performance close to the globally optimal centralized planning. In order to validate the results for physical systems, we developed five new metrics to analyze the quality of physical grasps quantitatively. The metrics were used in physical experiments to confirm the primary finding from the simulation that the probabilistic planning approaches are superior to baseline.

The traditional grasp quality measures showed poor predictive performance for physical experiments especially in the case of lifting a heavy object. This warrants future study in task specific grasp quality analysis which would take into account the physical properties of the object such as mass distribution as well as the wrenches required by a particular task such as lifting.

We would like to point out two issues about the experimental protocol. Firstly, repeatability in grasping experiments requires careful documentation. For example, marking the locations of disturbances enables their repetition. Secondly, when comparing between different approaches, it is sufficient that the experimental conditions are the same for each approach, resulting in comparable results. Defining disturbances without any ambiguity is very difficult and thus results between studies are likely not directly comparable. However, this is likely to be the case also for other reasons such as differences in robot embodiments. Our experiments were carefully documented to allow repeatability and minimize any bias in the results.

Several kinds of uncertainties affect cooperative grasping and manipulation, including registration uncertainties for target object poses and kinematic control inaccuracies. Furthermore, each robot uses perception to estimate the grasp location of other robots, causing further inaccuracies in knowledge. Finally, the knowledge of one robot’s hardware is incomplete to other robots. In the approaches proposed in this paper, only the last one, incomplete embodiment knowledge, is addressed explicitly through the probabilistic approach. However, the approaches seem to provide some robustness towards the other, unmodeled disturbances and uncertainties. Those disturbances could also be treated explicitly, for example as proposed for pose uncertainty in [176], and combined with the presented approach. This would likely offer
superior results and warrants further study.
Part III

Cooperative Manipulation under Constraints and Heterogeneity
7. Local Redundancy Resolution for Cooperative Manipulators

As a background to the developed controller in Chapter 8, this Chapter begins with the fundamental derivations on direct and inverse differential kinematics of a robotic manipulator. Then, we review redundancy resolution methods that locally solve the inverse differential kinematic problems of the redundant manipulator. Optimization of a performance criterion and resolving the secondary tasks are primarily addressed by the methods for online control. A derivation using the relative Jacobian formulation for cooperative manipulators that facilitates coordination of motions is presented in the final part of this Chapter.

7.1 Differential kinematics of a robotic manipulator

Consider a robotic manipulator with \( n \) joints that is required to perform a task described by \( m \) variables in the operational workspace \( r \). The relationship between joint vector \( \vec{q} \in \mathbb{R}^n \) and task vector \( \vec{x}_e \in \mathbb{R}^m \) is described by the following direct kinematic equation:

\[
\vec{x}_e = f(\vec{q})
\]  

(7.1)

where \( f(\ast) \) is a continuous non-linear function that associates each \( \vec{q} \) to unique \( \vec{x}_e \). In general, kinematic control solutions are sought at differential level. Differentiating \ref{eq:7.1} the forward kinematics can be obtained as

\[
\dot{\vec{x}}_e = J(\vec{q})\dot{\vec{q}}
\]  

(7.2)

where \( J \in \mathbb{R}^{mxn} \) is the analytic Jacobian matrix that maps the joint velocity vector \( \dot{\vec{q}} \in \mathbb{R}^n \) to the corresponding task velocity vector \( \dot{\vec{x}}_e \in \mathbb{R}^m \). A Jacobian can be analytic or geometric. Analytic Jacobian is computed when the pose of the end effector is expressed with reference to a minimal representation in the operational
space such as euler angles (differential quantities) in the orientation denoted as \( \dot{\hat{x}}_e = [\dot{\hat{P}}_e, \dot{\hat{Q}}_e]^T \) whereas a geometric Jacobian \( J_g \in \mathbb{R}^{6\times n} \) mainly depends on the manipulator configuration that relates the task velocity to the velocity of the end-effector which is expressed as twist consisting of linear and angular velocity and denoted as \( \dot{x}_e = [\dot{\hat{P}}_e, \dot{\hat{Q}}_e]^T \). Both forms of Jacobian can be associated with \( J_g(\hat{q}) = TJ(\hat{q}) \).

In (7.2), the analytical Jacobian becomes a square matrix and achieves a full rank with respect to operational space if \( m = n \). Thus the joint velocity required to accomplish the desired end effector velocity will be unique and that can be calculated by inverting the Jacobian such as

\[
\dot{\hat{q}} = J^{-1}(\hat{q})\dot{x}_d \tag{7.3}
\]

Since the inverse kinematics algorithm run on digital signal processors (DSP), integration of the joint velocity to reconstruct the joint variables \( \dot{\hat{q}}_k \) at each time instants is common in the process of discretization. We ignore the time instant subscript \( k \) to improve the readability. The numerical integration and initial value uncertainty in joint positions can causes drift in the computed inverse kinematics solution. In simpler terms, the computed joint variables for the end effector pose differs from the desired pose. Apart from reducing the sampling time, this problem can be easily tackled by treating the operational space error \( \dot{e} = \dot{x}_d - \dot{x}_e \) with a simple feedback correction.

Figure 7.1 illustrates a inverse kinematics algorithm with a inverse Jacobian function and feedback correction term which allows to calculate the end effector velocity as

\[
\dot{\hat{q}} = J^{-1}(\hat{q})(\dot{x}_d + K\dot{e}) \tag{7.4}
\]

\[\text{Figure 7.1. Closed Loop Inverse Kinematics with Inverse Jacobian}\]
where $K \in \mathbb{R}^{n \times m}$ is a positive-definite gain matrix that facilitates the convergence of the tracking pose errors. The higher the gain value the faster the convergence. Equation 7.4 also can be rewritten as

$$J^{-1}(\ddot{q})(\ddot{e} + K\ddot{e}) = 0 \to \lim_{t \to \infty} ||\ddot{e}||^2 = 0$$ (7.5)

Thus the closed form inverse kinematic (CLIK) algorithms allows the manipulator to perform a desired task by computing admissible joint space solutions and ensuring tracking pose error convergence $\ddot{e} + K\ddot{e} = 0$.

### 7.2 Redundancy resolution of a redundant manipulator

A generic open chain manipulator is defined as *kinematically redundant* when its degree of motion $n$ (number of joints) is higher than the number of variables $m$ describing a given task, $n > m$ [177]. In particular, when the manipulator also has a degree of motion higher than the dimension of the operational space $r$ in which the manipulator operates, $n > r$ with $r \geq m$, it is defined as *intrinsically redundant*. Otherwise, if $n = r$ with $r > m$ (and thus $n > m$), it is defined as *functionally redundant*. The last definition does depend on the number of the task variables $m$, so that the same manipulator can be functionally redundant with respect to a specific task $T_1$ with $m_1 < r$, and non-redundant with respect to another task $T_2$ with $m_2 = r$.

