Data-driven Design of Expressive Robot Hands and Hand Gestures

Applications for Collaborative Human-Robot Interaction

by

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Abstract

Fast and reliable communication between human workers and robotic assistants (RAs) is essential for successful collaboration between these agents. This is especially true for typically noisy manufacturing environments that render verbal communication less effective. This thesis investigates the efficacy of nonverbal communication capabilities of robotic manipulators that have poseable, three-fingered end-effectors (hands). This work explores the extent to which different poses of a typical robotic gripper can effectively communicate instructional messages during human-robot collaboration. Within the context of a collaborative car door assembly task, a series of three studies were conducted. Study 1 empirically explored the type of hand configurations that humans use to nonverbally instruct another person (N=17). Based on the findings from Study 1, Study 2 examined how well human gestures with frequently used hand configurations were understood by recipients of the message (N=140). Finally, Study 3 implemented the most human-recognized human hand configurations on a 7-degree-of-freedom (DOF) robotic manipulator to investigate the efficacy of having human-inspired hand poses on a robotic hand compared to an unposed hand (N=100).

Contributions of this work include the presentation of a set of hand configurations humans commonly use to instruct another person in a collaborative assembly scenario, as well as *Recognition Rate* and *Recognition Confidence* measures for the gestures that humans and robots expressed using different hand configurations. These experimental results indicate that most gestures are better recognized with a higher level of confidence when displayed with a posed robot hand. Guidelines and principles are provided based on these results for the mechanical design of robotic hands.

Preface

This thesis is submitted in partial fulfillment of the requirements for the degree of Master of Applied Science in Mechanical Engineering at the University of British Columbia (UBC).

The material presented in this thesis is available as two works: A conference paper and a journal paper. The author was responsible for performing a literature review, developing software, conducting human studies and data analysis, and writing the manuscripts. The conference paper was presented by the author at the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2015. The journal paper has been recommended for publication in the International Journal of Robotics Research (IJRR) (impact factor 2.54, ranked #1 in Robotics).

Conference Publications

Sara Sheikholeslami, AJung Moon, and Elizabeth A. Croft. Exploring the effect of robot hand configurations in directional gestures for human-robot interaction. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '15)*, Hamburg, Germany, September–October 2015

Journal Articles (accepted)

Sara Sheikholeslami, AJung Moon, and Elizabeth A. Croft. Cooperative gestures for industry: Exploring the efficacy of robot hand configurations in expression of instructional gestures for human-robot interaction. *International Journal of Robotics Research*

An outline of the three experiments presented in this thesis has been accepted as part of a book chapter, which was under its last round of revisions at the time this thesis was submitted:

Book Chapters (Pre-print)

Justin W. Hart, Sara Sheikholeslami, and Elizabeth A. Croft. Developing robot assistants with communicative cues for safe, fluent HRI. In J. Scholz H. Abbass and D. Reid, editors, *Foundations of Trusted Autonomy.* Springer, Berlin, Germany, 2016 - pre-print

All human-participant experiments described in this thesis were approved by the University of British Columbia Behavioural Research Ethics Board (H10-00503).

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Glossary

CAGR compound annual growth rate. 1

DOF degree(s) of freedom. ii

GPS global positioning system. 2

HCI human-computer interaction. 3

HHI human-human interaction. v, 6, 8

HRC human-robot collaboration. 1, 3

HRI human-robot interaction. v, 1, 2, 3, 6, 7, 8, 64, 71

RA robotic assistant. ii, 1, 2

WAM Whole Arm Manipulator. 10, 29

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Chapter 1

Introduction

In the past thirty years, robotics technology has become well-established in the manufacturing industry for reducing worker ergonomic stress and workload by performing operations quickly, repetitively, and accurately [20, 25]. Robotics technology is approaching the point in which an industrial robotic assistant (RA)—such as Baxter from Rethink Robotics—is mechanically safe enough to be used outside of work cells, having minimum to no physical barriers between it and human workers [16]. Other promising avenues for RA hardware include lightweight robots designed specifically for safety [21] and existing industrial robot platforms augmented with improved sensing and control [17]. As we continue to integrate robots as versatile aids for industry automation, it is important to develop human-robot interaction (HRI) mechanisms that facilitate seamless cooperation and intuitive communication between humans and robots. The global robotics market is anticipated to reach $67-billion (USD) by 2025, with industrial robotics representing the largest segment of the market and growing at a compound annual growth rate (CAGR) of 7.6% [36].

As robots become more adaptive and capable working alongside human co-workers, it is imperative that intuitive HRI methods are designed to facilitate direct and physical human-robot collaboration (HRC) [38]. Such collaboration would benefit productivity by effectively combining the capabilities of each partner: the intelligence, experience, and responsiveness of human co-workers, and the accuracy, repeatability, and speed of RAs [22]. Proximate HRI could be used extensively in manufacturing for tasks such as assembly, inspection, box packing, and part delivery, among others. In such scenarios, while there is ongoing direct interaction between human and robot co-workers, it is important to allow human co-workers to focus their attention on completing the task at hand, rather than controlling the robot utilizing complex teaching pendants or other keyboard based interfaces.

However, the manufacturing assembly line environment has inherent restrictions and limitations that make implementation of human-robot collaboration systems challenging. Ambient acoustic noise is one such factor. While speech control has come to be useful for devices like the Amazon Echo and speech interfaces to instruments such as global positioning system (GPS), the denoising of speech presents significant signal processing challenges [10]. Further, in manufacturing environments, workers are often encouraged or required to use earplugs; for those workers, spoken verbal communication is unreliable and in some cases prohibited [7]. As an alternative, workers often use hand gestures to communicate, motivating our investigation of task-based gestural communication as a plausible HRI medium in industrial settings.

Much of the related work on improving industrial HRI has focused on interactions in which the human demonstrates or instructs a robot on how to perform a task [44]; however, natural and balanced HRI must be bilateral [12]—the robot must be able to react and respond to the given demonstrations and instructions by its human co-worker(s). Future industrial scenarios envision an ongoing human-robot interaction in which not only the human instructs and communicates with the robot, but also the robot is capable of responding and communicating back with its human coworker(s). The broad goal of this work is to develop HRI methods that will facilitate more intuitive and effective cooperation and collaboration between humans and robots on industrial tasks.

Today, the predominant robotic form factor used in manufacturing is that of single-arm robotic manipulators with no face or body. Since workers are required to pay attention to the task in front of them, they may be more likely to attend to the robot's gripper than to a face, as it is positioned where they are already looking [28]. Therefore, to bridge the gap between current systems and future robot embodiments, this thesis focuses on the development and evaluation of communicative robot gestures on a single-arm manipulator. Related work demonstrated human recognition of gestures expressed by a single-arm RA [20]; while this related study was successful in conveying information without articulation of the robot's fingers, the usefulness of robot fingers in gesturing has yet to be systematically explored.

More specifically, this work develops and evaluates a cardinal set of user-generated gestures applicable to industrial scenarios in which the robot is providing a set of instructions to a co-located person while collaborating on a shared task in an intuitive and effective manner. Three studies were performed to explore the following interrelated research questions:

1. **"What kind of hand gestures do humans commonly use to nonverbally instruct one another in industrial assembly contexts?"** This research question explores the lexicon of gestures naturally generated and interpreted in human-human interactions situated within a particular task context. Grounding these gestures within a particular task is important, as the gestures might mean something else in a different context (and, conversely, other gestures might mean something else within this same context).

2. **"How well do humans recognize the hand gestures presented by another human?"** This research question establishes a baseline for human interpretation of naturally occurring gestures within the task context to which robot gestures (inspired by the human gestures) will be compared.

3. **"How well do untrained human observers recognize robot hand gestures that are accompanied by human-inspired hand poses compared to those that are exhibited with an unposed robot hand?"** This research question investigates the novel generation of human-inspired situated gestures on a non-anthropomorphic robotic hand common in industrial settings, and the interpretation of these gestures by human observers.

Answers to these question will help in designing a fluent HRI with reliable sets of communicative gestures. This work extends the body of work in nonverbal HRI, the key contributions of which are:

- a methodology for designing and implementing task-based communicative gestures to be expressed by a robot in HRI;
- a cardinal set of user-generated task-based communicative hand gestures and accompanying hand poses for human-robot collaborative tasks;
- an evaluation and validation of the identified gesture set with respect to human *Recognition Rate* and *Recognition Confidence* within a human-robot collaboration scenario; and
- a set of guidelines for the mechanical design of robot hands.

1.1 Thesis Outline

This section describes the organization and contents of chapters in this thesis.

