

Inferring the level of collaboration in object handover tasks: From one-to-one to one-to-many

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I. INTRODUCTION

The study of one-to-many handover is motivated by the scenario of (1) one autonomous robot serving many humans, and (2) human supervising multiple low-autonomy robots to serve their end users. The level of collaboration is about (1) whether the end user will perceive the autonomous robot or the entire human-robot teaming system to be collaborative or not, and (2) how to design such system to behave as a collaborative partner with all (or most) of the remote users.

Research in improving robot performance in handover tasks focuses on inferring human intent and planning robot motion such that it is efficient, intuitive, safe and comfortable for the human partner. Robot efficiency in handover tasks depends on the reaction time and accuracy of the robot response. Often, observations from human-human handover studies [1]–[3] are used to model expected human behaviour. Human posture, arm length and gaze can be used to predict a prior static estimate of the object transfer point [3], [4]. This static estimate can then be updated based on the observed human motion to promptly and accurately plan the robot reach-to-grasp motion [4].

Although predictive control leads to efficient and functional handovers, planning legible motions that clearly indicate the robot’s intent lead to a more fluent collaboration [5]. Characteristics of collaborative fluency, such as the subjective and objective fluency metrics, observer and participant fluency perception, etc, help to evaluate the fluency of human-robot handovers [6]. Apart from fluency, factors like adaptability [7], compliance [8] and trust [9] also indicate the level of collaboration of the human or robot partner. For sequential tasks, adaptability can be measured based on the probability with which one partner adapts to the other partner’s reward function [7]. Inferring the robot’s reward function in a task also helps to build a human partner’s trust in the robot’s capabilities [10].

Although handovers have been studied for face-to-face, dynamic, repetitive and sequential task scenarios, the majority of the research deals with one-to-one handover tasks. A non-sequential one-to-many handover task would involve the additional problem of scheduling the robot’s actions to cater to multiple users. In the case of mixed human-robot teams where a human leader has to allocate tasks to a human assistant and a robotic co-leader [11], task scheduling was done by minimizing the maximum amount of work

assigned to an agent. Constraints for this problem considered lower bounds on time, number of tasks assigned to each agent and other temporal and spatial constraints of the task. However, the study only focused on how human satisfaction was affected by the level of robot autonomy and not the level of collaboration. In our proposed study, we aim to evaluate the aspects of a robot’s performance that affect a human partner’s perception of the robot’s level of collaboration.

II. ONE-TO-ONE OBJECT HANDOVER

To determine the factors that indicate the level of collaboration of a partner in an object handover task, we conducted a one-to-one human-human handover experiment.

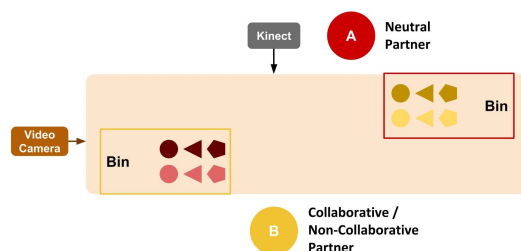


Fig. 1. Experiment setup for Pilot Study

As shown in Fig. 1, the subjects A and B were asked to stand on opposite sides of a table. 6 objects with different affordances were placed in each of the bins on either side of the table. The subjects were asked to collaborate in moving all the red objects to the red bin and yellow objects to the yellow bin. They were only allowed to handle one object at a time. A trial was considered complete when all the objects were in their respective bins.

The study comprised of 2 trials. In one trial, Subject B was asked to be **Collaborative** i.e. *be helpful to their partner*. In the other trial, Subject B was asked to be **Non-Collaborative** i.e. *offer minimum help to their partner*. Subject A was provided with no specific instruction and was unaware of Subject B’s instruction. Subject A’s behaviour was assumed to be neutral or collaborative. The order of collaborative and non-collaborative trials for all subjects was decided based on balanced latin square.