#### 7.2.1 Jacobian pseudo-inverse method

So for $n > m$, the manipulator is known to be redundant and the Jacobian matrix in (7.2) becomes non square and its inversion admits infinite solution for a given task. To determine an admissible solution, the problem is usually formulated as a constraint linear optimization problem which aims at minimizing the norm of the joint velocity expressed as $\min_{\dot{q}} ||\dot{q}||^2$ and task error expressed as $\min_{\dot{q}} ||(\ddot{x}_{d} - J(\ddot{q})\dot{q})||$.

In the case of a full rank Jacobian matrix, the Moore-Penrose pseudo inverse of the Jacobian is known to be an attractive joint velocity solution which can be formulated by replacing the inverse Jacobian as

$$\ddot{q}_{P} = J^\dagger(\ddot{q})(\dddot{x}_{d})$$ (7.6)

where the Moore-Penrose pseudo inverse of the Jacobian matrix can be expressed as

$$J^\dagger = J^T(JJ^T)^{-1}$$ (7.7)
Since the Moore-penrose pseudo inverse has the least square property the obtained solution locally minimizes the notion of joint velocity.

### 7.2.2 Jacobian null space method

Apart from the primary task, the manipulator is expected to handle joint limits, obstacles and satisfy other performance criterion by managing the redundant joints without affecting the primary task. One possible strategy is to project an arbitrary joint space velocity vector $\dot{q}_a$ in the Jacobian null space to handle the secondary tasks. The null space of the Jacobian is a region where there is redundancy of solution. The $n \times n$ orthogonal projector facilitating projection of secondary task is expressed as

$$P_k = (I - J^\dagger(\bar{q})J(\bar{q}))$$  \hspace{1cm} (7.8)

which is symmetric, hermitian and idempotent and $I$ is the identity matrix.

Pseudo inverse with null space projection is a well known technique [60, 178] to satisfy primary task while accommodating secondary task. Thus the pseudo-inverse kinematic solution in (7.6) can be formulated accordingly:

$$\dot{q}^{PN} = J^\dagger(\bar{q})\dot{x}_d + P_k \dot{q}_a$$ \hspace{1cm} (7.9)

where $P_k \dot{q}_a \in \text{N}(J)$ is the homogeneous solution which is orthogonal to $J^\dagger(\bar{q})\dot{x}_d$ (least norm solution), such that the redundant joint velocities satisfy

$$J(I - J^\dagger(\bar{q})J(\bar{q}))\dot{q} = 0$$ \hspace{1cm} (7.10)

thus, at each end effector configuration, the set of Jacobian null space velocities yield zero task space velocity. In simpler words, the homogeneous solution generates self motion that has no effect on the end effector goal.

The arbitrary vector $\dot{q}_a$ in homogeneous solution can be selected to improve the performance of the redundant manipulator by optimizing performance criterion $H(\bar{q})$, without affecting the end-effector velocity. Gradient projection method [179, 180] is a well known optimization method to resolve redundancy locally (e.g. online control). The underlying idea in such method is to project the gradient of the arbitrary task vector in the Jacobian null space. Using GPM, the equation in (7.9) is expressed as

$$\dot{q}^{PNG} = J^\dagger(\bar{q})\dot{x}_d + P_k(k_g \nabla_\bar{q}H(\bar{q}))$$ \hspace{1cm} (7.11)

where $k_g$ is a scalar parameter and $\nabla_\bar{q}H(\bar{q})$ is the gradient of $H(\bar{q})$. 

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7.2.3 Task prioritization method

Redundancy can be used to perform one or more secondary tasks, which possess lower execution priority with respect to the main task. The maximum number of tasks \( l \) that can be simultaneously handled, depends on the number of degrees of motion equal to the number of joints \( n_{ab} \) and the rank \( s \) of the Jacobian associated with each task \([181]\). Therefore, when choosing tasks in a non-conflicting way, it is possible to add tasks until

\[
\sum_{i=1}^{l} s_i = n_{ab} \tag{7.12}
\]

In order to avoid task conflicts, Chiaverini et al. \([182]\) introduced a hierarchic prioritized task architecture, in which lower priority tasks are projected on the null space of the higher priority ones. In this way, the lower priority tasks do not affect performance of the higher priority tasks and the performance of the highest priority task is always guaranteed.

Therefore, given a generic single manipulator and three prioritized tasks \( \dot{x}_1, \dot{x}_2 \) and \( \dot{x}_3 \) (where the subscript having lowest value indicates the highest priority task), it is possible to obtain the joint velocity vector \( \dot{\mathbf{q}}^{\text{PNT}} \) according to the hierarchic prioritized task architecture

\[
\dot{\mathbf{q}}^{\text{PNT}} = J_i^\dagger \dot{x}_i + P_1 \left( J_2^\dagger \dot{x}_2 + P_2 J_3^\dagger \dot{x}_3 \right) \tag{7.13}
\]

where \( J_i^\dagger (i = 1, 2, 3) \) is the pseudo inverse of the Jacobian of each task, while \( P_j (j = 2, 3) \) indicates the orthogonal projector on the null space \( N_j \), that is obtained by \( P_j = I - J_j^\dagger J_j \) (where \( I \) indicates the identity matrix).

7.3 Inverse kinematic solution for cooperative manipulators

A pair of cooperative manipulators that manipulates a rigid body forms a closed kinematic chain \([183]\). For this reason, the manipulators need to maintain precise kinematic coordination and movement synchronisation to avoid damage. To maintain the coordination, we adopt the relative Jacobian method which was introduced by Lewis \([184]\) and recently expressed in a more compact formulation by Jamisola et al. \([185]\).

The relative Jacobian approach allows to develop a single kinematic control for two cooperative manipulators as a single redundant manipulator, which possesses the end-effector motion equals to the relative end-effector motion, and the number of joints equals to the total number of joints possessed by the cooperating manipulators. The relative Jacobian approach allows kinematic control of cooperative manipulators by
exploiting the Jacobians of each individual manipulator, thus providing a convenient framework for coordinated motions.

7.3.1 Relative Jacobian formulation

Let us consider two cooperative manipulators $A$ and $B$ as shown in Figure 7.2, which possess a number of joints equal to $n_a$ and $n_b$, respectively. Manipulator $A$ is considered to have the role of master. The frame of the end-effector $B$ (denoted as $B_e$) is expressed with respect to the frame of end-effector $A$ (denoted as $A_e$), by using vectors $\vec{P}_R$ and $\vec{\phi}_R$. In detail, the vector $\vec{P}_R$ defines the end-effector’s relative position by Cartesian coordinates, while the vector $\vec{\phi}_R$ describes the end-effector’s relative orientation by using a minimum orientation representation (see, e.g., [177]).

Differentiating these two vectors with respect to time, it is possible to define a unique vector $\dot{\vec{x}}_{R_k}$, which contains the end-effector’s relative velocity components at time instant $k$

$$\dot{\vec{x}}_{R_k} = \begin{bmatrix} \dot{\vec{P}}_R \\ \dot{\vec{\phi}}_R \end{bmatrix}$$ (7.14)

where $\dot{\vec{x}}_{R_k}$ is a $r_{ab}$ dimensional column vector; note that $r_{ab} \leq 6$ in a three dimensional space.