Chapter 2 highlights relevant works from the field of psychology, HRI, and human-computer interaction (HCI). The chapter mainly focuses on studies that discuss the significance of human nonverbal communication with an emphasis on hand gestures (Section 2.1), nonverbal human-robot communication within various contexts (Section 2.2), and the hardware limitations of robot hands available in the industry compared to that of a human hand (Section 2.3). There have been many research contributions addressing the usefulness of human hand gestures, and their implementation in HRC contexts; however, the added value of having poseable fingers on a robot for nonverbal communication purposes has yet to be explored in a systematic manner. We address this knowledge gap by exploring how effectively an articulated robot arm can communicate approximated human hand-gestures to its human co-workers with and without hand poses.

Chapter 3 explores each of the aforementioned research equations in three studies. Section 3.1 presents the first of three human-subject studies, Study 1, designed to empirically identify a sample of appropriate task-based human hand gestures and hand poses used for expressing the gestures. In this study, participants are asked to perform a collaborative assembly task, nonverbally communicating their intentions to a human confederate. The motions that they produce are analyzed to determine the gestures and hand poses they used during the study answering the first research question, "What kind of hand gestures do humans commonly use to nonverbally instruct one another in industrial assembly context?"

Based on the findings from Study 1, Study 2 (Section 3.2) presents videos of the identified human gestures with the selected hand poses to participants within an analogous assembly context to analyze how well the gestures are perceived by human observers, answering the second research question, "How well do humans recognize the hand gestures presented by another human?"

Section 3.3 of Chapter 3 presents the third human-subject experiment, Study 3, which empirically tests the efficacy of a mechanically limited robotic hand in communicating the identified gestures in study 1 to human observers. This study utilizes a commonly used robotic manipulator to approximate the human gestures. Videos of the produced gestures are presented to participants to identify which gestures and hand poses are best understood when implemented on the robotic system in this fashion. This study answers the third and final research question, "How well do untrained human observers recognize robot hand gestures that are accompanied by human-inspired hand poses compared to those that are exhibited with unposed robot hand?"

Chapter 4 evaluates and analyzes the hypotheses that most gestures are better recognized with a higher level of confidence when displayed with a human-inspired posed robot hand than an unposed robot hand by examining Recognition Rates (accuracy) and Recognition Confidence of human observations of the implemented robot hand gestures. Section 4.1 presents the identified human hand gestures and accompanying hand poses from Study 1. Section 4.2 presents which human gestures and hand poses participants recognize more confidently and evaluates how well the robot implementation of the same hand gestures and hand poses performs.

Chapter 5 expands upon the results found in this thesis to provide a set of guidelines for the mechanical design of individual regions and features of robotic hands. Section 5.1 discuses these region and feature considerations. Section 5.2 presents the application of these principles to the design of real robot hands. Section 5.3 proposes further steps to formalize these guidelines.

Chapter 6 summarizes the thesis work. Section 6.1 reviews the key contributions of this work. Limitations of the approaches employed are also discussed and resolutions to these limitations proposed as future work (Section 6.2), followed by concluding remarks (Section 6.3).

Chapter 2

Background and Motivating Literature

Section 2.1 highlights the significance of human nonverbal communication with an emphasis on hand gestures in human-*human* interactions (HHI). Section 2.2 provides an overview of the relevant work on the topic of human-like nonverbal communication in human-*robot* interactions (HRI) within various contexts, such as turn-taking, hesitation, and hand gestures. Section 2.3 further explores the different types of robot hands available in the industry, discusses the hardware limitations of robot hands compared to that of a human hand, and highlights the challenges the kinematic differences pose in robot hand gestural communication.

2.1 Nonverbal Communication in HHI

In HHI, people use both verbal and nonverbal communication to convey information to one another. Different nonverbal signals—hand and arm gestures, body movements, facial expressions, eye and head gaze, touch, etc.—function in three distinct ways: (1) they regulate social situations and communicate attitudes and emotions (e.g., anxiety, happiness, depression, etc.) to others, (2) they strengthen speech by providing additional information about the content of the speech, and (3) they replace spoken language to convey meaning (e.g., sign language often used within communities of people with hearing impairments) [1, 2, 19]. In summary, people use nonverbal signals to convey their internal states and intentions to other people, and they have the ability to read and understand the internal states and intentions of other people from these nonverbal signals [1, 13].

In particular, human hand gestures are one of the most vital nonverbal channels; while the hands were evolved for grasping, they are also very useful in social signaling [19]. For instance, *conversational gestures*—hand movements that accompany and are often related to speech—tend to increase speech fluency [34, 35]. Hand gestures can also be used alone (i.e., in the absence of speech) and deliver a clear communicative message. For example, *symbolic gestures*—hand configurations and movements that can be directly translated into words—are often used to send a particular message to others [5, 26]. Contextual information can influence/modify the meaning of symbolic gestures. For example, the “thumbs up” is a familiar symbolic gesture that is often interpreted as “good/positive”; however, context information can influence or add to its meaning—it can be used to greet someone, to indicate understanding the point of a conversation, or as an insult [41]. Thus, even though nonverbal gestures can convey messages without an accompanied speech, their meanings are still influenced by context.

Harrison [23] explored gestural communication among workers in a noisy production line of a salmon factory. This related work showed that workers commonly use hand gestures to communicate with one another, and that the workers often have to shout when speaking to be heard due to the high ambient noise. In industrial environments with high ambient noise, it has been shown that gestural communication is preferred and has been well adapted in different industries to replace verbal communication [3]. This thesis work explores the efficacy of gestural communication in human-robot teams.

2.2 Nonverbal Communication in HRI

Just as how nonverbal communication can replace speech in environments in which verbal communication is unreliable or undesirable, nonverbal communication is expected to take a similar role in HRI. Various human-like nonverbal cues—hand gestures in particular—have been explored as communication mechanisms between humans and robots during turn-taking [8, 11], playing games [42], hesitation [30, 31], and hand gestures within collaborative working processes [15, 18, 20, 33, 37].

Past research in human-robot turn-taking (e.g., selecting the role of speaker vs. listener) has shown that vocal communication when accompanied with nonverbal cues, such as hand gestures and head nods, improves task performance of human-robot teams by making the robot more understandable and predictable to the human teammate [8, 11]. However, the focus of these works is often on situations in which nonverbal communication is used to support and strengthen speech. This thesis work considers conditions in which only nonverbal communication is applicable (i.e., vocal communication is not feasible).

Other HRI studies have investigated robots using gestures to play games with people. For instance, Short et al. [42] performed an experiment involving a robot playing the rock-paper-scissors game against a human partner; however, due to mechanical limitations of the robot hand, a set of modified rock-paper-scissors gestures were deployed for the robot to use. Thus, participants had to be trained before the game to understand the meaning of each robot hand pose. In contrast, this thesis work explores a set of gestures that allows a mechanically limited robotic hand to communicate information to untrained human observers.

Few studies have focused on the effectiveness of nonverbal communication of non-anthropomorphic robotic manipulators in industrial settings [15, 18, 20, 30, 31]. In one such study, Moon et al. [30] studied the efficacy of robot hesitation gestures as a means to convey robot planner uncertainty in a human-robot resource conflict that arises when both the robot and the person reach for the same object at the same time; results of this related work showed that human observers can easily recognize the hesitation gestures expressed by the robotic manipulator. This result demonstrates that non-anthropomorphic robotic manipulators have the potential to effectively convey communicative messages as well.

In the context of collaborative work processes, Sauppé and Mutlu [37] evaluated the communicative effectiveness of a set of referencing (deictic) gestures performed by a human-like robot in six diverse settings, including one scenario replicating the noisy environment of industrial settings; this related work discusses design implications for the use of gestures in different settings. Ende et al. [15] explored which human-like nonverbal gestures are communicative for robotic systems of different levels of anthropomorphism; this related work found that referencing gestures—conveying "this one" and "from here to there"—and terminating gestures—conveying "stop" or "no"—are well recognized on various types of robots. In a study by Haddadi et al. [20], a set of gestures from human dyads (pairs) performing an assembly task was collected and implemented on a robotic arm with an unarticulated (i.e., not actuated) stuffed glove at the robot end-effector to provide anthropomorphic context; this related work found that, upon evaluating the human recognition of the robotic gestures, the robot's lack of hand pose articulation tends to confuse rather than help human observers.

While many of the aforementioned studies extracted useful hand gestures from HHI and implemented them in HRI contexts, to date, the added value of having poseable fingers on a robot for nonverbal communication purposes has yet to be explored in a systematic manner. This thesis work addresses the knowledge gap by exploring how effectively an articulated robot arm can communicate approximations of human hand-gestures to human coworkers with and without articulated hand poses.

