Task Specific Cooperative Grasp Planning for Decentralized Multi-Robot Systems

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***Abstract*— Grasp planning in multi-robot systems is usually studied in a centralized setting with all robots sharing common knowledge about the overall system. Relaxing this assumption would allow multiple mobile manipulators to cooperate even without strict and precise coordination. Moreover, most typical tasks for cooperative settings, such as transporting heavy objects, require certain forces/torques to be exerted along/around particular directions, for instance, compensating for the weight of the transported object. In this paper, we propose task specific multi-robot grasp planning strategies that allow decentralized planning. Each agent plans its own actions without precise information about the other's plans. The approach is based on analysing a task specific grasp quality metric in a probabilistic context, compensating thus for the incomplete knowledge. Results from simulation experiments demonstrate that task independent planning is clearly inferior when task characteristics are known and thus task specific quality measures should be used. Furthermore, the proposed decentralized planning approaches clearly outperform the baseline and show close to globally optimal performance.**

I. INTRODUCTION

Multi-robot systems (MRS) have recently gained increased popularity and interest in robotics community owing to their increased potential over single robots [1], [2]. Most works in the literature consider a centralized coordination architecture with precise information rather than decentralized ones [2]. Coordination is a key challenge and hence the development of coordination strategies is a major research topic in the area [3]. Planning is also an inseparable part of multi-robot coordination and plays a major role. However, few existing works have considered planning in the context of manipulation; most works focus on task and motion planning. Nevertheless, object transportation tasks can benefit greatly from the use of multiple mobile manipulators, especially in the case of large or heavy objects. Additionally, most typical tasks for cooperative settings require forces and torques to be exerted along and around particular directions, for example, compensating for the weight of the transported object, which is contradictory to the majority of common grasp planners for single robots using quality function, that consider all dimensions of the wrench space equally important.

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In this paper, we propose task specific multi-robot grasp planning strategies that allow decentralized planning towards performing effective cooperative manipulation tasks. Even though decentralized architectures often have better reliability, flexibility, adaptability and robustness, they suffer from suboptimal solutions owing to incomplete knowledge. In our setting, agents do not have information about the embodiments of other agents and each agent thus plans its own actions.

The main contributions of this work are summarized as follows:

1) two task specific grasp planning strategies are proposed for decentralized settings,
2) an analysis of the importance of task specific quality measures in cooperative grasping settings is provided,
3) the performance of the proposed decentralized planning strategies is studied in comparison to a global optimal solution.

The grasp planning strategies cope with the incomplete information by analysing a task specific grasp quality metric in a probabilistic context. The analyses are based on simulated grasping experiments. The comparison between task independent and task specific quality measures shows that task specific measures are beneficial in planning when certain information on the task is available. The analysis of the overall planning strategies reveals also that the proposed strategies clearly outperform the baseline-generic planning algorithm and that the decentralized planners may yield performance very close to the optimal centralized one.

The paper is organised into six sections. Following the introduction, Sec. II presents the related works and Sec. III introduces the task specific quality metric. In Sec. IV, the cooperative grasp planning framework is explained in a step by step way. Experiments in Sec. V demonstrate the importance of task specific metrics and illustrate numerically and graphically the performance of the decentralized planning strategies. Finally, conclusions are drawn in Sec. VI.

II. RELATED WORKS

Various grasp planners [4],[5] and quality metrics [6],[7], that ensure desirable grasp properties, have been proposed in the related literature. Most of them were developed for single or bi-manual robots and were applied in various domains for performing certain tasks efficiently. Moreover, during grasp planning, certain sensing components such as vision [8] and tactile [9] may be utilized to reduce uncertainties and to improve the manipulation capabilities. These components assist in terms of partial awareness in a Decentralized Multi-Robot Grasping Strategy (DMRGS). Even though the robot's mechatronics is getting advanced, a comprehensive review on multifingured robotic hands [10] and dual arms [11] indicates the need of similar technological advancements in MRS. A review on MRS focusing on coordination in terms of taxonomy, system classification, task and domain is given in [3]. However, to the best of our knowledge, despite the recent progress, there are no research works carried out concerning the development of task specific cooperative grasp planning approaches for decentralized MRS.