The kinematic relations between the two manipulators permit to obtain a single equivalent manipulator having a number of joints equal to $n_{ab} = n_a + n_b$ and relative end-effector velocity components defined by the vector $\dot{\vec{x}}_{R_k}$. Therefore, it is possible to calculate the Jacobian matrix associated with this equivalent manipulator, namely relative Jacobian $\dot{J}_R$, which is a $(r_{ab} \times n_{ab})$ dimensional matrix, which can be ex-
expressed in the following compact form [185]

\[
J_R(\tilde{q}_{a_k}, \tilde{q}_{b_k}) = \begin{bmatrix}
-\Psi_{AB} & \Omega_{A_b} J_A \\
\Omega_{B_b} J_B
\end{bmatrix}
\] (7.15)

where \( J_R \) matrix depends on joint position vectors of both manipulators, \( n_a \)-dimensional column vector \( \tilde{q}_{a_k} \) and \( n_b \)-dimensional column vector \( \tilde{q}_{b_k} \), respectively. The \( J_R \) matrix, expressed in the compact form, shows explicitly the analytic Jacobians of the standalone manipulators, namely \( J_A \) of dimension \( (r_{ab} \times n_a) \), and \( J_B \) of dimension \( (r_{ab} \times n_b) \). Since the relative end-effector motions are expressed in frame \( A_e \), the two block diagonal matrices \( \Omega_{A_b} \) and \( \Omega_{B_b} \) are used in (7.15) to transform the Jacobians from each manipulator base frame, \( A_b \) and \( B_b \), to frame \( A_e \), as shown in Figure 7.2.

These matrices can be expressed in terms of rotation matrices as

\[
\Omega_{A_b} = \begin{bmatrix}
R_{A_b} & 0 \\
0 & R_{A_b}
\end{bmatrix}, \quad \Omega_{B_b} = \begin{bmatrix}
R_{B_b} & 0 \\
0 & R_{B_b}
\end{bmatrix}
\] (7.16)

Finally, \( \Psi_{AB} \) represents the wrench transformation matrix that compensates the translation component of the relative velocity, originating from the cross product of end-effector \( A \) orientation velocity \( \dot{\phi}_A \) with the end-effector position vector \( \tilde{P}_R \).

\[
\Psi_{AB} = \begin{bmatrix}
I & -S(\tilde{P}_R) \\
0 & I
\end{bmatrix}
\] (7.17)

where \( S(\tilde{P}_R) \) is the skew symmetric matrix generated by vector \( \tilde{P}_R \).

The relative Jacobian matrix \( J_R \) expressed in (7.15) presents several advantages. First of all, the relative Jacobian is simple to obtain from the Jacobians of the individual manipulators. Moreover, configuration changes are easy to handle since it is sufficient to change the respective Jacobian matrix with that of the new manipulator.

The relation between the relative end-effector motion vector \( \dot{x}_{R_k} \) and the joint velocity vectors of both manipulators, \( \dot{\tilde{q}}_{a_k} \) and \( \dot{\tilde{q}}_{b_k} \), can be written using \( J_R \) as

\[
\dot{x}_{R_k} = J_R \dot{\tilde{q}}_{ab_k}
\] (7.18)

where \( \dot{\tilde{q}}_{ab_k} = [\dot{\tilde{q}}_{a_k}, \dot{\tilde{q}}_{b_k}]^T \) is a \( n_{ab} \)-dimensional vector. Since \( r_{ab} < n_{ab} \), the inversion of (7.18) admits infinite solutions, therefore a criterion has to be adopted to choose the suitable solution. A possible criterion is to minimize the norm of \( \dot{\tilde{q}}_{ab_k} \) using the Moore-Penrose pseudo-inverse resulting in [177]

\[
J_R^+ = J_R^T (J_R J_R^T)^{-1}
\] (7.19)
Finally, in order to reduce the relative end-effector position and orientation error $\vec{e}_{R_k}$, defined as the difference between desired relative end-effector pose $\vec{x}_{R_{d_k}}$ and the measured pose $\vec{x}_{R_k}$, namely

$$\vec{e}_{R_k} = \vec{x}_{R_{d_k}} - \vec{x}_{R_k} = \begin{bmatrix} \vec{P}_{R_d} & \vec{\phi}_{R_d} \end{bmatrix}^T - \begin{bmatrix} \vec{P}_R & \vec{\phi}_R \end{bmatrix}^T$$

(7.20)

it is possible to add a feedback correction term to inversion of (7.18). Therefore, the following first-order kinematic control based on Closed-Loop Inverse Kinematics (CLIK) [66], can be adopted

$$\dot{q}_{ab_k} = J_k^T(\dot{\vec{x}}_{R_{d_k}} + K_R \vec{e}_{R_k})$$

(7.21)

where $\dot{\vec{x}}_{R_{d_k}}$ is the desired relative end-effector motion vector, while $K_R$ is a constant positive-definite gain matrix that defines the convergence rate of $\vec{e}_{R_k}$ [177].

### 7.4 Discussion

In this chapter we formulated the relative Jacobian for the kinematic control of cooperative manipulators that are heterogeneous (mixed redundancy) and presented a closed loop inverse kinematic solution $\dot{q}_{ab_k}$. To investigate local resolution methods, we first gave a background on the differential kinematics of the robotic manipulator. Then for a redundant manipulator, three classes of local resolution methods for solving the inverse differential kinematics problem were overviewed. First is the Jacobian-based method which allows to determine a single solution from the huge space of possible solutions based on a criterion (e.g. minimizing a weighted norm). Second is the null space method which drives the above method with additional homogeneous solution. The last one is the task prioritization method which allows to add additional tasks in the null space. The null space based methods facilitate secondary tasks such as joint limit avoidance without violating the primary task carried out by the manipulator. We adopt Moore-Penrose pseudo inverse and null space projections to handle relative motion, trajectory tracking and joint limit avoidance in cooperative manipulators in the next Chapter.
8. Cooperative Manipulation under Joint Limit Constraints

Cooperative manipulation of a rigid object is challenging and represents an interesting and active research area, especially when these robots are subject to joint and task prioritization constraints. In cooperative manipulation, a primary task is to maintain the coordination of motions, to avoid severe damage caused by the violation of kinematic constraints imposed by the closed chain mechanism.

This chapter presents a kinematic controller for dual-arm cooperative manipulation that ensures safety by providing relative coordinated motion as highest priority task and joint limit avoidance and world-space trajectory following at a lower priority. In particular, a smooth activation function is proposed for joint limit avoidance task. Moreover, the coordination of motions is based on the relative Jacobian formulation which was presented in the previous chapter. The approach is applicable to systems composed of redundant or non-redundant manipulators. Experiments in simulation demonstrate the behaviour of the approach under different redundancy configurations. Experiments on two robots with different number of redundant motions show the applicability of the proposed approach to cooperative manipulation under joint limit constraints.

8.1 Related work

The handling of joint motion constraints, that is to say limits on joint position or velocity, has been addressed extensively in the single manipulator case \cite{68, 186, 187}. In manipulators with redundancy, joint position limits can be usually avoided without sacrificing the end-effector position tracking accuracy while in non-redundant systems joint limit avoidance can cause trajectory tracking errors.