2.3 A Review of Industrial Robotic Hands

Industrial applications are dominated by single-arm robotic manipulators equipped with different end-effectors [20]. In a review paper, Tai et al. [43] presented a recent survey on the applications and advancements of industrial robotic grippers. Industrial robotic grippers are commonly used for mass production purposes and are mounted on a robotic arm on a stationary platform. Depending on the application, modern industrial robotic arms and grippers can outperform humans in many tasks and are capable of lifting 1000 kg [32], are repeatable to $10\mu m$ [29], and are faster with accelerations up to 15 g [27]. Additionally, the cost of industrial robotic grippers is decreasing while manual labor costs are increasing. This has encouraged industry and academia to develop more advanced robotic arms and grippers addressing the needs of industry.

An industrial robotic gripper can often be categorized into one of four broad categories: vacuum grippers, pneumatic grippers, hydraulic grippers, and servo-electric grippers [6]. Each category is described below.

1. *Vacuum grippers* have a high level of flexibility and have been the standard gripper used in manufacturing. This type of robot gripper is equipped with a rubber or suction cup to manipulate items. An example of a vacuum gripper is the Schmalz Vacuum Gripper (FXC/FMC-SG) gripper developed by Millsom Vacuum Handling[1] for flexible handling of non-rigid workpieces, such as cardboard boxes (Figure 2.1).

2. *Pneumatic grippers* have a compact and lightweight design. These grippers can easily be incorporated into tight spaces, which can be helpful in the manufacturing industry. Schunk's Pneumatic parallel grippers[2] are commonly used for safe and precise handling of small- to medium-sized workpieces. Figure 2.2 highlights an example of Schunk's MPG Series 2-finger pneumatic gripper.

3. *Hydraulic grippers* are most often used in applications that require significant amounts of force and, thus, require specialized equipment that has a hydraulic power source for actuation. Figure 2.3 illustrates an example of a hydraulic gripper by Schunk.

4. *Servo-electric grippers* are highly flexible and allow for different material tolerances when handling parts. As such, these grippers are start-

[1] http://www.millsom.com.au/

[2] http://us.schunk.com/us$_e n/homepage/$

ing to appear more in industry. Baxter's 1D gripper [16] and Robotiq's 3-finger gripper[3] are examples of common servo-electric grippers. Figure 2.4 shows the Robotiq's 3-finger gripper which is capable of manipulating a variety of object shapes and sizes.

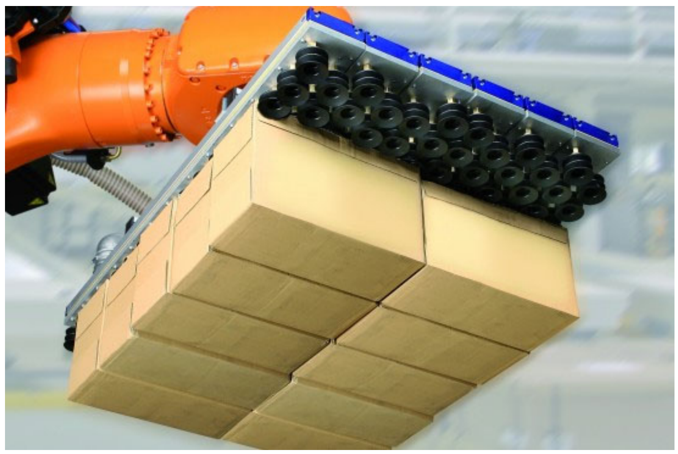


Figure 2.1: Vacuum Gripper System FXC-FMC-SG (http://www.millsom.com.au/products/vacuum-components/vacuum-gripping-systems/fxc-fmc-sg).

In addition, various tools can be directly mounted on the tip of the manipulator (e.g., welding tips or suction cups). These commonly used end-effectors are highly non-anthropomorphic and are often limited in actuation. This makes it challenging, if not impossible, to map onto these end-effectors the communicative human hand configurations/poses (the articulation or pose of the fingers, such as in finger-crossing) for expressing a gesture.

Robotic hands that more closely resemble human kinematics are able to produce better approximations of human gestures (e.g., the GCUA Humanoid Robotic Hand [9]); however, such hands are likely to be much more expensive and less useful in industrial manufacturing.

Therefore, to maximize the applicability of our results, this thesis research uses a commonly available non-anthropomorphic robotic hand that balances capabilities between *physical manipulation* and *social expressiveness*. Approximations of human instructional hand gestures are programmed on a 7-DOF Barrett Whole Arm Manipulator (WAM)[4] equipped with a

[3] http://robotiq.com/

[4] WAM^{TM}, Barrett Technologies, Cambridge, MA, USA

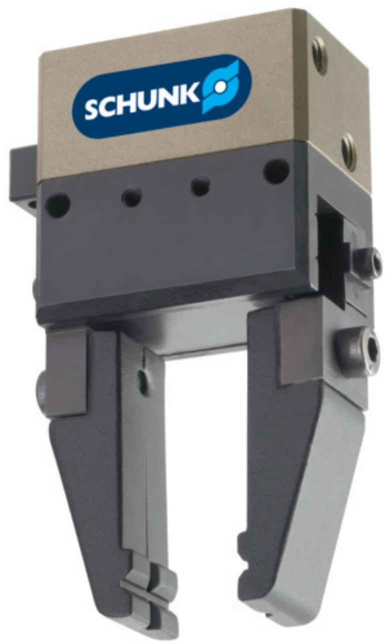


Figure 2.2: Shunk's 2-finger pneumatic parallel gripper MPG Series (http://us.schunk.com/us$_{e}n/gripping - systems/series/mpg - plus$).

Figure 2.3: Shunk's 2-finger hydraulic gripper HGN Series (http://www.directindustry.com/prod/schunk/product-69812-1283431.html).

Figure 2.4: Robotiq's 3-finger gripper (http://robotiq.com/products/).

three-fingered Barrett Hand[5]. The Barrett Hand is similar to (but not actually used as) morphologies of robotic hands common in industry, see Figure 2.5. This work focuses on evaluating (1) if approximations of human instructional hand gestures can be successfully generated on these non-anthropomorphic robotic hands, and (2) the efficacy of these robotic hands in communicating the gestures to human partners.

[5]Barrett Hand^{TM}, Barrett Technologies, Cambridge, MA, USA.

Figure 2.5: The Barrett Hand
(http://www.barrett.com/products-hand.htm).

This chapter discussed nonverbal communication in both human-human and human-robot interaction, and introduced categories of robotic grippers commonly used in industry. Informed by this background literature, the next chapter presents three studies designed to explore each of the research questions introduced in Chapter 1:

1. "What kind of hand gestures do humans commonly use to nonverbally instruct one another in industrial assembly context?"

2. "How well do humans recognize the hand gestures presented by another human?"

3. "How well do untrained human observers recognize robot hand gestures that are accompanied by human-inspired hand poses compared to those that are exhibited with an unposed robot hand?"

Chapter 3

Methodology

This chapter presents the three user studies conducted to address the three interrelated research questions introduced in Chapter 1. In Study 1 (a pilot study; Section 3.1), to identify appropriate task-based hand gestures and hand poses used for expressing the gestures, participants were asked to use single-handed gestures to instruct a human confederate in a collaborative car door assembly task. In Study 2 (Section 3.2), videos of the identified gestures with the selected hand poses were presented to participants within an analogous assembly context to analyze how well the gestures are perceived by human observers. In Study 3 (Section 3.3), approximations of these gestures were implemented on a robotic manipulator, and videos of the produced gestures were presented to participants to identify which gestures and hand poses were best understood when implemented on the robotic system. All studies were approved by the UBC Behavioural Research Ethics Board.

3.1 Study 1 (Pilot): Identifying Human Hand Gestures Based on Observations from Human-Human Collaboration

To identify a sample lexicon of robot gestures that are both natural and effective in communicating instructions to human partners, a pilot study was conducted involving human dyads collaborating on a vehicle door assembly task—the goal was to generate a sample of gestures that would be appropriate and naturally occurring in the application domain, accepting that this would not generate an exhaustive exploration of the space or cover the cultural, regional, or other variations in gestures.

The experimental setup consisted of six car door parts, and an unassembled car door with seven spots to which the door parts could be attached using Velcro^{TM} strips. The participant stood in front of the car door and the worker stood to the right of the car door, with the car door parts placed on a table between them. This setup allowed the participant and the confederate to easily access the vehicle door as well as the parts (Figure 3.1).

Figure 3.1: Assembly task designed for human-participants experiment.

First, participants were asked to use hand gestures to instruct a human confederate—referred to henceforth as the "worker"—to assemble the parts into specific locations on the car door according to a provided picture of the completed assembly.

Next, a second picture of the vehicle door was given to the participants. The picture contained changes in the orientation/location of three of the six items already assembled on the door. The participants were asked to direct the experimenter to rearrange the items on the door to achieve the new assembly arrangement (see Appendix A for instructions and the car door pictures provided to participants).

To provoke a wider range of intuitive gestures in each round of the experiment, the worker would intentionally and as naturally as possible:

1. assemble/place the part at an incorrect location or orientation;
2. pick up an incorrect part from the table; and
3. maintain natural eye contact with the participant to get him/her to either confirm or correct the ongoing task.