Subject B’s movements were tracked through a Kinect sensor using the NI Mate motion capture system. The skeleton data was used to calculate the **object transfer point** and the **orientation** of the subject’s body and head. A video camera on the side of the table captured the task scene. The video data was used to record **verbal communication**, **object affordance**, the **timing of actions** and **total time**. At the end of the study both the subjects answered a questionnaire:

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- Do you think your partner was collaborative? Explain. (Only Subject A)
- What did you do to act collaborative/non-collaborative? (Only Subject B)
- Who took the charge? Explain.
- Were there any conflicts? If yes, how were they solved?

III. PRELIMINARY WORK

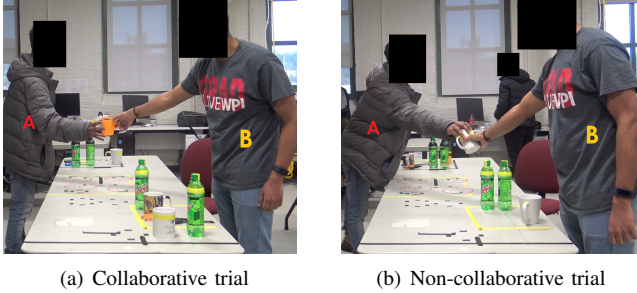


Fig. 2. Object transfer point changes based on level of collaboration

A pilot study of the one-to-one handover experiment was performed with 6 pairs of subjects. **Affordance** of the objects had no impact on collaboration intent. As the objects did not have a function in the task, affordance was not considered by Subject B. But the **object transfer point** during the non-collaborative trial was lower and closer to the yellow bin than in the collaborative trial. **Attention** of Subject B was modelled using the body and head orientation. During the collaborative trial Subject B paid attention to all actions initiated by Subject A. While in the non-collaborative trial Subject B gave and received objects without acknowledging Subject A's intended actions. The average **reaction time** of Subject B was consistent for all actions in the collaborative trial. While the average reaction time during the non-collaborative trial was slower or inconsistent. Conflicts occurred when both subjects tried to handover an object at the same time. **Resolution of conflicts** was much faster in the collaborative trial than the non-collaborative trial.

IV. ONE-TO-MANY OBJECT HANDOVER

The significant variables inferred from the one-to-one handover experiment will be used to model and contrast how the level of collaboration is estimated in a one-to-many handover scenario. We utilize the results of the pilot study to design a similar one-to-many handover experiment (Fig. 3). Here the **affordances** of objects will be enforced by defining how the objects should be placed in the bin. Along with the factors mentioned in the one-to-one scenario, **task scheduling** will now affect how the level of collaboration of subject B is perceived by Subjects A1, A2, and A3.

The human subjects can initiate a *Give* action where they would offer an object to the robotic agent or a *Demand* action where they would raise their arm to demand an object from the robotic agent. The robot can respond with a *Take* or *Give* action. The robot can also initiate a *Demand* action. The robot requires t_t time to execute the *Take* action and t_g

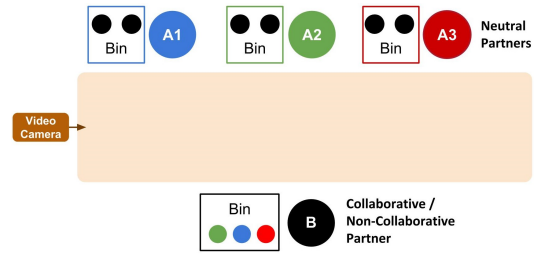


Fig. 3. Experiment setup for one-to-many handover study

time to execute the *Give* action. The task scheduling problem will select actions based on the following cost function:

$$\min \sum_{i=1}^3 (C_{G_i} * t_{w_i} + C_{D_i} * t_{w_i}) + t_{total}$$

Where, t_{w_i} is the waiting period for subject i , $C_{G_i} * t_{w_i}$ is the cost associated with the *Give* action and $C_{D_i} * t_{w_i}$ is the cost associated with the *Demand* action. t_{total} is the time required to complete the total task. The problem can be formulated with additional temporal and spatial constraints.

We propose a one-to-many human-human user study to learn the cost factors C_G and C_D and the weights for the one-to-one factors: **object transfer point**, **attention**, **verbal communication** and **conflict resolution** that lead to a collaborative behaviour. This study will help to analyze the low-level and high-level factors that affect how a service robot will be perceived by its users.

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