Joint limit avoidance of cooperative manipulators has been considered by only few authors \cite{188, 189} even though the additional coordinated motion constraint is a
potential cause of complications. Both approaches employ the relative Jacobian to coordinate relative motions and a prioritized task hierarchy to coordinate between possibly conflicting tasks. Both methods exhibit binary switching behavior in joint limit avoidance. As identified in [189], this may cause strong velocity transients that would require extremely high accelerations and could be a possible source of system failure.

In order to avoid such transients, we propose to use a smooth activation function for the joint limit avoidance task, similar to [67, 187, 190] for individual manipulators. In particular, we propose to use the hyperbolic tangent as the activation function [67]. The function provides a smooth ($C^\infty$) but fast transition and its advantage compared to a binary activation matrix was experimentally demonstrated in [191]. As a further difference to [188, 189], this work considers a heterogeneous setting, which allowed us to make interesting observations and findings about control of heterogeneous dual-arm systems, as presented in Section 8.4.

### 8.2 Kinematic control for joint limit avoidance

A pair of cooperative manipulators that manipulates a rigid body forms a closed kinematic chain [183]. For this reason, the manipulators need to maintain precise kinematic coordination and movement synchronisation to avoid damage. To maintain the coordination, we adopt the relative Jacobian method which was introduced by Lewis [184] and recently expressed in a more compact formulation by Jamisola et al. [185]. The relative Jacobian approach allows to develop a single kinematic control for two cooperative manipulators as a single redundant manipulator, which possesses the end-effector motion equals to the relative end-effector motion, and the number of joints equals to the total number of joints possessed by the cooperating manipulators.

Although the method enables cooperative tasks, its application under constraints, such as joint limits, is not straightforward. The handling of joint motion constraints, that is to say limits on joint position or velocity, has been addressed extensively in the single manipulator case [68, 186, 187]. In manipulators with redundancy, joint position limits can be usually avoided without sacrificing the end-effector position tracking accuracy while in non-redundant systems joint limit avoidance can cause trajectory tracking errors. Joint limit avoidance of cooperative manipulators has been considered by only few authors [188, 189] even though the additional coordinated motion constraint is a potential cause of complications.
We propose a kinematic controller for cooperative manipulation under joint limit constraints by using the relative Jacobian method. In particular, the proposed controller assigns a priority execution level to each sub-task of the cooperative manipulation, in the following decreasing order of priority:

1. relative end-effector motion;

2. world-space end-effector motion;

3. joint limit avoidance by using redundant motions.

The combination of a redundant and a non-redundant manipulator is redundant with respect to relative motions. However, our study considers the case where there is also a world-frame task with a lower priority. This world-frame task constrains all degrees of freedom of the non-redundant manipulator. Therefore, the world frame task cannot necessarily be satisfied if the non-redundant manipulator is at a joint limit. On the other hand, the redundant manipulator is able to satisfy the world frame task even at a joint limit. This is true even though the number of total degrees of freedom is the same in both cases.

Therefore, when the redundancy is not able to avoid all joint limits, the proposed controller temporarily assigns the joint limit avoidance task a higher priority equal to the world-space end-effector motion. In this way, the performance on trajectory tracking is temporarily reduced, while the relative end-effector motion (with highest priority) is not affected.

### 8.2.1 Hierarchical controller

As proposed in [185][192], in the dual arm system based on the Jacobian null space projection, we set the highest priority task to retain motion coordination represented by $\dot{x}_{R_{kl}}$, while the secondary task is given by the desired $A_c$ motion $\dot{x}_{A_{kl}}$, which is expressed with respect to its base frame $A_b$. Moreover, if the system possesses redundant motions, in accordance with (7.12), it is possible to add a third task in order to satisfy further constraints (e.g., increasing the system manipulability [193] or avoiding joint position limits [192]). Since the study in this paper is focused on the joint limits avoidance, it can be expressed as a repulsive joint velocity vector $\dot{q}^+_k$, which pushes the joint positions away from their limits. By expressing the three tasks de-
Cooperative Manipulation under Joint Limit Constraints

Figure 8.1. (a) Activation function for one component \( w_i \) of \( W \) matrix, (b) Operating principle of the joint limits avoidance strategy for a generic not redundant manipulator

scribed in (7.13) according to the relative Jacobian of (7.21), a kinematic controller for the dual arm system can be written as

\[
\dot{q}_{ab} = J_R^\dagger(\ddot{x}_{Rd} + K_R\ddot{e}_R) + P_R \left( [J_A 0]^\dagger (\ddot{x}_{Ad} + K_e) + P_{AB}\ddot{q}_k^+ \right) \tag{8.1}
\]

where \( K \) is the feedback gain related to the end-effector \( A \) position error \( \ddot{e}_k = \ddot{x}_{A2k} - \ddot{x}_{A1k} \). Finally, the \((n_A \times n_B)\) dimensional matrix, \( P_{AB} \), can be defined as

\[
P_{AB} = \begin{bmatrix}
P_A & 0 \\
0 & P_B 
\end{bmatrix}
\tag{8.2}
\]

which contains the orthogonal projectors into the Jacobian null spaces of the both manipulators \( A \) and \( B \), respectively \( P_A = (I - J_A^\dagger J_A) \) and \( P_B = (I - J_B^\dagger J_B) \), while \( P_R = (I - J_R^\dagger J_R) \) is the orthogonal projector matrix into the relative Jacobian null space \( N_R \).

**Remark.** Note that the subscript \( k \) related to time will be ignored in the following to improve readability.

### 8.2.2 Joint Limit avoidance strategy

A classical approach to avoid joint limits is to define the gradient of a cost function as the lowest priority task [177]. This approach guides each joint towards the middle of its range, regardless of the joint position’s closeness to the limit. In order to optimize the number of redundant motions that are employed in the joint limit avoidance task, we use a repulsive joint velocity that moves only the critical joints away from their limits [187]. In particular, we define for the \( i \)-th joint of position \( q_i \), the following sets:

- joint position limits, \( q_L_i = [q_{i_{min}}, q_{i_{max}}] \);
• the activation threshold for the repulsive motion, $q_{Ti} = [q_{Tmin,i}, q_{Tmax,i}]$, where $q_{Tmin,i} \geq q_{Lmin,i}$ and $q_{Tmax,i} \geq q_{Tmax,i}$;

• the size of the interval where the activation function is smooth, $\beta_i = [\beta_{min,i}, \beta_{max,i}] = [q_{Tmin,i} - q_{Lmin,i}, q_{Lmax,i} - q_{Tmax,i}]$, as shown in Figure 8.1(a);

• the distances from its limits, $\alpha_i = [\alpha_{min,i}, \alpha_{max,i}] = [q_i - q_{Lmin,i}, q_{Lmax,i} - q_i]$.