(See Appendix A, Section A.1 for instructions provided to the worker.) Participants were requested to observe the following rules[6]:

1. not to speak/verbally communicate with the worker;
2. only use one hand to direct the worker;
3. only make one gesture and hold only one part at a time;
4. wait for worker task completion before making the next gesture; and
5. remain at the home position at all times.

In total, 17 participants ($N = 17$; 7 female, 10 male) between 19 and 36 years of age ($M = 24.41$, $SD = 4.05$) participated in the study; all but two were right-handed. The results dataset came from video recordings of the study and the observed hand gestures that participants naturally used to convey common instructional commands to their partner. In executing the assembly task, participants expressed an average of 20 gestures in total, which was reduced to a lexicon of 14 gestures based on the following criteria: gestures must be (1) understandable without trained knowledge of the gesture, (2) critical to task completion, and (3) commonly used among all participants. The selected gestures were classified into four categories based on the nature of the gestures:

1. **Directional Gestures**, G_D, indicating that the worker should move (translate) a part in the specified direction, where: $G_D = \{\textbf{Up}, \textbf{Down}, \textbf{Left}, \textbf{Right}\}$.
2. **Orientation Gestures**, G_O, indicating that the worker should rotate (orient) a part the specified number of degrees, where: $G_O = \{< \mathbf{45^\circ}, \mathbf{90^\circ}, \mathbf{180^\circ}\}$.
3. **Manipulation gestures**, G_M, indicating that the worker should apply the specified operation to a part or parts, where: $G_M = \{\textbf{Install}, \textbf{Remove}, \textbf{PickUp}, \textbf{Place}, \textbf{Swap}\}$.
4. **Feedback gestures**, G_F, indicating approval or disapproval of worker action, where: $G_F = \{\textbf{Confirm}, \textbf{Stop}\}$.

[6]The implications of imposing these restrictions are discussed in Section 6.2.

All of the selected gestures—except for the **Confirm** gesture—involved some sort of movement of the wrist/forearm. Many different hand configurations were observed for expressing each gesture. The two most commonly observed human-generated hand poses/configurations were selected for each gesture. For instance, the “Move Part Up” gesture was most commonly expressed using (1) an Open-Hand (OH) configuration, and (2) a Finger-Pointing (FP) configuration (Figure 3.2). Section 4.1 provides the percentage of participants that used each of the two most commonly observed hand poses for expressing each of the four types of identified gestures. The selected hand gestures and their corresponding hand poses are depicted in Table 3.1 and Figure 3.2 for **Directional Gestures**, Table 3.2 and Figure 3.3 for **Orientation Gestures**, Table 3.3 and Figure 3.4 for **Manipulation Gestures**, and Table 3.4 and Figure 3.5 for **Feedback Gestures**.

Table 3.1: **Directional Gestures**, G_D, and frequently observed accompanying hand poses found in Study 1.

Directional Gestures (G_D) indicate that the worker should move (translate) a part in the specified direction		
Gesture, $g \in G_D$	**Hand Poses**	**Figures**
Up	OH FP	3.2a 3.2b
Down	OH FP	3.2a 3.2b
Left	OH FP	3.2c 3.2d
Right	OH FP	3.2c 3.2d

Hand Poses:
OH: Open-Hand
FP: Finger-Pointing

Table 3.2: **Orientation Gestures**, G_O, and frequently observed accompanying hand poses found in Study 1.

Orientation Gestures (G_O) indicate that the worker should rotate (orient) a part the specified number of degrees		
Gesture, $g \in G_O$	**Hand Poses**	**Figures**
$< \mathbf{45°}$	HOH	3.3a
90°	HOH FP	3.3a 3.3b
180°	HOH FP	3.3a 3.3b

Hand Poses:
HOH: Half Open-Hand
FP: Finger-Pointing

Table 3.3: **Manipulation Gestures**, G_M, and frequently observed accompanying hand poses found in Study 1.

Manipulation Gestures (G_M) indicate that the worker should apply the specified operation to a part or parts		
Gesture, $g \in G_M$	**Hand Poses**	**Figures**
Install	OH FP	3.4a 3.4b
Remove	OH HOH	3.4c 3.4d
PickUp	OH	3.4e
Place	FP	3.4f
Swap	FP VS	3.4g 3.4h

Hand Poses:
OH: Open-Hand
HOH: Half Open-Hand
FP: Finger-Pointing
VS: V-Sign

Table 3.4: **Feedback Gestures**, G_F, and frequently observed accompanying hand poses found in Study 1.

Feedback Gestures (G_F) indicate approval or disapproval of a worker's action		
Gesture, $g \in G_F$	**Hand Poses**	**Figures**
Confirm	TU	3.5a
Stop	OH FP	3.5b 3.5c

Hand Poses:
TU: Thumbs-Up
OH: Open-Hand
FP: Finger-Pointing

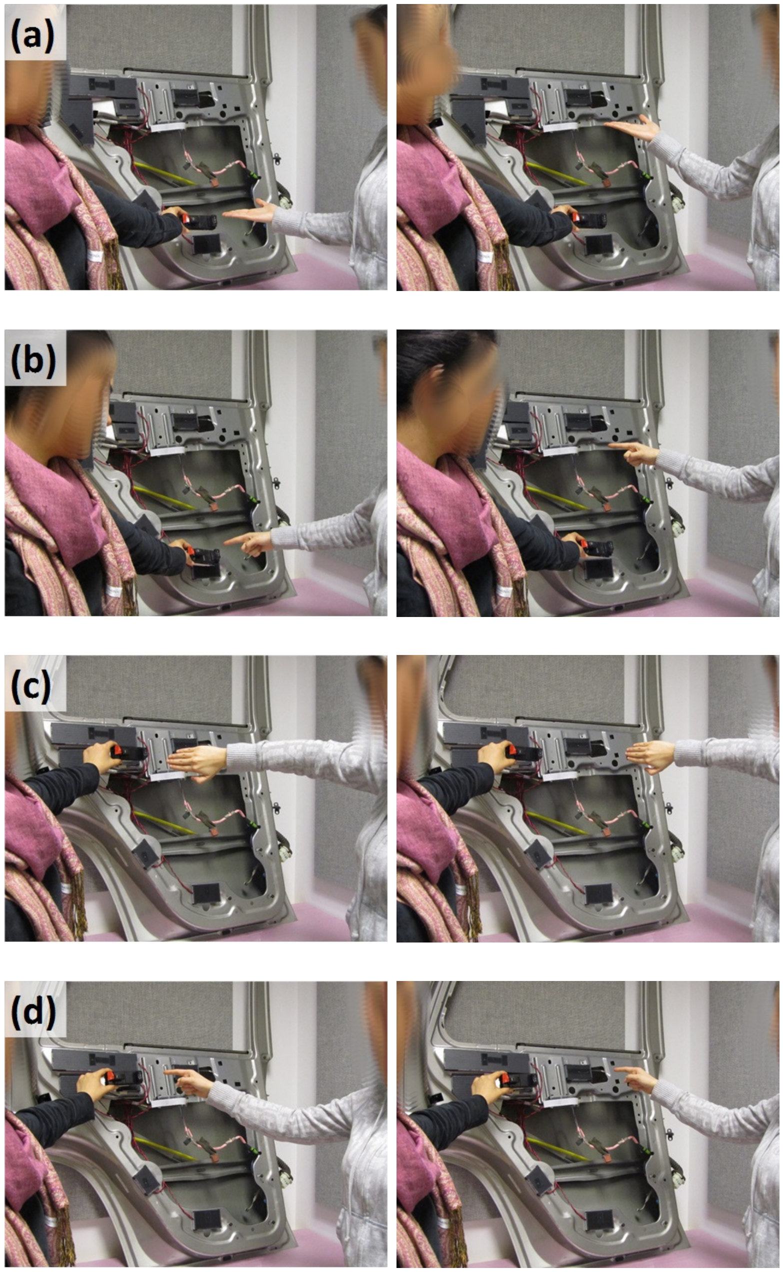


Figure 3.2: **Directional Gestures**, G_D, and frequently observed accompanying hand poses found in Study 1: **Up** [and **Down**] gesture with (a) an Open-Hand pose, and (b) a Finger-Pointing pose; and **Left** [and **Right**] gesture with (c) an Open-Hand pose and (d) a Finger-Pointing pose.