Regarding the problem of deriving optimal grasp plans under a detailed task description, various related methodologies have been proposed in the past. In [12] the authors searched for optimal grasps using the branch-and-bound method based on a required external set. Teichmann [13] minimized the number of contact points, needed to balance any external force and moment contained in a given set. Other works utilize the index proposed by Chiu that measures the compatibility of a manipulator to perform a given task [14], as well as the concept of the task ellipsoid proposed by Li and Sastry [15]. A task specific grasp selection scheme has been proposed in [16] for underactuated robotic hands as well. Unfortunately, most of the aforementioned approaches suffer from major drawbacks, such as the difficulty in modelling the task ellipsoid, as well as the fact that force closure[1] is not generally guaranteed by the yielded configuration, limiting thus their applicability.

This paper extends our recent work in cooperative grasp planning for multiple decentralized agents [18] by addressing task specificity and offering new insights on the decentralized planning strategies.

III. Grasp Quality Measure

In this work, we consider a multi-robot system, grasping a rigid object with n_p point-to-point frictional contacts. The hard contact model is adopted, which implies that all force components are transmitted through the contacts. Additionally, the friction coulomb model dictates that each of the n_p forces should lie within the corresponding friction cone in order to avoid slippage. Moreover, linearizing the friction cone by an n_g-sided polyhedral cone, we may define the primitive grasp wrenches that are generated by a force exerted along each edge of the linearized friction cone. In this sense, an object grasp is force closured if and only if the primitive wrenches positively span the entire wrench space, or equivalently the origin of the wrench space lies strictly inside the convex hull of the primitive wrenches [19].

As opposed to the euclidean grasp quality metrics that employ symmetric norms (i.e., $\mathcal{L}_i$, $i = 1, \ldots, \infty$), herein, we consider a task specific measure that is based on the concept of Q-distance, originally proposed in [20] for curved objects. Given a compact, polyhedral convex set $Q \subset \mathbb{R}^m$ that contains the origin (i.e., $\mathbf{0} \in \text{int}(Q)$), the authors in [20] defined the Q-distance from a point $p \in \mathbb{R}^m$ to a convex polyhedron $A \subset \mathbb{R}^m$ (i.e., $d_Q(p, A)$), as follows:

If $p \notin \text{int}(A)$:	If $p \in \text{int}(A)$:
$d_Q^+(p,A) = \min \sum_{k=1}^{K} \rho_k$ s.t. $\left\{ \begin{array}{c} \sum_{k=1}^{K} \rho_k q_k = \sum_{i=1}^{N} \alpha_i \mathrm{a}_i - p \\ \sum_{i=1}^{N} \alpha_i = 1 \\ \rho_k, \alpha_i \geq 0 \end{array} \right\}$	$d_Q^-(p,A) = \max_{k=1,\ldots,K} d_Q^-(k)$ where $d_Q^-(k) = \min(-\rho)$ s.t. $\left\{ \begin{array}{c} \rho q_k = \sum_{i=1}^{N} \alpha_i \mathrm{a}_i - p \\ \sum_{i=1}^{N} \alpha_i = 1 \\ \alpha_i, \rho \geq 0 \end{array} \right\}$

where q_k, $k = 1, \ldots, K$ and 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 W contains the primitive wrenches of the grasp configuration, the inequality $d_Q^-(\mathbf{0}, \mathbf{co}(W)) < 0$ is equivalent to $\mathbf{0} \in \text{int}(\mathbf{co}(W))$ and can be considered as a sufficient condition for force closure. Moreover, $\left| d_Q^-(\mathbf{0}, \mathbf{co}(W)) \right|$ can be geometrically interpreted as the largest radius of the Q-sphere contained in $\mathbf{co}(W)$. Therefore, larger $\left| d_Q^-(\mathbf{0}, \mathbf{co}(W)) \right|$ leads to a grasp configuration with larger radius of the Q-sphere 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 $\left| d_Q^-(\mathbf{0}, \mathbf{co}(W)) \right|$) is directly related to Q. Hence, from the aforementioned statement and aiming at formulating a task oriented metric [21], 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 [20], the obtained configuration will be able to compensate disturbances in particular directions corresponding to the task specifications with relatively low forces.