Then the $i$-th joint is said to be a critical joint if $\alpha_{min,i} < \beta_{min,i} \lor \alpha_{max,i} < \beta_{max,i}$, i.e., if a generic $q_i$ crosses the activation threshold $q_{Tmin,i}$ or $q_{Tmax,i}$, as shown in Figure 8.1(a). In detail, the symbols $\beta_{min,i}$ and $\beta_{max,i}$ are parameters that can be chosen by the designer: higher absolute values imply a smoother (slower but safer) repulsion motion, while smaller values a stiffer (faster but less safe) repulsion. $\alpha_{min,i}$ and $\alpha_{max,i}$ indicate instead the current distance between the joint from its lower and upper limits. When the $i$-th joint of position $q_i$ gets closer to those limits, then the repulsive velocity has the objective to push it away from the closest limit. Following the form of the smooth activation function provided in (8.5), then the repulsive velocity applies as soon as the $i$-th joint crosses the actuation threshold, before reaching the respective limit. In this way, the joint can actively avoid its limit, before getting too close to it.

For the dual arm system composed of two manipulators, it is possible to obtain a repulsive joint velocity vector for each manipulator, $\dot{q}_A^+$ and $\dot{q}_B^+$, respectively as

$$\dot{q}_A^+ = H_A W_A (\tilde{q}_T - \tilde{q}_A)$$

(8.3)

$$\dot{q}_B^+ = H_B W_B (\tilde{q}_T - \tilde{q}_B)$$

(8.4)

where $\tilde{q}_T$ is an $n_a + n_b$ dimensional column vector, which contain the joint threshold positions closest to the current joint position (i.e., $q_{Txi} = q_{Txi}^{min}$ when $\alpha_{Amin} < \alpha_{Amax}$), while $\tilde{q}_A$ and $\tilde{q}_B$ are the current joint positions. $H_A$ and $H_B$ are $(n_a \times n_a)$ and $(n_b \times n_b)$ dimensional diagonal matrices representing the gains of the control law of this task. However, these gains are weighted by the two smooth activation diagonal matrices $W_A$ and $W_B$, whose component values $w_i(q_i)$ belong to $[0,1]$, as shown in Figure 8.1(a). By expressing $w_i$ functions with respect to $\alpha$, it is
possible to define formally the Figure 8.1(a), as reported in (8.5).

\[
    w_i(\alpha_i) = \begin{cases} 
    1 & \alpha_{\min,i} < 0 \vee \alpha_{\max,i} < 0 \\
    \frac{1}{2} & \left(1 - \text{tanh}\left(\frac{1}{\alpha_{\min,i} - \beta_{\min,i}}\right)\right), \alpha_{\min,i} \in [0, \beta_{\min,i}] \\
    \frac{1}{2} & \left(1 - \text{tanh}\left(\frac{1}{\alpha_{\max,i} - \beta_{\max,i}}\right)\right), \alpha_{\max,i} \in [0, \beta_{\max,i}] \\
    0 & \text{otherwise} \end{cases} 
\] (8.5)

The smooth transition allows to reduce the discontinuities in the joint velocity signals compared to a binary activation matrix [67].

Finally, setting \( \dot{\mathbf{q}}^+ = \left[\dot{\mathbf{q}}_A^+, \dot{\mathbf{q}}_B^+\right]^T \) in (8.1), it is possible to obtain the following final compact matrix equation

\[
    \dot{\mathbf{q}}_{ab} = J_R^T(\dot{x}_{Rd} + K\dot{e}_R) + P_R \left( [J_A 0]^T(\dot{x}_{Ad} + K\dot{e}) + P_{AB}H_{AB}W_{AB}(\dot{q}_{T_{ab}} - \dot{q}_{AB}) \right) 
\] (8.6)

where \( \dot{q}_{T_{ab}} = [\dot{q}_{Ta}, \dot{q}_{Tb}]^T \), \( \dot{q}_{AB} = [\dot{q}_A, \dot{q}_B]^T \), while \( H_{AB} \) and \( W_{AB} \) are defined as

\[
    H_{AB} = \begin{bmatrix} H_A & 0 \\ 0 & H_B \end{bmatrix}, \quad W_{AB} = \begin{bmatrix} W_A & 0 \\ 0 & W_B \end{bmatrix}. \] (8.7)

Note that the joint limit avoidance task has lower priority than trajectory following. This can appear counterintuitive. However, if the system is redundant, the joint limit avoidance task avoids losing trajectory tracking performance while still using the redundancy to avoid joint limits. In case of a dual-arms system is composed by at least one non-redundant manipulator, the submatrices \( P_A \) (or/and \( P_B \)) of the \( P_{AB} \) matrix projects the joint limit avoidance task into the zero dimension null-spaces, so that it results to be irrelevant. Hence, it is necessary to assign the same priority execution of the trajectory tracking task to the joint limit avoidance task, by opportunely editing the \( P_{AB} \) matrix.

In detail, to ensure that the joint limits are satisfied, we let the trajectory performance related to \( \dot{x}_{Ad} \) degrade gradually and temporarily by having same priority for trajectory tracking and joint limit avoidance. To keep this specific to the non-redundant manipulator, Eq. (8.6) is adapted by replacing the null-space projection matrix of the non-redundant manipulator with an identity matrix \( I \) having the same dimension. In other words, \( P_{AB} \) in (8.6) can be replaced with one of the orthogonal
projectors

\[ P_{IB} = \begin{bmatrix} I & 0 \\ 0 & P_B \end{bmatrix} \quad P_{IA} = \begin{bmatrix} P_A & 0 \\ 0 & I \end{bmatrix} \]  

(8.8)

where \( P_{IX} \) is the projector matrix when the manipulator \( X \) is non-redundant. Finally, if both manipulators are non-redundant, \( P_{AB} \) matrix is replaced by an identity matrix \( I_{AB} \).

Figure 8.1(b) shows an example of the proposed joint limit avoidance for a standalone cooperating non-redundant manipulator having the same joint limit values. If the manipulator has a critical joint \( q_1 \), this joint will converge to an equilibrium joint position \( q_{e1} \), where two opposite velocity components cancel out each other. In detail, the first component, defined as \( \dot{q}_{d1} = k_1(q_{d1} - q_1) \), pushes \( q_1 \) towards its desired position \( q_{d1} \) according to the desired end-effector trajectory, while the second one, defined as \( \dot{q}_{1}^+ = h_1w_1(q_{T1} - q_1) \) (with \( w_1 \neq 0 \)), pushes \( q_1 \) towards the minimum threshold position \( q_{T_{min}} \). On the other hand, a non-critical joint \( q_2 \) is not affected by the second velocity signal \( (w_2 = 0) \), therefore its equilibrium joint position \( q_{e2} \) will converge to its desired position \( q_{d2} \). Therefore, it is possible to formalize this example according to (8.6):

\[
\begin{bmatrix} q_{e1} \\ q_{e2} \end{bmatrix} = \begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix} \begin{bmatrix} q_{d1} - q_1 \\ q_{d2} - q_2 \end{bmatrix} + \begin{bmatrix} h_1 & 0 \\ 0 & h_2 \end{bmatrix} \begin{bmatrix} w_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} q_{T_{min1}} - q_1 \\ q_{T_{min2}} - q_2 \end{bmatrix} \Delta t
\]

(8.9)

where \( \Delta t \) indicates the sample time. However, the equilibrium joint positions, \( q_{e1} \) and \( q_{e2} \), are not the final joint positions, because of the added effect due to the relative end-effectors motions, as expressed by the first term of (8.9). Therefore, this example shows that an out-of-limit joint position is managed by the proposed method by allowing world-space trajectory deviations, but not losing cooperation performance.