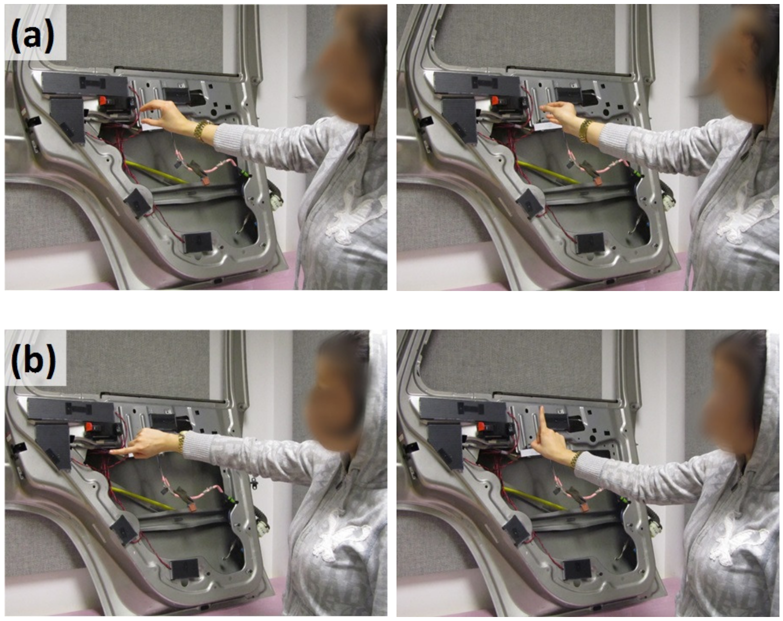
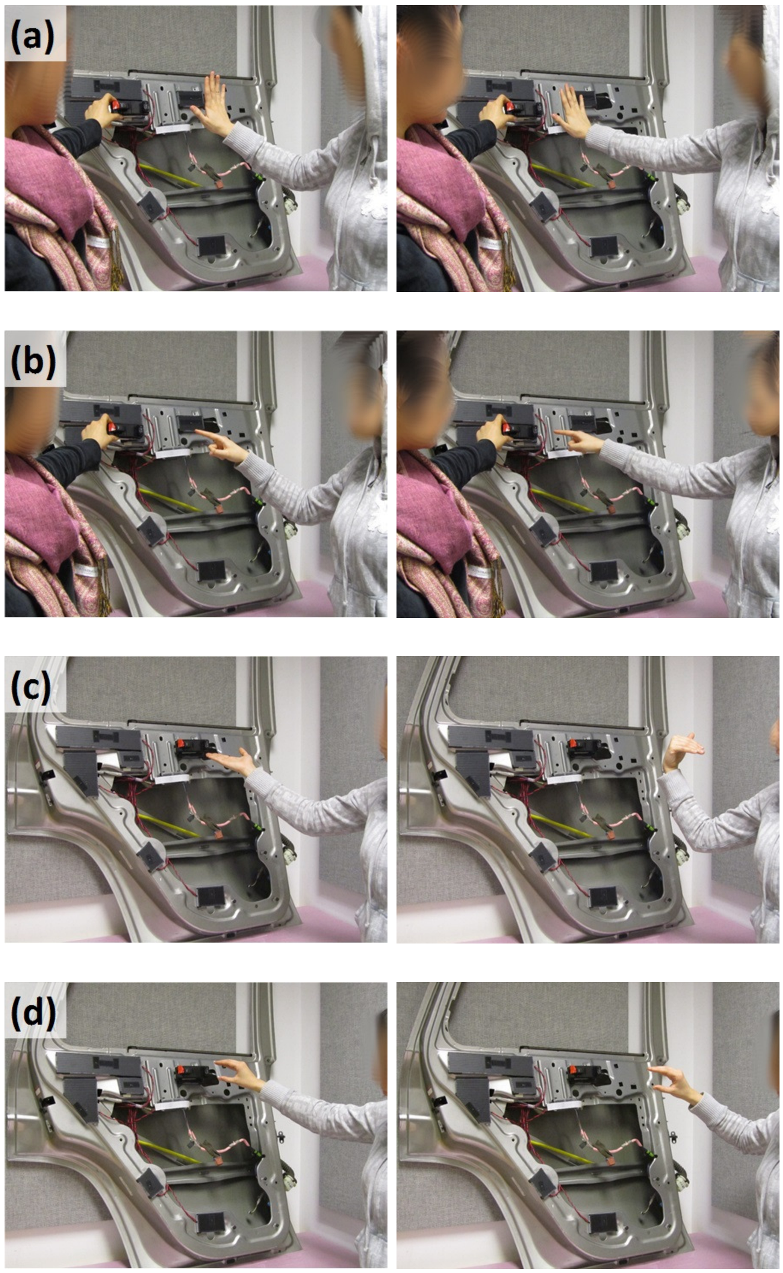


Figure 3.3: **Orientation Gestures**, G_O, and frequently observed accompanying hand poses found in Study 1: **90**° [and **180**° and $<$ **45**°] gesture with (a) a Half-Open-Hand pose, and (b) a Finger-Pointing pose. Note: the HOH pose was the only frequently observed pose for $<$ **45**° gesture



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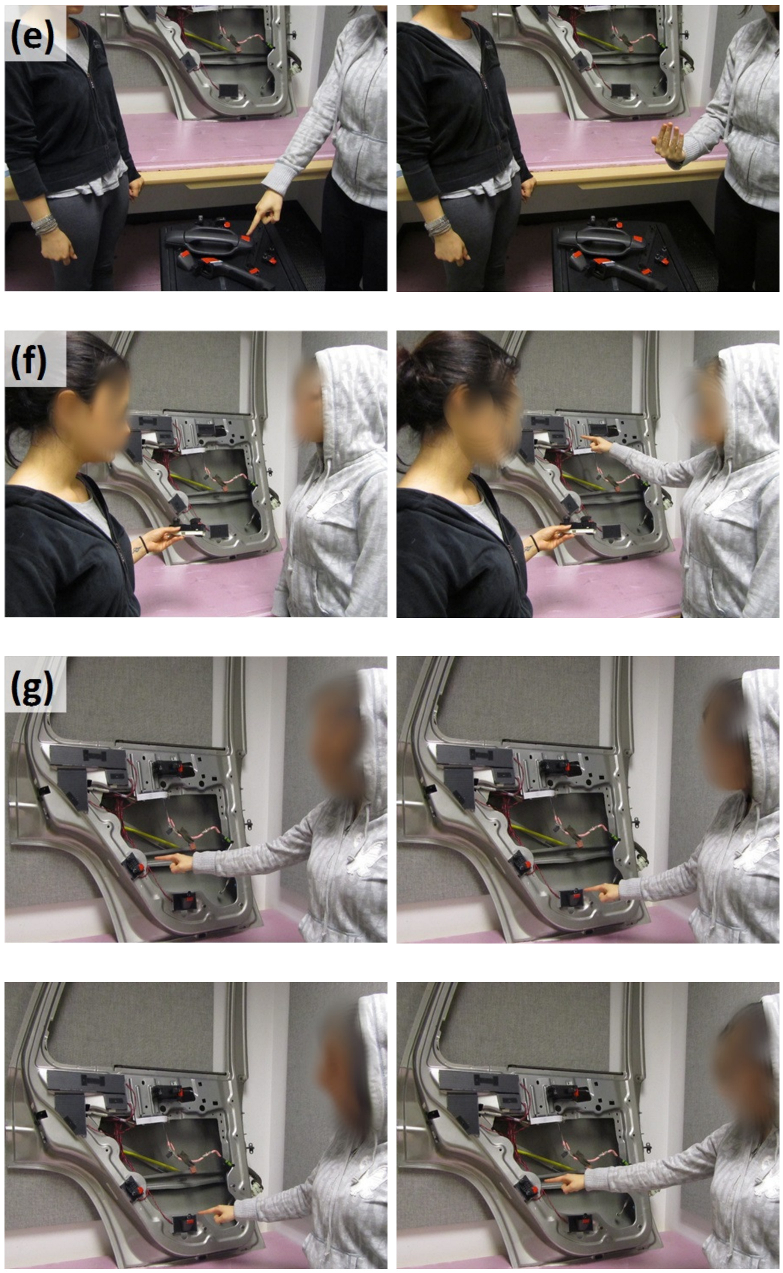

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Figure 3.4: **Manipulation Gestures**, G_M, and frequently observed accompanying hand poses found in Study 1: **Install** gesture with (a) an Open-Hand pose, and (b) a Finger-Pointing pose; **Remove** gesture with (c) an Open-Hand pose, and (d) a Half Open-Hand pose; **PickUp** gesture with (e) an Open-Hand pose; **Place** gesture with (f) a Finger-Pointing pose; and **Swap** gesture with (g) a Finger-Pointing pose, and (h) V-Sign pose.

