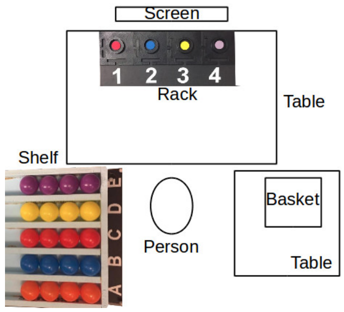

Figure 2: The top view of experimental setup for Study 1

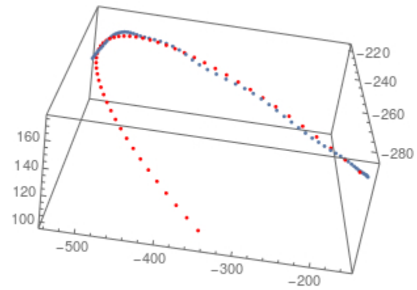

Figure 3: The cartesian positions of the hand in cm as it moves through space for a random participant (blue), and our model of the best fit ellipse to the hand trajectory (red)

- **H2:** Robot motion following an elliptical model is more legible.

We aim to create a single, unified model for describing reaching motions that can be used for both motion prediction/understanding, and motion production, in order to facilitate fluent human-robot collaborations.

3 METHODOLOGY

Study 1: Building Models of Human Reaching Motions

We use Vicon motion capture data to first construct high-fidelity human reaching motion models. The study simulated a "box packing" task in which participants were asked to fulfill the role of a packer in a shipping operation while we recorded their reaching motions. Each participant sat at a desk with a monitor in front. Surrounding them was a shelf with color-coded ball supplies, a rack with four spaces for intermediate ball placement, and a square basket with four spaces for final packing, Figure 2.

In each trial, the monitor provided pictographic instructions of ball placements onto the rack and the basket, and the participant followed the instruction to pack the balls into the rack, then into the basket, then back to the shelf as a reset for the next trial.

The task was repeated 25 times, yielding a total of 200 reaching motion samples per participant. 30 participants were recruited.

Study 2: Generating an Intent-Expressive Model of a Human-Like Reach for the Robot

A motion planner was developed based on the elliptical motion model constructed in Study 1, and was implemented onto a 7-DOF Barrett Whole Arm Manipulator (WAM)[1] equipped with a three-fingered Barrett Hand[2]. This involved the construction of an algorithm based on "spatial control" hypothesis by Morasso [7] that transforms the cartesian trajectory of the end effector (hand) in task space into coordinated trajectories in joint space in real-time.

Study 2 will be an entertainment study determining whether the robot incorporating our elliptical path planner will improve the quality and speed of interaction. This study will simulate a collaborative human-robot "box packing" task that will require the agents to share resources, and resolve unwanted resource conflicts. The task will specifically invoke situations that would require the agents to work based on intentions behind each other's motions such as:

- Handing objects from the human to robot, or the reverse action, wherein the human hands objects to the robot.
- Both agents reaching for the same object at the same time

4 PRELIMINARY RESULTS OF STUDY 1

Preliminary data analysis of Study 1 indicates that human reaching motion follows a predictable elliptical path. Figure 3 illustrates a sample of spatial trajectories of the hand (in blue) overlaid by the elliptical motion model. The predicted ellipse closely fits the reach.

5 SUMMARY

This abstract has discussed two studies. The first of these studies aims to understand and construct models of human reaching motions to facilitate prediction of the timing and location of the end of human arm reaching motions in tasks such as grasping or object handover. Based on the identified model, we have constructed a robot trajectory generator. In the second study, we will test our trajectory generator to confirm that it produces predictable and legible motion, and improves fluency and speed in human-robot interaction.

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