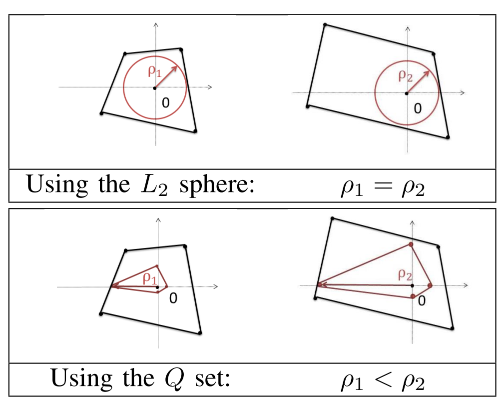


Fig. 1: A hypothetical example illustrating the advantage of the Q-distance over the L_2 norm in evaluating the task specificity of grasp configurations.

[1]Force closure ensures object immobility in the presence of any external disturbance [17].

To illustrate the aforementioned, let us consider Fig. 1. In these images two hypothetical convex hulls are depicted, for two grasp configurations. The quality 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.

IV. Task specific Cooperative Grasp Planning

In DMRGS setting, agents (robots) do not have information about the embodiments of other cooperating agents. They are able to observe the other agents actions imprecisely, for example by visual means. Thus, conventional centralized planning approaches can not be used directly since each agent plans its own actions. Therefore, we adopt a sequential approach where the agents plan and act in turn so that each agent is able to observe the previous agents actions before planning its own. However, it is important to notice that the observations are incomplete, that is, the agents are only able to observe roughly the location of the earlier grasps.

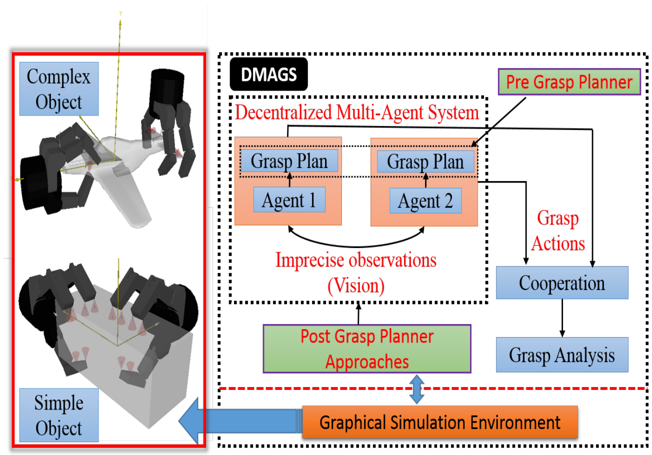
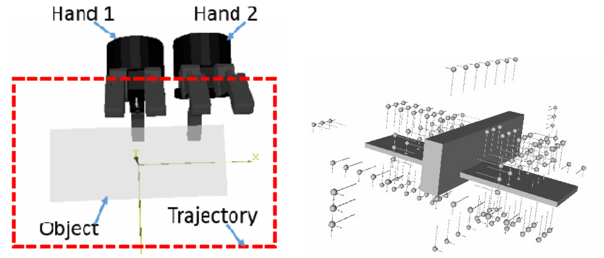


Fig. 2: Structure of Decentralized Multi-Robot Grasp System and graphical output through Graspit!.

The structure of DMRGS and the graphical outcomes are shown in Fig. 2, where the cooperative grasp planning is devised according to pre and post grasp planner. A more detailed explanation on DMRGS framework is given in [18]. The pre grasp planner uses existing heuristic grasp planning methods to generate grasp hypotheses for a single agent, using the models of the current agent and the target object as inputs. The post grasp planner then chooses a grasp from the set of hypotheses, considering the planning problem as choosing a subset of grasp hypotheses, one for each agent. Both pre grasp planner and post grasp planner use task specific and epsilon metrics for their quality computations. In this paper, the establishment of task specific cooperation is build and analysed upon the decentralized cooperative approaches of post grasp planners with respect to manipulation tasks. A global optimal (centralized) approach with and without task specificity requiring complete information is also presented for comparison.



(a) Trajectory Based Planner (b) Primitive Based Planner

Fig. 3: Sampling-based heuristic pre planners for Box(a) and Aeroplane(b) object.