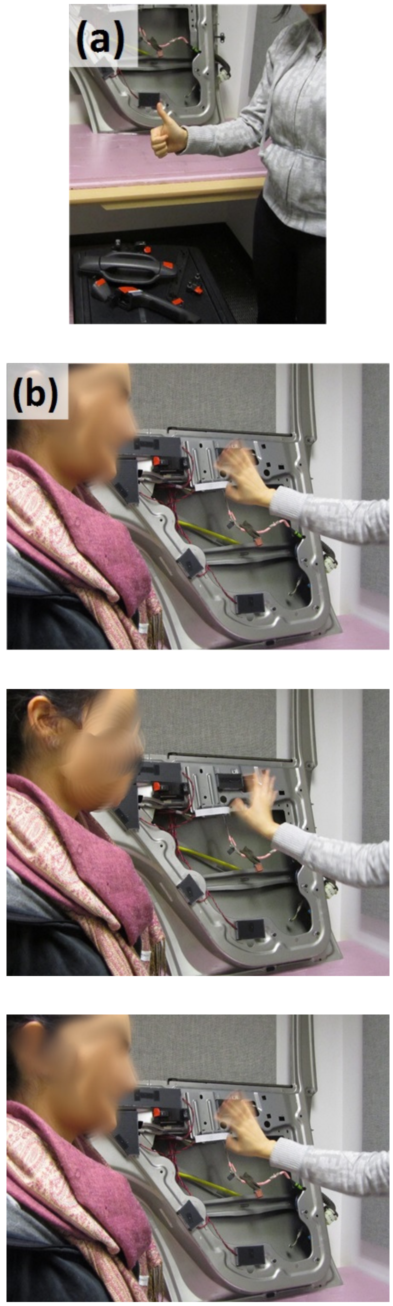

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Figure 3.5: **Feedback Gestures**, G_F, and frequently observed accompanying hand poses found in Study 1: **Confirm** gesture with (a) a Thumbs-Up pose; and **Stop** gesture with (b) an Open-Hand, and (c) a Finger-Pointing pose.

3.2 Study 2: Human Perceptions of Human Hand Gestures Based on Observations from Human-Human Collaboration

The results of Study 1 yielded a collection of gestures that are intuitive and commonly used in a human-human collaboration scenario. Study 2 involved a video-based online survey to analyze how well human observers understand these gestures when conveyed with the different hand configurations. The survey consists of a randomly ordered set of video clips, each of a person (referred to as the "director") exhibiting one of the identified gestures with a selected hand configuration to direct a "worker" in an assembly task analogous to Study 1. To avoid eliciting unintentional biases associated with other bodily gestures (e.g., differences in posture), only the gesturing hand and arm were shown in the videos.

In this between-participants study, each participant saw all of the 14 collected gestures; however, each gesture was shown with only one of the two identified hand configurations for that gesture.

Each video clip (one video clip per gesture) consisted of a short lead-in sentence instructing the respondents to watch the video with special attention to the hand motions of the "director". After each video clip, the participants were instructed to answer the following questions[7]:

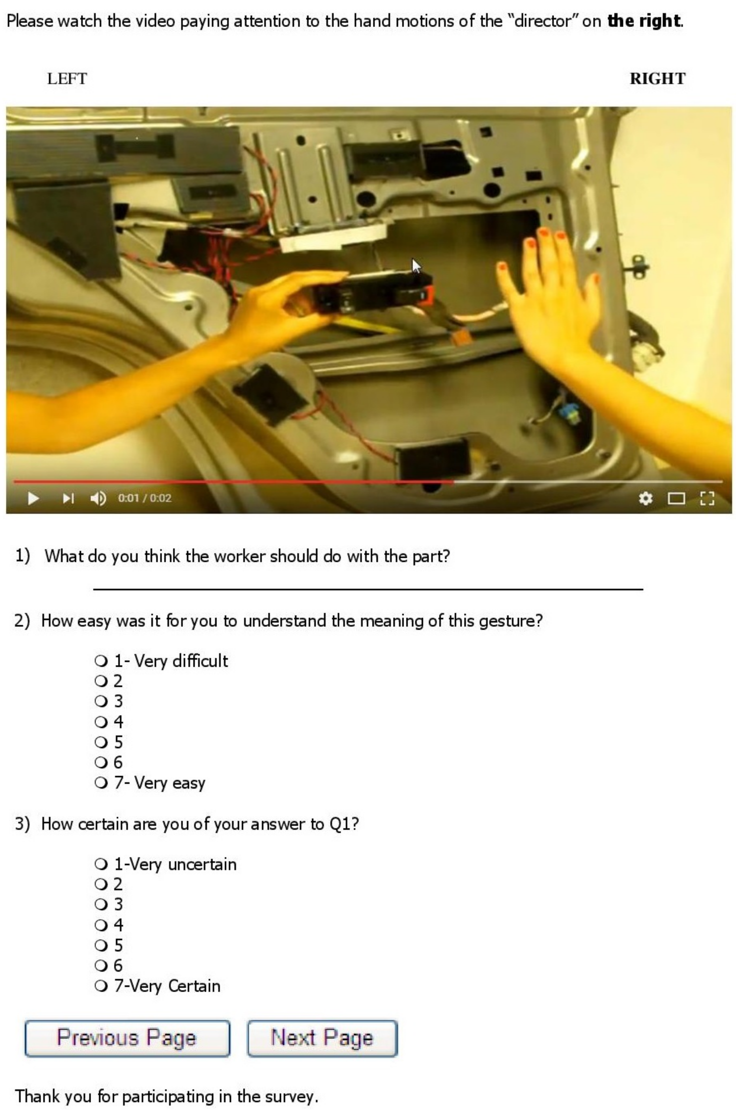
1. "What do you think the 'worker' should do with the part?" (participants were asked to respond "I don't know" if they did not understand a gesture);

2. "How easy was it for you to understand the meaning of this gesture?" (on a semantic-differential scale from 1 (very difficult) to 7 (very easy)); and

3. "How certain are you of your answer to question 1?" (on a semantic-differential scale from 1 (very uncertain) to 7 (very certain)).

Figure 3.6 shows a screen capture from the online survey with one of the video clips. Appendix B Section B.1 shows the consent form for running this online study.

[7]The use of open-ended questions for gesture identification was selected to avoid leading answers; however, it might have resulted in some difficulty in assessing recognition as some interpretation of the answer given.


Please watch the video paying attention to the hand motions of the "director" on **the right**.

LEFT RIGHT

1) What do you think the worker should do with the part?

____

2) How easy was it for you to understand the meaning of this gesture?

- 1- Very difficult
- 2
- 3
- 4
- 5
- 6
- 7- Very easy

3) How certain are you of your answer to Q1?

- 1-Very uncertain
- 2
- 3
- 4
- 5
- 6
- 7-Very Certain

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Thank you for participating in the survey.

Figure 3.6: An example of one of the 14 pages of the Study 2 online survey. All pages of the survey contained the same questions in the same order; however, the video content of each page was randomly selected. Each video clip contained one of the selected gestures. In this study, each participant saw all of the 14 collected gestures; however, each gesture was shown with only one of the two identified hand configurations for that gesture

The semantic scale used for answering the three above questions was treated as a continuous scale since each interval of the scale was of equal proportion; therefore, the data collected from the second and third questions were treated as continuous measures.

Answers to the first question were indicative of whether participants understood the gesture correctly (i.e., *Recognition Rate*). Answers to the second and third questions had a high level of internal consistency and were combined as a confidence measure (i.e., *Recognition Confidence*) of responses to the first question (Cronbach's $\alpha = 0.882$).

Recruitment of survey respondents involved two social media platforms (Twitter and Facebook) and distribution of advertisements to university students (Appendix B, Section B.1). Survey respondents received no compensation. In total, $N = 120$ participants responded to the survey. Two coders analyzed participant responses with partial overlap, and had a high level of internal consistency (Cronbach's $\alpha = 0.905$).

Analyses and results for this study can be found in Section 4.2.

3.3 Study 3: Human Perceptions of Robot Hand Gestures Based on Observations from Human-Robot Collaboration

Study 2 investigated whether robot hand gestures accompanied with human-inspired hand configurations are better recognized by untrained observers than the same gestures expressed with an unarticulated robot hand. Approximations of the gestures identified in Study 1 were programmed on a 7-DOF Barrett Whole Arm Manipulator (WAM)[8] equipped with a three-fingered Barrett Hand[9]. Each gesture was video recorded three times: once with each of the two human-inspired hand configurations (Figure 3.7), and once while the robot kept its hand closed (Figure 3.8); this latter Closed-Hand (CH) configuration served as a baseline.