### 8.3 Simulation study

In this section, we show how to use the proposed methodology to ensure that joint limits are preserved (i.e., there is no violation of joint position constraints) in a dual-arm system performing a desired task. We consider two identical planar manipulators with 3-DoF in three different cases:
Cooperative Manipulation under Joint Limit Constraints

Case I both manipulators are non-redundant;

Case II both manipulators have one redundant motion;

Case III manipulator A has no redundant motions, while manipulator B has one redundant motion.

The manipulators considered in the simulation study are functionally redundant, as described in Section 7.3.1. Therefore, the degrees of redundancy of each manipulator, $d_{rA}$ and $d_{rB}$, can be calculated by applying the rank-nullity theorem $n - r = dr$. Since both manipulators have the same number of joints ($n_A = n_B = 3$), the degree of redundancy of each manipulator can be changed by assigning different number of task variables to each end-effector. Hence, the tasks proposed in Case I are defined by three variables $r_A = r_B = 3$, so that the degree of redundancy is equal to zero for both manipulator $d_{rA} = d_{rB} = 0$. Case II presents two tasks described by only two motion variables $r_A = r_B = 2$ (translation motions along x and y axes), so that the degree of redundancy is equal to one, $d_{rA} = d_{rB} = 1$. Finally, Case III presents the cooperation of manipulators having different degree of redundancy. The task of Case I is assigned to manipulator A, while the task of Case II is assigned to manipulator B. Therefore, the degrees of redundancy are $d_{rA} = 0$ and $d_{rB} = 1$.

8.3.1 Task description

The proposed task consists of translating the dual arm system from the initial A end-effector position $P_1 = [1, 1.5] \text{ m}$ (see Figure 8.2(a)) to final position $P_2 = [2, 1.5] \text{ m}$, while keeping the relative pose constant. Moreover, two joint limits $q_{A2}$ and $q_{B1}$ are enforced using (8.3) and (8.4) with the values reported in Table 8.1 (with $\beta = \beta_{\text{min}} = \beta_{\text{max}}$).
Table 8.1. Joint limits.

<table>
<thead>
<tr>
<th>Critical Joint</th>
<th>$q_{\text{L,min max}}$</th>
<th>$q_{\text{T,min max}}$</th>
<th>$\beta$</th>
<th>$k_i$</th>
<th>$h_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_{A2}$</td>
<td>$[-1.7, 3.14]$</td>
<td>$[-1.5, 2.94]$</td>
<td>0.2</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>$q_{B1}$</td>
<td>$[-0.7, 3.14]$</td>
<td>$[-0.5, 2.94]$</td>
<td>0.2</td>
<td>10</td>
<td>20</td>
</tr>
</tbody>
</table>

The proposed task is decomposed into prioritized subtasks according to (8.6). Since the execution of the joint limit avoidance depends on $d_{rA}$ and $d_{rB}$, their execution priority changes for each cooperation case, as reported in Table 8.2.

![Figure 8.3](image.png)

**Figure 8.3.** A (B) manipulator joint position space relative to $q_{A1}$-$q_{A2}$ (a) ($q_{B1}$-$q_{B2}$ (b)).

### 8.3.2 Results

**Case I**

In this case both manipulators have no degree of redundancy available for the execution of the joint limit avoidance, $d_{rA} = d_{rB} = 0$. Therefore, it is possible to assign to this task the priority of the higher priority task $\dot{x}_{A_i}$, by replacing the $P_{AB}$ in (8.6) with an identity matrix $I_{AB}$ as described in Section 7.3.1. Figure 8.3 shows the joint position space relative to the first two joints of each manipulator. In particular, the difference between the joint trajectory without the proposed joint limit avoidance strategy (blue line) and with it (violet line). The figure shows that the joint limit avoidance works correctly, pushing both joints away from their limits when $q_{A2}$ and $q_{B1}$ exceed their threshold limits (green dotted line). Due to the joint limit avoidance,
the trajectory tracking accuracy is degraded temporarily for both end-effectors, as shown in Figure 8.4. Moreover, Figure 8.2(b) shows that the final end-effector orientations assumed by both manipulators are equal to the initial ones (see Figure 8.2(a)), enforced by the relative motion task $\dot{\mathbf{x}}_{R_d}$.

**Case II**

In this case each manipulator possesses one degree of redundancy, because both end-effector orientation velocities are not specified. Therefore, (8.6) is applied directly. Since a redundant manipulator admits an infinite number of solutions for the inverse kinematic problem, it is possible to note in Figure 8.3 that the joint trajectories ob-

---

<table>
<thead>
<tr>
<th>Case</th>
<th>Priority</th>
<th>Sub-task description</th>
<th>dim</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>3</td>
<td>$\dot{\mathbf{x}}_{R_d} = [0 \text{ m/s}, 0 \text{ m/s}, 0 \text{ rad/s}]^T$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{\mathbf{x}}_{A_d} = [0.01 \text{ m/s}, 0.01 \text{ m/s}, 0 \text{ rad/s}]^T$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{\mathbf{x}}_{B_d} = [0.01 \text{ m/s}, 0.01 \text{ m/s}, 0 \text{ rad/s}]^T$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{q}<em>{A_2}^+ = 20w</em>{A_2}(-1.5 \text{ rad} - q_{A_2})$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{q}<em>{B_1}^+ = 20w</em>{B_1}(-0.5 \text{ rad} - q_{B_1})$</td>
<td>1</td>
</tr>
<tr>
<td>II</td>
<td>3</td>
<td>$\dot{\mathbf{x}}_{R_d} = [0 \text{ m/s}, 0 \text{ m/s}, 0 \text{ rad/s}]^T$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{\mathbf{x}}_{A_d} = [0.01 \text{ m/s}, 0.01 \text{ m/s}]^T$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{\mathbf{x}}_{B_d} = [0.01 \text{ m/s}, 0.01 \text{ m/s}]^T$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>$\dot{q}<em>{A_2}^+ = 20w</em>{A_2}(-1.5 \text{ rad} - q_{A_2})$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>$\dot{q}<em>{B_1}^+ = 20w</em>{B_1}(-0.5 \text{ rad} - q_{B_1})$</td>
<td>1</td>
</tr>
<tr>
<td>III</td>
<td>3</td>
<td>$\dot{\mathbf{x}}_{R_d} = [0 \text{ m/s}, 0 \text{ m/s}, 0 \text{ rad/s}]^T$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{\mathbf{x}}_{A_d} = [0.01 \text{ m/s}, 0.01 \text{ m/s}, 0 \text{ rad/s}]^T$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{\mathbf{x}}_{B_d} = [0.01 \text{ m/s}, 0.01 \text{ m/s}]^T$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$\dot{q}<em>{A_2}^+ = 20w</em>{A_2}(-1.5 \text{ rad} - q_{A_2})$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>$\dot{q}<em>{B_1}^+ = 20w</em>{B_1}(-0.5 \text{ rad} - q_{B_1})$</td>
<td>1</td>
</tr>
</tbody>
</table>
Cooperative Manipulation under Joint Limit Constraints

tained (sky blue) are completely different from the trajectories tracked without joint limit avoidance (blue). However, the repulsive joint velocities generate self-motions in each manipulator not affecting their relative pose or their translation task. Therefore, the final configurations of the manipulators obtained (Figure 8.2(c)) are different from the starting ones (Figure 8.2(a)), and the path following error is negligible (green line in Figure 8.4).