A. Pre Grasp Planning and Grasp Analysis

Any existing grasp planners in the literature could be used as the Pre-grasp planners to produce hypotheses for the post grasp planning. In the experiments of this paper, the grasp hypothesis are produced by a trajectory and a primitive based planner shown in Fig. 3. In particular, the primitive grasp planner [5] generates hypotheses by using a set of grasp pre-shapes for a simplified object model rather than the agent embodiment. The primitive-based grasps are shown in Fig. 3(b), where the long and short arrows represent the approach and thumb directions. The quality of grasps, with and without task specificity is analysed using the W_{L_1} wrench space quality measure [7], which corresponds to the largest ball fitting inside the convex hull of the primitive wrenches, and the Q-distance from Sec.III respectively. The quality measures are used to evaluate both single and multi-agent grasps.

B. Definitions for Post Grasp Planning

Let $G_x = \{k|1 \leq k \leq N_x\}$ denote the set of grasp hypotheses for an agent x with k denoting the corresponding grasp of each hypothesis (defined as a pose of the hand w.r.t. the target object) and N_x is the number of hypotheses for agent x. For simplicity, in the sequel we consider two agents grasping an object such that $G_1 = \{i|1 \leq i \leq N_1\}$ and $G_2 = \{j|1 \leq j \leq N_2\}$. Let $Q_x(i)$ denote the quality measure value for agent x executing grasp hypothesis i, and $Q_T(i,j)$ denotes the joined quality measure of agents 1 and 2 executing grasps i and j respectively. In the decentralized approaches, we also use $Q_x(i,j)$ to denote the joined quality measure of executing both grasps i and j simultaneously using the embodiment of agent x. This last term is used in the decentralized approaches to approximate $Q_T(i,j)$ without the knowledge of the embodiment of the other agent.In our work, multi-robot grasp planning is a high level planning meant for multiple decentralized robots, which utilize existing low level grasp planner for its hypothesis generation purpose. The following approaches are developed for MR grasp planning and the grasp quality computation are performed for both task-specific and non task-specific grasps.

C. Global Optimal Approach

The global optimal approach maximizes the grasp quality over all possible grasps by optimizing over the joined quality measure $Q_T(i,j)$. Thus, the optimal quality C_{qm} is

$$C_{qm} = \max_{i \in G_1, j \in G_2} [Q_T(i,j)] \tag{1}$$

which is obtained for grasps C_1, C_2 of agent 1 and 2 respectively, as follows:

$$(C_1, C_2) = \underset{i \in G_1, j \in G_2}{\arg\max} \, [Q_T(i,j)]. \tag{2}$$

The global optimal approach provides the best grasp configuration over all hypotheses considering precise observations and complete embodiments information and it sets a benchmark for the following decentralized approaches.

D. Decentralized Approaches

Each agent assumes that the physical capabilities of other agents are equal to its own, that is, the other agents are able to grasp the target object in the same fashion as the agent itself. As this might not be the case in reality, we also consider that the assumption of equal capabilities has only a limited degree of belief. The development of the following approaches is based on the imprecise observations of the grasp locations and the embodiment, which emphasizes on the decentralization.

1) Decentralized Independent (DI): We propose an approach called decentralized independent planner which greedily optimizes the grasp quality while considering all grasps that other agents have already executed. In a two agent case, the first agent thus maximizes only its own grasp quality

$$DI_1 = \underset{i \in G_1}{\arg\max} [Q_1(i)] \tag{3}$$

while the second agent observes the grasp made by the first agent, optimizing the joined quality:

$$DI_2 = \underset{j \in G_2}{\arg\max} [Q_2(DI_1, j)]. \tag{4}$$

This approach serves as a baseline for decentralized grasping.

2) Decentralized Average (DA): To benefit from the knowledge that multiple agents will be grasping under incomplete knowledge of other agents' capabilities, we propose to maximize the expectation of the grasp quality of the multi-agent grasp configuration. For a two agents case, the first agent thus aims at selecting a grasp that maximizes the expected quality over the unknown grasp of the second agent:

$$\underset{i \in G_1}{\arg\max} \, E_{j \in G_2} [Q_1(i,j)]. \tag{5}$$

Notice that such function can be evaluated on one agent without any knowledge about the other assuming that the joined quality $Q_T(i,j)$ can be approximated by $Q_1(i,j)$, which is quite accurate when the embodiments of the agents are similar.