[8]WAM^{TM}, Barrett Technologies, Cambridge, MA, USA

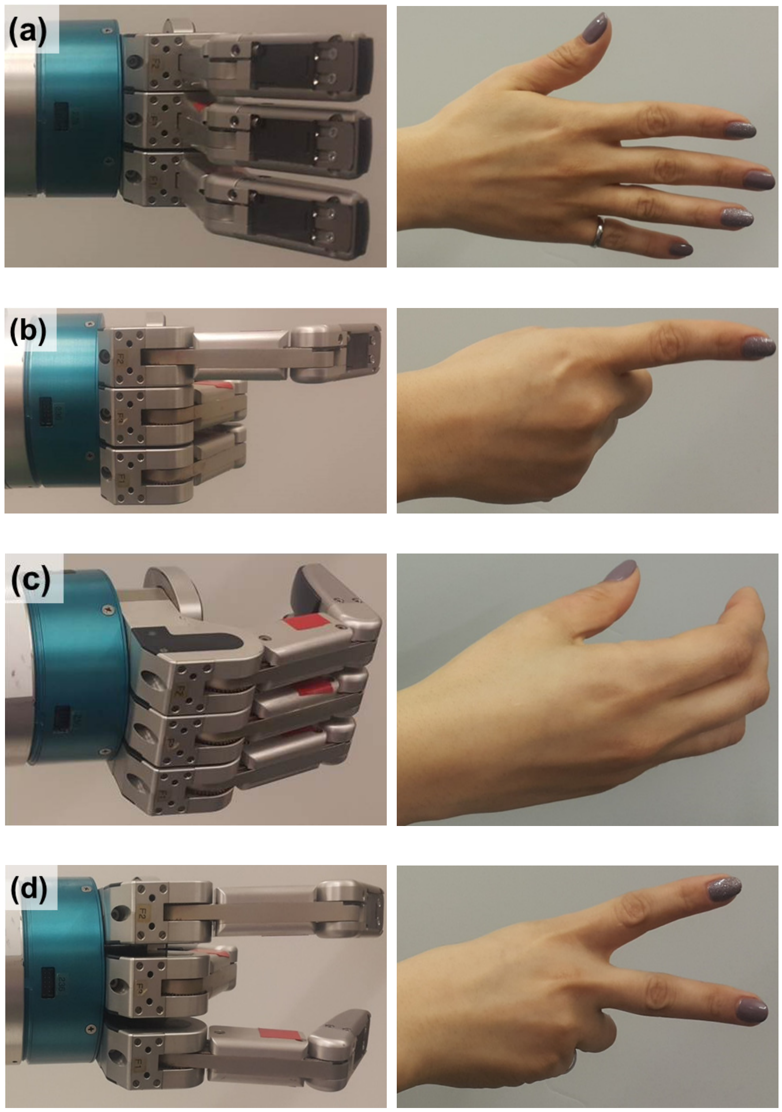
[9]Barrett Hand^{TM}, Barrett Technologies, Cambridge, MA, USA.

Although it has more degrees of freedom than most industrial robot grippers, the Barrett Hand is still relatively non-anthropomorphic in shape and pose. To produce recognizable gestures, an iterative design approach was employed similar to [20]. The robot arm was manually moved to imitate each human gesture, and the resulting motion trajectories were recorded. Next, the trajectories were played back and tuned until the gestures were visually similar to the human gestures. A small pilot study ($N = 4$; two naive participants and two expert participants) was conducted to get feedback on the produced gestures, and their feedback was applied to improve the implementation of the gestures.

A video-based online survey was conducted consisting of randomly ordered videos of the robotic arm exhibiting one of the identified gestures with one of the three robot hand configuration (two human-inspired hand configurations, and one CH configuration) to direct a worker in an assembly task analogous to Study 1 (Section 3.2). The questions used for this survey were the same as in Study 2. Figure 3.9 shows a screen capture from the online survey with the robot arm exhibiting one of the identified gestures. Appendix B, Section B.2 shows the consent form for running this online study.

Recruitment of survey respondents involved two social media platforms (Twitter and Facebook) and distribution of advertisements to university students (Appendix B, Section B.2). Survey respondents received no compensation. A total of $N = 100$ participants responded to the survey. Two coders analyzed participant responses with partial overlap, and had a high level of internal consistency (Cronbach's $\alpha = 0.877$).

Analyses and results for this study can be found in Section 4.2.



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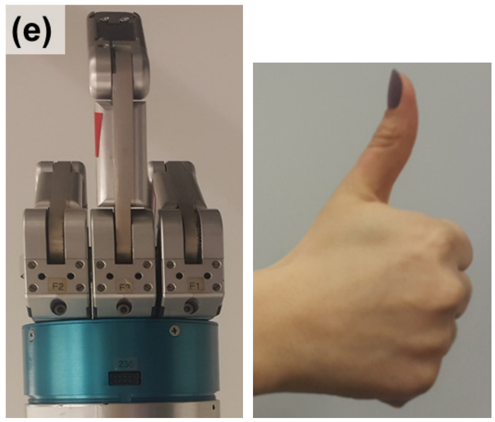


Figure 3.7: Human hand poses observed in Study 1, and the corresponding human-inspired robot hand poses: (a) Open-Hand, (b) Finger-Pointing, (c) Half Open-Hand, (d) V-Sign, and (e) Thumbs-Up. Due to the limited morphology of the hand, (e) was considered the best implementation of the Thumbs-Up hand pose despite its unfortunate resemblance to an insulting gesture; the hand has only three fingers and lacks a poseable thumb, so sticking out one of the side fingers could be mistaken as a Finger-Pointing hand pose.

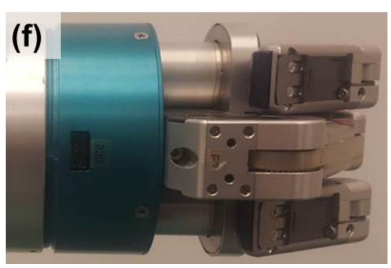
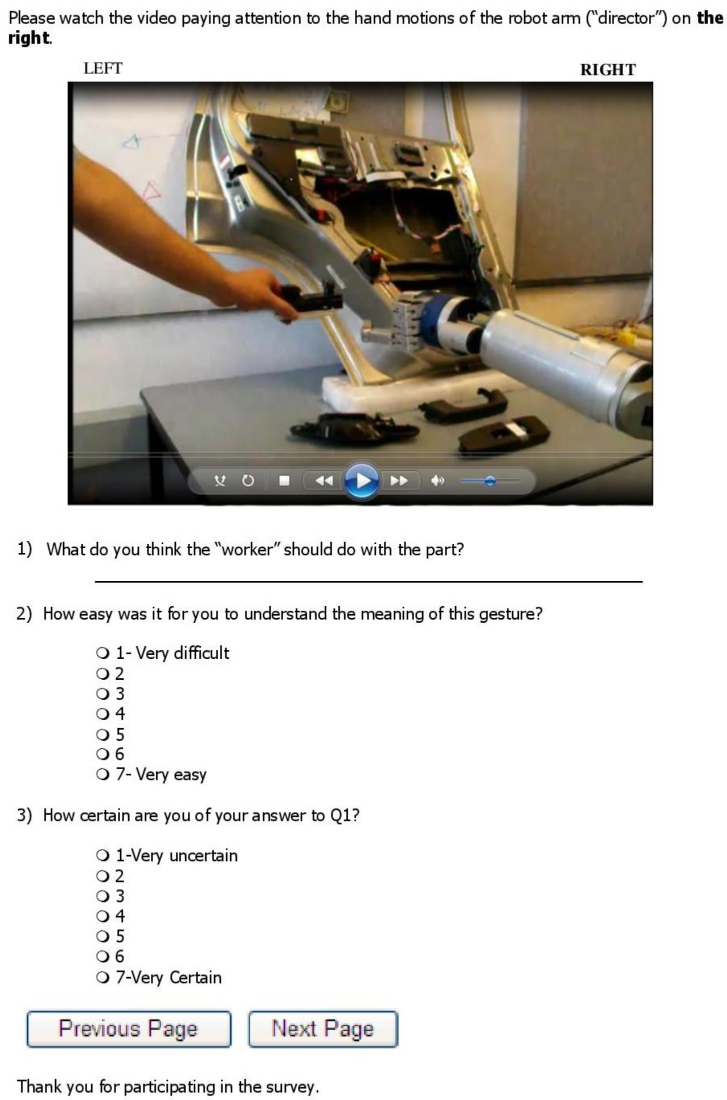


Figure 3.8: Robot Closed-Hand Pose. The Closed-Hand Pose served as our baseline for analysing participant *Recognition Rates* of robot gestures.



Please watch the video paying attention to the hand motions of the robot arm ("director") on **the right**.

LEFT RIGHT

1) What do you think the "worker" should do with the part?

____

2) How easy was it for you to understand the meaning of this gesture?

- ❍ 1- Very difficult
- ❍ 2
- ❍ 3
- ❍ 4
- ❍ 5
- ❍ 6
- ❍ 7- Very easy

3) How certain are you of your answer to Q1?

- ❍ 1-Very uncertain
- ❍ 2
- ❍ 3
- ❍ 4
- ❍ 5
- ❍ 6
- ❍ 7-Very Certain

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Thank you for participating in the survey.