Case III

This last case is a combination of the previous ones. Since manipulator A is non-redundant ($\dot{\phi}_A$ is assigned), it is necessary to replace the $P_{AB}$ in (8.6) with the matrix $P_{IB}$ defined in (8.8). In this way, $\dot{q}_A$ has the execution priority of $\dot{x}_{A_d}$, while $\dot{q}_B$ has lower priority (see Table 8.2).

It is interesting to note that while the joint limit of $q_{A2}$ is satisfied (see red line in Figure 8.2(a)), the joint limit of $q_{B1}$ is violated (see red line in Figure 8.2(b)). In fact, although the $\phi_B$ is not assigned, $\phi_B$ must be kept constant respect to $\phi_A$ as specified from highest priority task $\dot{x}_{R_d}$. Therefore, $\phi_B$ depends on $\phi_A$, and consequently the B manipulator loses its degree of redundancy, so that the $\dot{q}_B^+$ can not be performed. In order to satisfy the joint limit of $q_{B1}$, it is necessary to assign to $q_{B1}$ the same priority execution level of the higher priority task $\dot{x}_{R_d}$ as demonstrated in Case I. Therefore, the trajectory tracking performances of both manipulators are temporary degraded as described in Case I, and the final end-effector orientations are equal to those shown in Figure 8.2(b).

Joint velocities during motion are illustrated in Figure 8.5. This shows that unlike the existing method proposed in [189], the proposed controller strategy and the smooth activation function eliminate discontinuities in joint velocity commands.

![Figure 8.4](image-url) A and B manipulators Cartesian path for the three considered simulation cases.

---

1 1.2 1.4 1.6 1.8 2 2.2 2.4 2.6 2.8 3
X [m]

1.2
1.3
1.4
1.5
Y [m]

Cartesian Space

A desired path B desired path I case II case III case start position final position
8.4 Real Experiments: Heterogeneous robots with mixed redundancy

8.4.1 Experimental setup and task description

The experimental setup is composed of two dissimilar robots holding a woodblock using their end-effector’s (Figure 8.6). The coordinate framed for the set-up are depicted in Figure 7.2. Using the set-up, we investigate four cases (Cases A–D) of cooperative manipulation, with joint position constraints shown in Table 8.3 (— denoting no joint limits). The goal of the experiment is to analyse how the proposed controller handles the task and joint constraints in the practical setting with different sources of error and uncertainty.

The manipulators adopted in the experimental set-up are a 6-DOF Kinova Jaco (non-redundant) [173] and a 7-DOF KUKA LWR4+ (intrinsically redundant) [174].
placed opposite and parallel to each other with a distance of 1.48 m. Their task is to cooperatively manipulate a woodblock of 0.9 kg. The task priorities are similar to earlier:

1. Task 1 (highest priority): maintaining relative position and orientation of the end-effector’s such that \( \vec{P}_R = (0, 0.5, 0) \) m.

2. Task 2: moving the Jaco end-effector \( A_e \) along the predefined path.

3. Task 3: joint limit avoidance for cooperative manipulators (see Table 8.3).

The target trajectory is a circle with radius 0.04 m, as illustrated in Figure 8.7(a).
Jaco starts from initial position $A_e^o = [0.262, -0.258, 0.388]^T$ m. Joint limits to be enforced are shown in Table 8.4 (with $\beta = \beta_{\text{min}} = \beta_{\text{max}}$).

Table 8.4. Joint limit parameters.

<table>
<thead>
<tr>
<th>Critical Joint</th>
<th>$q_{L_{\text{min,max}}}$</th>
<th>$q_{T_{\text{min,max}}}$</th>
<th>$\beta$</th>
<th>$k_i$</th>
<th>$h_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_{A3}$</td>
<td>[0.1, 0.59]</td>
<td>[0.15, 0.54]</td>
<td>0.05</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>$q_{B1}$</td>
<td>[0.1, 0.88]</td>
<td>[0.15, 0.83]</td>
<td>0.05</td>
<td>10</td>
<td>20</td>
</tr>
</tbody>
</table>

(a) Trajectory tracking by Jaco

(b) Cooperative tracking by Kuka

Figure 8.7. Coordinated manipulation results of tightly-coupled manipulators under joint constraints (Case B and C).
8.4.2 Results

Figure 8.8 illustrates the Cartesian tracking errors and the relative pose error for Cases A-C. Case D is not shown as its behavior is almost identical to Case B. Case A (without joint limits) serves as a reference for the achievable performance due to
limitations of the hardware, in particular Kinova Jaco. The maximum relative pose error during steady state is 5.1 mm.

In Case B with joint limit in the non-redundant robot (Jaco), the joint limit is avoided as shown in Figure 8.9(a). During joint limit avoidance, path following accuracy is temporarily sacrificed to up to 15 mm position error (shown by the red line in Figure 8.8(a)–(b)). The coordination of motion (Task 1) is kept enforced as the relative motion error is not increased over baseline (Figure 8.8(c)), with maximum error 5.9 mm. The same behavior is illustrated in the Cartesian space in Figures 8.7(a)–(b).

In Case C with joint limit in the redundant robot (KUKA LWR), the proposed controller is able to avoid the joint limit as illustrated in Figure 8.9b. Due to the redundancy, the accuracy of Cartesian trajectory or relative position are not deteriorated as shown in Figures 8.7 and 8.8 where the maximum relative pose error is 4.9 mm.

Even though KUKA can use its redundancy to avoid conflicts in joint and task space, this extra degree of freedom does not solve the problem of joint limit occurring on Jaco. Therefore the cooperative behaviour in Case D (joint limits for both) is similar to Case B (Jaco joint limit).

Looking more closely at the relative position errors in Figure 8.8(c), the errors remain small in all cases. In Case B the cooperative manipulators need to change Cartesian path to avoid joint limits, increasing the path following error temporarily but the limited relative motion error is maintained. This demonstrates the ability of the proposed approach to handle cooperative manipulation in a safe manner. Finally, cooperation between intrinsically redundant and non-redundant coupled robots demonstrates the proposed controller ability to take advantage of redundancy, as well as to temporarily sacrifice the Cartesian trajectory accuracy to comply with joint limits.