It should be reiterated now that the first agent uses its own grasp hypotheses also for the second agent and thus both G_1 and 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 the second agent. Therefore, we assume that each grasp in the hypothesis set is equally likely, that is, $P(G_2 = i) = 1/N_1$ for all i. Thus, (5) becomes

$$DA_1 = \underset{i \in G_1}{\arg\max} \frac{1}{N_1} \sum_j Q_1(i,j) \tag{6}$$

This approach is termed the decentralized average approach due to the average quality appearing in (6). Afterwards, the second agent plans its grasp similarly to the decentralized independent approach:

$$DA_2 = \underset{j \in G_2}{\arg\max} [Q_2(DA_1, j)]. \tag{7}$$

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 agents grasping after the first agent. The extension to more agents is straightforward; the expectation is taken over all agents who have not yet executed their grasps (i.e. the incomplete knowledge).

3) Decentralized Expectation (DE): While the equal probabilities model is simple and probably outperforms the sequential planning, the approach fails to use the information that the other agents are also trying to choose optimal grasps from their perspective. Thus, we propose a second model, where the expectations of the grasps are not equal but analogous to the quality of the grasp (i.e., the higher quality grasps are more likely to be chosen). Again, let us consider the two agent case for simplicity. The underlying idea is that the second agent will choose the best grasp that it is able to execute. However, we assume that grasp hypotheses produced by the first agent have a limited probability of success for the second agent (for example, they might not be force closure grasps for the second agent).

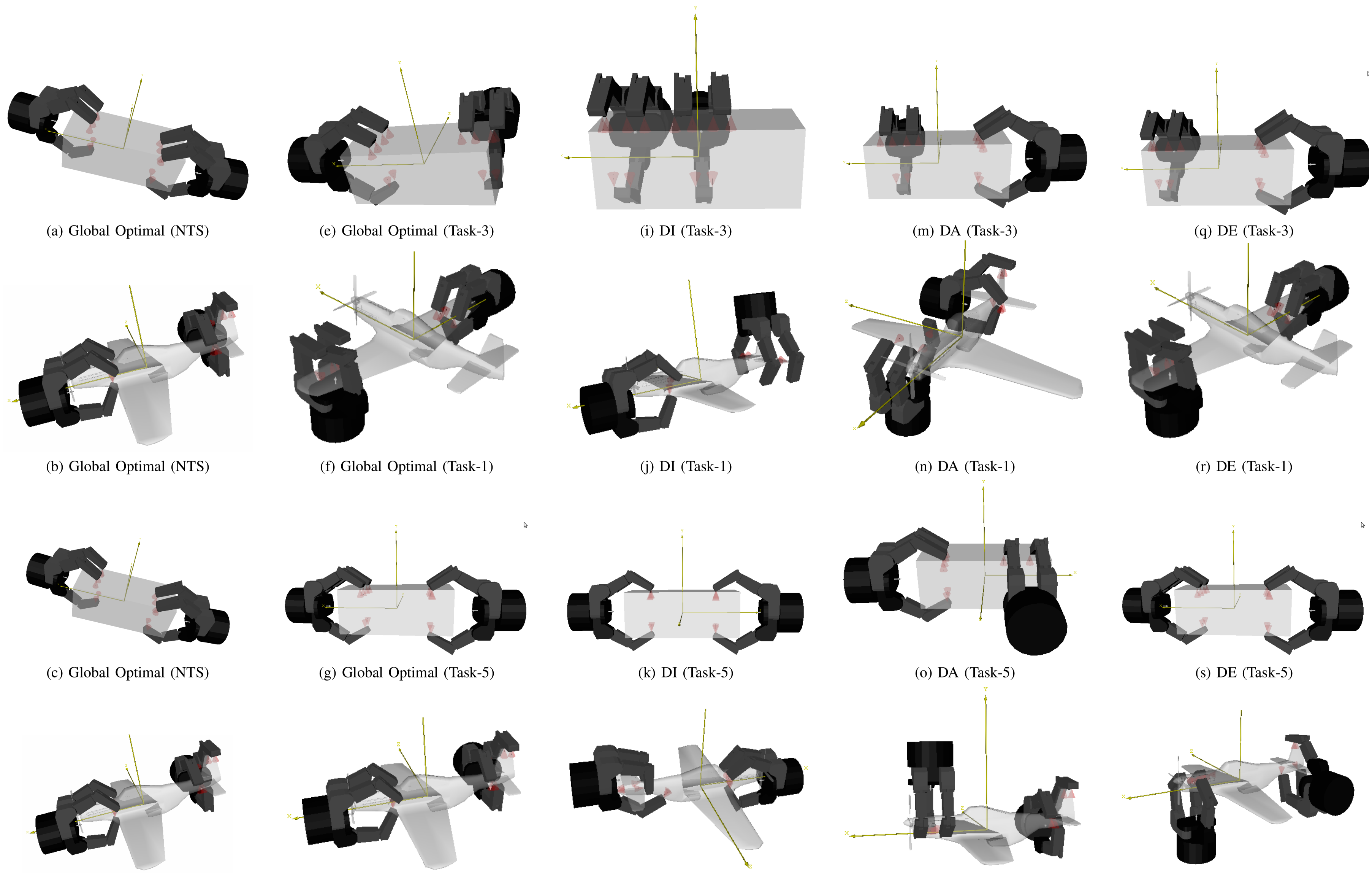
Let us denote by P_S the probability that a grasp hypothesis of a first agent can be executed by the second agent. Let w_k denote the permutation of grasps for agent 2 so that the joined quality $Q_1(i,j)$ is ordered in a decreasing order, that is, $Q_1(i, w_k) > Q_1(i, w_{k+1})$. Under these assumptions, the expected quality will be maximized as follows:

$$DE_1 = \underset{i \in G_1}{\arg\max} \sum_k P_S (1 - P_s)^{k-1} Q_1(i, w_k). \tag{8}$$

The second agent plans its grasp again similarly to the two previous approaches:

$$DE_2 = \underset{j \in G_2}{\arg\max} [Q_2(DE_1, j)]. \tag{9}$$

Notice that larger P_S means that the approximation of Q_T by Q_1 is trusted more. Particularly, in case $P_S = 1$ the approximation is expected to be fully correct whereas for $P_S \ll 1$, this approach becomes equivalent to the decentralized average approach. In this work, P_S has been chosen empirically.



(a) Global Optimal (NTS) (e) Global Optimal (Task-3) (i) DI (Task-3) (m) DA (Task-3) (q) DE (Task-3)

(b) Global Optimal (NTS) (f) Global Optimal (Task-1) (j) DI (Task-1) (n) DA (Task-1) (r) DE (Task-1)

(c) Global Optimal (NTS) (g) Global Optimal (Task-5) (k) DI (Task-5) (o) DA (Task-5) (s) DE (Task-5)

(d) Global Optimal (NTS) (h) Global Optimal (Task-6) (l) DI (Task-6) (p) DA (Task-6) (t) DE (Task-6)

Fig. 4: Simulated Global Optimal and Decentralized approaches (DI,DA,DE) for grasping objects (box,aeroplane) by two Barrett hand with regards to trajectory Fig.3 (a) and primitive Fig.3 (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.II)and last two rows (refer to Table.III) emphasize more and less improvements of task specific grasping.

Global Optimal (GO) Approach	**Box Object**	**Aeroplane Object**
Task Specific (TS)	**Non Task Specific (NTS) From [18]**	
Task 1	17.50%	72.97%
Task 2	38.50%	38.70%
Task 3	40.58%	36.38%
Task 4	14.78%	72.97%
Task 5	2.40%	4.70%
Task 6	38.50%	0%
Avg	***25%***	***37.62%***

TABLE I: Increase in Global optimal quality of Task Specific (TS) over Non Task Specific (NTS) Measure

V. Experiments

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 in multi-robot systems of decentralized nature. Experiments are conducted in simulation with GraspIt! simulator [22] simulating the kinematics of the hands, detecting contacts and providing visualization, while the multi-robot grasp planning and quality metrics are performed by our software.

For all experiments, two Barrett hands are used as agents. Two target objects of differing complexity in shape, a box and an aeroplane, are used. Six manipulation tasks are 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 use the epsilon (ϵ) metric identical to GraspIt!. As a task specific (TS) metric, the Q-distance (ρ) introduced in Sec. III is used.