### 8.5 Discussion

This chapter presented a kinematic controller for coordinated cooperative manipulation based on the relative Jacobian method. Using a hierarchy of tasks and smooth activation, the controller ensures coordinated motion and joint limit avoidance. The same formulation allows joint limit avoidance for both redundant and non-redundant manipulators. Results from simulations showed that the approach avoids discontinuities in velocity commands unlike existing methods for the same problem. Experi-
mental results from a two-robot system of mixed redundancy showed that the relative position errors remained small, indicating that the proposed approach is applicable in practice to collaborative manipulation.

The experimental results indicated one interesting observation for heterogeneous systems: The lower performance robot sets the performance limit for the entire system. This has a significant consequence for the system design in that the lower performance robot should be used as the master, whose trajectory tracking error is used as feedback. That is, in the context of this paper the lower performance robot should be manipulator A whose trajectory error, $\bar{e}$ in (8.1), should be used as the trajectory feedback. This ensures that the performance of the highest priority coordinated motion task will not depend on the performance of the lower performance robot.

Experimental implementation of a controller for heterogeneous robots is challenging because the access to hardware is usually not uniform. To implement the controller, we developed a hardware plugin compatible with ROS-control framework to
abstract the two systems as a single robot and developed the controller presented in this paper for that abstraction. The implemented controller communicated with robot-specific native low-level controllers at 100 Hz. The low-level controller of Kinova Jaco was fixed and did not allow tuning. The performance of the low-level controllers differed significantly. To address this, the gains of the proposed controller were tuned manually. Nevertheless, the performance of the low-level controller for Jaco was limited which can be seen in Figure 8.8[a] as tracking errors even for the baseline Case A without joint limits. Despite this limitation, the experiments indicated no increase in tracking error unless forced by the joint limit avoidance.

The relative position errors were at most 5 mm in all configurations. Thus the proposed approach is applicable in practice to collaborative manipulation. The remaining position errors were due to limitations in the performance of native low-level controllers as shown with the simulation results where the relative pose errors remained much below measurement accuracy in all cases. Applications requiring higher performance would likely need an integrated custom low-level controller controlling both manipulators.
9. Conclusions and Future Work

This dissertation focused on developing grasp coordination and kinematic control to tackle the challenges that arise in MRS such as limitations on communication, sensing and knowledge sharing and cooperative manipulation tasks such as joint limit constraints.

We set out to study grasp planning to coordinate a heterogeneous group of robots in a decentralized fashion. The robots possessed no knowledge about the physical embodiments of cooperating robots but had access to local imprecise information perceived through vision sensors. Probabilistic approaches demonstrated the ability to treat the embodiment uncertainty of heterogeneous robots in decentralized grasp planning. Results from simulation confirmed that with sufficiently similar robots the projection of a robot’s own model can be used to model another robot in order to enable effective collaboration. Physical experiments with light weight objects indicated that the assumption of embodiment similarity is sufficiently good to allow handling uncertainties caused by heterogeneity in decentralized setting and probabilistic treatment showed potential to reduce the effect of modelling inaccuracies as an unintended but valuable side-effect.

Grasp planning was also studied under a stricter decentralized setting that imposes observation constraint on the heterogeneous group of robots with assigned roles. Probabilistic approaches failed to maximize the expected grasp quality over the embodiment uncertainty due to the lack of information. This emphasizes the crucial role of information and its potential to improve decisions in decentralized settings. For tasks priorly known, incorporation of task specific information in decentralized grasp planning increased grasp qualities. Our future work will be on verifying the importance of multi-robot grasps optimized for particular tasks using physical hardware. Apart from that, studying multi-robot grasp planning under object pose and shape uncertainty is an appealing research topic.
Relevance of the decentralized grasping problem and applicability of dexterous hands in industrial setting to be quite far in the future. At the same time, the robotics industry is dramatically growing and dedicated companies and the research community are building robot hands for both industrial and domestic settings as well as advancing the state of the art methods in grasping. Robots with simple grippers are already in industrial settings and grasp coordination can be a relevant problem to further manipulate a large object. Moreover, the decentralized approaches are applicable not only for complex hands but also if the robots have simple grippers of different brands and have limitations in centralized planning.

Multiple robots with large and high load capability grippers can be employed for handling large parts (e.g. windmill parts) while avoiding dexterous hands. Grasp coordination and cooperative manipulation become vital in this process. Approaches from Chapter 4 are applicable also for simpler grippers. However, due to the complexity of the decentralized setting, further research is needed to take the proposed solutions into industrial applications.

In human-centred robot applications, a robot is expected to collaborate with humans and accomplish manipulation tasks together. Such systems are then inherently decentralized and heterogeneous. Moreover, the robot may lack information about the target object and the cooperating human which makes the use of traditional wrench space quality measures inapplicable for grasp planning. Recently in [194], we proposed a method for grasp coordination for multiple agents that allows coordinated grasping of unknown objects. The underlying idea of the method is to share the object load among the cooperative agents. To be specific, the method allows decentralized multi-agent grasp planning to determine cooperative grasps with minimal wrenches for a desired manipulation task.

We also set out to study safe collaborative control for heterogeneous robots manipulating a common object under kinematic and joint position constraints. Kinematic redundancy in cooperative manipulators offers greater flexibility and that was exploited to satisfy relative motion constraints and achieve secondary tasks by using task prioritization with null space projection. To ensure safe cooperation, a control strategy that provides gradual smooth activation of joint limit avoidance for both redundant and non-redundant manipulators was developed.

The combination of a redundant and a non-redundant manipulator is redundant with respect to relative motions. For cases when an individual manipulator had insufficient redundant motions, the control strategy allowed temporary degradation of world space trajectory tracking performance and successfully avoided joint limits
Conclusions and Future Work

without affecting the relative end effector motions. We studied the kinematic controller behaviour and performance in heterogeneous dual-arm system and observed that the lower performance robot set the performance limit for the entire system. Moreover, the experimental results showed only small errors in the relative positions and that to because of imprecise calibration. Thus, the proposed kinematic control strategy is applicable in practice to collaborative manipulation and shows a great potential for heterogeneous MRS. Furthermore, the control strategy from Chapter 8 is immediately applicable in an industrial setting.

We mainly studied cooperative manipulation with two robots. The concept of relative Jacobian could also be extended to a homogeneous or heterogeneous groups that consist of more than two robots. A study on coordinated motion constraints between larger groups can be interesting since the relative Jacobian is expressed in terms of pairwise constraints. This is an appealing topic for further research. Apart from that, the local redundancy resolution schemes and relative Jacobian method can be applied to solve grasping and in-hand motion control problems in multi-fingered robot hands. Development of decentralized manipulation systems will require decentralization in both grasp coordination and manipulation control.
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Multi-robot systems have shown potential over single robot systems in handling long, large and heavy objects. Manipulation with multiple robots increases task precision and decreases required load capabilities of individual robots while saving cost and space. However, the limitations of multi-robot systems in communication, sensing and knowledge sharing pose challenges for coordination and control. These challenges are emphasized in cases with heterogeneous robots, that is, where the robots’ physical embodiments differ.

This dissertation explores approaches for multi-robot grasp planning in heterogeneous and decentralized settings and develops a control strategy to ensure safety in collaborative manipulation under joint limit constraints.