A. *Task Specific vs Non Task Specific Metrics*

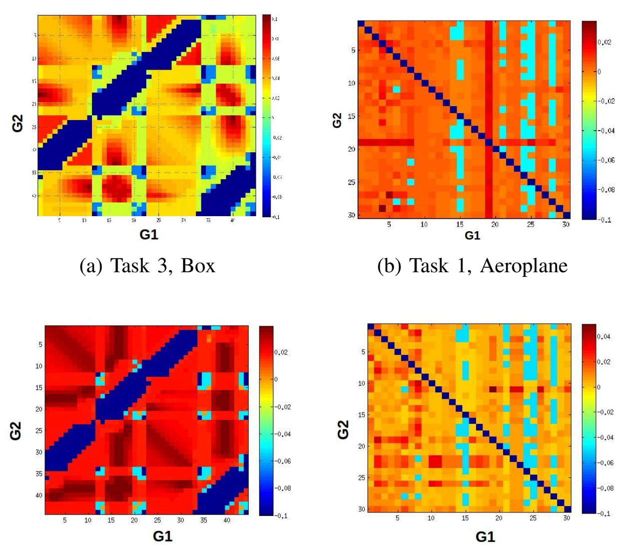
We first study the importance of task specific grasp quality metrics in planning cooperative grasps. This is done by comparing the task specific quality of grasps planned using task specific versus non task specific metrics. The comparison is made in a centralized planning setting, resulting in globally 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. 3) for simple (box) and complex (aeroplane) objects are utilized to generate grasp hypotheses in the pre-grasp planning stage. However, only the top 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 is chosen as the non task specific best grasp. These are illustrated in Figs. 4a and 4b. 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 is then compared to the globally optimal quality. The results of this comparison are shown in Table I which shows the percentual increase in quality when the task specific metric is used. In 9 out of 12 cases the increase in quality is 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. 4e) and T1 (for aeroplane, Fig. 4f) show the largest improvements and T5 (for box, Fig. 4g) and T6 (for aeroplane, Fig. 4h) 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 II and III, with **GO** 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. 5a–5d, 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



(a) Task 3, Box (b) Task 1, Aeroplane

(c) Task 5, Box (d) Task 6, Aeroplane

Fig. 5: Task specific quality measures for all two agent grasps for particular manipulation tasks.

Object / Task	Box / No task		Box / Task 3			Aeroplane / No task		Aeroplane / Task 1		
Approach	**Grasp Config.**	ϵ	**Grasp Config.**	ρ **/ TS**	ρ **/ NTS**	**Grasp Config.**	ϵ	**Grasp Config.**	ρ **/ TS**	ρ **/ NTS**
GO	Fig.4 (a)	0.2394	Fig.4 (e)	**0.10407**	**0.07403**	Fig.4 (b)	0.1438	Fig.4 (f)	**0.0343**	**0.01983**
DI	Refer to [18]	0.1559	Fig.4 (i)	**0.07146**	**0.04608**	Refer to [18]	0.1438	Fig.4 (j)	**0.00718**	**0.00718**
DA		0.2262	Fig.4 (m)	**0.08989**	**0.08753**		0.1438	Fig.4 (n)	**0.02066**	**0.001983**
DE		0.2394	Fig.4 (q)	**0.10406**	**0.08885**		0.1438	Fig.4 (r)	**0.0343**	**0.001983**

TABLE II: Numerical comparison: Tasks with large improvements in global quality with a TS over NTS measure.

Object / Task	Box / No task		Box / Task 5			Aeroplane / No task		Aeroplane / Task 6		
Approach	**Grasp Config.**	ϵ	**Grasp Config.**	ρ **/ TS**	ρ **/ NTS**	**Grasp Config.**	ϵ	**Grasp Config.**	ρ **/ TS**	ρ **/ NTS**
GO	Fig. (c)	0.2394	Fig . (g)	**0.03929**	**0.03837**	Fig. (d)	0.1438	Fig. (h)	**0.0498**	**0.0498**
DI	Refer to [18]	0.1559	Fig . (k)	**0.0388**	**0.03189**	Refer to [18]	0.1438	Fig. (l)	**0.03387**	**0.0224**
DA		0.2262	Fig. (o)	**0.03865**	**0.03848**		0.1438	Fig. (p)	**0.03677**	**0.0498**
DE		0.2394	Fig. (s)	**0.03929**	**0.03896**		0.1438	Fig. (t)	**0.03804**	**0.0498**

TABLE III: Numerical comparison: Tasks with small improvements in global quality with a TS over NTS measure.

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. 5c. On the other hand, T3 for the same object has much larger improvement while the quality landscape is much more varying (see Fig. 5a), corresponding to a more challenging multi-robot grasp planning problem. For the aeroplane (T1 in Fig. 5b and T6 in 5d), very 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.

B. Decentralized Approaches

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

On the basis of Table I, the cases with largest and smallest improvements were again picked out for visualization and detailed numerical results. In Fig. 4, (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 II and III 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 global optimal solution. In Table IV 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 ρ_{DI} and ρ_{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 IV, Task 3 gives a 31% and 13% of decrease in quality outcomes of DI and DA approach depicted in Fig. 4 (i) and (m), which is less performing in the overall manipulation tasks of box object. On the other side, Task 5 gives a great performance by getting closer to global measure for all the decentralised approaches shown in Fig. 4 (k), (o) and (s). Some results in I and IV are contrary to each other.In particular, for small % improvements of in Table I Tasks (Task 5) gives a grasp configuration closer to global optimal in IV and for large % improvements (Task 3) gives a grasp configuration far away to achieve global quality. In the similar fashion, analysing decentralized approaches based on TS for aeroplane object, Task 1 gives a 79% and 39% of decrease in quality outcomes of DI and DA approach depicted in Fig. 4 (j) and (n), which is worst performing in the overall manipulation tasks of aeroplane object. On the other side, Task 6 gives a worst performance for all the decentralised approaches shown in Fig. 4 (l), (p) and (t). For complex object, no convergence conclusion can be drawn, based on the % improvements from Table I. Overall from Table I, for complex objects, DI approach has a average of 64% decrease in task specific quality over GO, meaning that it is too far away from convergence for any manipulation tasks. Fortunately, the DE approach Fig. 4 (q) and (r) performs well in both objects for all manipulation tasks considered to obtain global optimal configuration. In our simulations, n^2 grasp pairs reflects the computational complexity of the algorithm. Both centralized and most of the decentralized approaches executes n^2 grasp pairs to find the best grasp configuration except 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

Object	Box			Aeroplane		
	DI Approach	DA Approach	DE Approach	DI Approach	DA Approach	DE Approach
Task 1	-13%	-4.90%	-1.17%	-79.07%	-39.77%	0%
Task 2	-23.40%	-4.63%	0%	-47.37%	0%	0%
Task 3	-31.33%	-13.62%	-0.01%	-85.70%	-33.22%	0%
Task 4	-25.16%	-12.08%	0%	-79.07%	-39.82%	0%
Task 5	-1.24%	-1.62%	0%	-66.42%	-0.48%	-0.48%
Task 6	-23.40%	-4.63%	0%1	-31.99%	-26.16%	-23.61%
Avg	**-19.60%**	**-6.90%**	**-0.19%**	**-64.93%**	**-23.24%**	**-4.01%**

TABLE IV: Decrease in task specific quality of decentralized approaches w.r.t. globally optimal solution.

was rejected with $p < 0.001$. Finally, DE was compared against the GO to see if the results show significant difference. The null hypothesis of no difference between GO and DE could not be rejected ($p = 0.125$), indicating that the experiments could not provide statistical evidence that DE would be worse than the globally optimal solution.

VI. Conclusion

In this paper, we developed task specific cooperative grasp planning approaches within the DMRGS framework. For manipulation tasks, simulation experiment results of global optimal approach demonstrates that overall task specific grasps has a 25% and 39% average improvements over non task specific grasps of simple and complex shaped objects. Moreover, the decentralized approaches such as DE and DA approaches outperforms DI approach and attain close to global optimal performance for all manipulation task, compensating for the lack of complete information. The task specific decentralized approaches revealed even more benefits for simple objects. In general, the importance of the task specific cooperative grasping was justified and verified by the qualitative analysis. In this way, adopting the task specific cooperative grasp planning framework, advances the current state of the art in decentralised manipulation systems by improving the quality of manipulation.

VII. Discussion

To apply the proposed multi-robot grasp planning strategies in practice, the following pipeline can be taken as a guideline. Initially, a 3D model of the object needed for manipulation tasks can be generated using the vision sensor and computer vision techniques. Then, the object model could be registered in real time using state of the art methods. Thereby, the registration could tackle the issues of pose and dimension of the object. Finally, calibration between the hardwares gives the multiple robots, the ability to carry out the grasping and manipulation task successfully.

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