Figure 3.9: An example of one of the 14 pages of the Study 3 online survey. All pages of the survey contained the same questions in the same order; however, the video content of each page was randomly selected. Each video clip contained one of the selected gestures. In this study, each participant saw all of the 14 collected gestures; however, each gesture was shown with only one of the two identified hand configurations for that gesture

Chapter 4

Results and Discussion

The aim of this work was to analyze whether people understand a set of collected gestures correctly (*Recognition rate*), and how confident they are in understanding the meaning of the gestures (*Recognition Confidence*). The hypothesis for this work was that most gestures have a higher level of *Recognition Rate* with a higher level of *Recognition Confidence* when displayed with a human-inspired posed robot hand than an unposed robot hand. This chapter evaluates and analyzes this hypothesis by examining *Recognition Rates* and *Recognition Confidence* of human observations of the implemented robot hand gestures. The identified human hand gestures and accompanying hand poses from Study 1 are presented in Section 4.1. In Section 4.2, the measures of *Recognition Confidence* and *Recognition Rate* from Study 2 and Study 3 are used together to evaluate how well the robot implementation of the same hand gestures and hand configurations perform with respect to human-human gesture communication, followed by a summary of findings in Section 4.3.

4.1 Study 1 (Pilot) Results: Identifying Human Hand Gestures

From the observations of human interactions in Study 1 (Section 3.1), a lexicon of task-based hand gestures was developed, as well as the types of hand poses that were frequently used for expressing the four types of gestures—the **Directional**, **Orientation**, **Manipulation**, and **Feedback Gestures**—which are shown in Tables 3.1 to 3.4 along with the top two most frequently observed hand poses for those gestures (unless only one common hand pose was observed).

The remainder of this section presents the percentage of participants who used each of the two most commonly observed hand poses for expressing each of the four types of identified gestures.

4.1.1 Directional Gestures

Based on the observations from Study 1, four **Directional Gestures** were identified: $G_D = \{\textbf{Up}, \textbf{Down}, \textbf{Left}, \textbf{Right}\}$, Table 3.1. These **Directional Gestures** were most frequently expressed using the Finger-Pointing (FP) and Open-Hand (OH) configurations (see Figures 3.7a and 3.7b for exemplars of these hand configurations).

Figure 4.1 illustrates the percentage of participants that used either FP or OH poses to express the **Directional Gestures**.

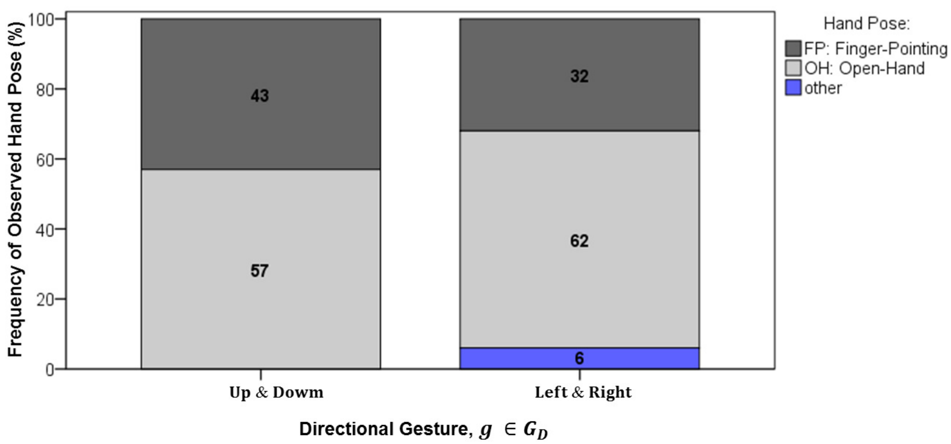

Figure 4.1: Most frequently observed hand poses for **Directional Gestures** (G_D) for Study 1 ($N = 17$).

4.1.2 Orientation Gestures

Another category of gestures identified in Study 1 included **Orientation Gestures**, $G_O = \{< \mathbf{45^\circ}, \mathbf{90^\circ}, \mathbf{180^\circ}\}$, Table 3.2. The $< \mathbf{45^\circ}$ gesture was frequently expressed with the Half Open-Hand (HOH) configuration. The $\mathbf{90^\circ}$ and the $\mathbf{180^\circ}$ gestures were most frequently expressed using the Finger-Pointing (FP) and HOH hand configurations (see Figures 3.7a and 3.7b for exemplars of these hand configurations).

Figure 4.2 illustrates the percentage of participants who used the HOH pose to express the $< \mathbf{45^\circ}$ gesture and either FP or HOH poses to express the $\mathbf{90^\circ}$ and $\mathbf{180^\circ}$ gestures.

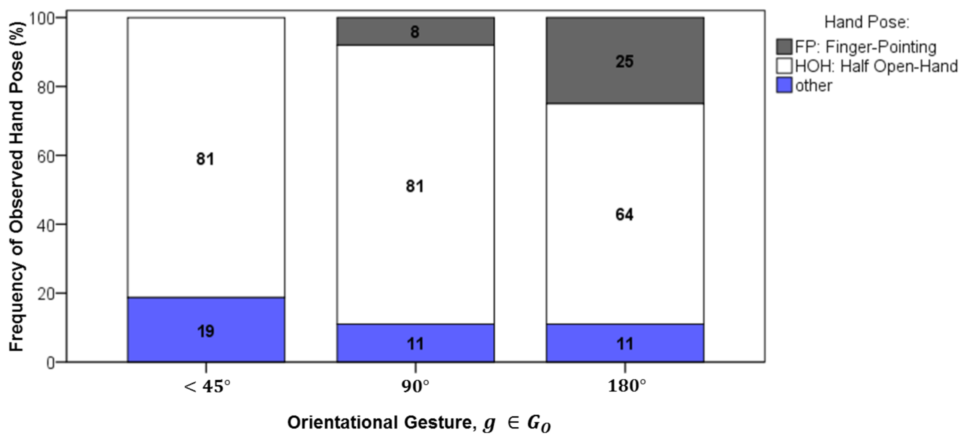

Figure 4.2: Most frequently observed hand poses for **Orientation Gestures** (G_O) for Study 1 ($N = 17$).

4.1.3 Manipulation Gestures

Five of the gestures observed in Study 1 were categorized as **Manipulation Gestures**, $G_M = \{\textbf{Install}, \textbf{Remove}, \textbf{PickUp}, \textbf{Place}, \textbf{Swap}\}$. Table 3.3 lists the most frequently observed hand poses for each of these gestures (see Figures 3.7 for exemplars of each of the identified hand configurations). Figure 4.3 shows the distribution of hand poses used to express the **Manipulation Gestures**.

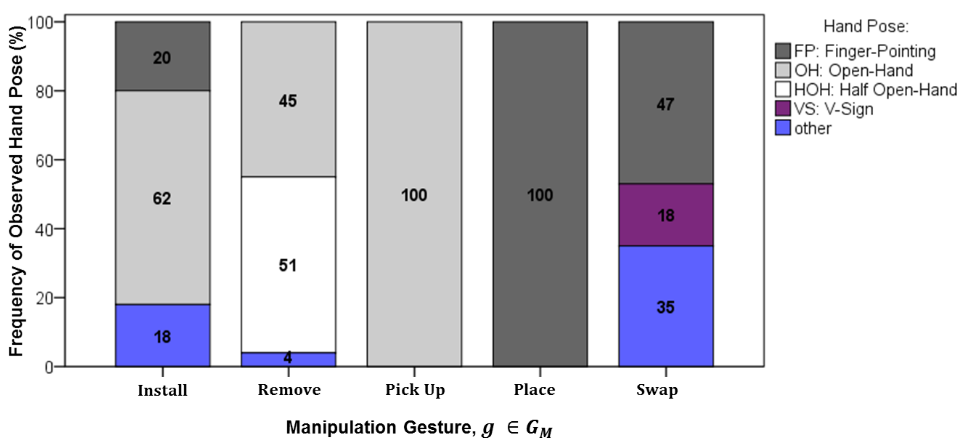

Figure 4.3: Most frequently observed hand poses for **Manipulation Gestures** (G_M) for Study 1 ($N = 17$).

4.1.4 Feedback Gestures

From the observations of human interactions in Study 1, two gestures were identified and categorized as **Feedback Gestures**, $G_F = \{\textbf{Confirm}, \textbf{Stop}\}$. The **Confirm** gesture was most frequently expressed using a Thumbs-Up (TU) hand configuration (shown in Figure 3.7e), and the **Stop** gesture was most frequently expressed using the Open-Hand (OH) and Finger-Pointing (FP) hand configurations (shown in Figures 3.7a and 3.7b, respectively).

Figure 4.4 shows the distribution of hand poses used to express the **Feedback Gestures**.

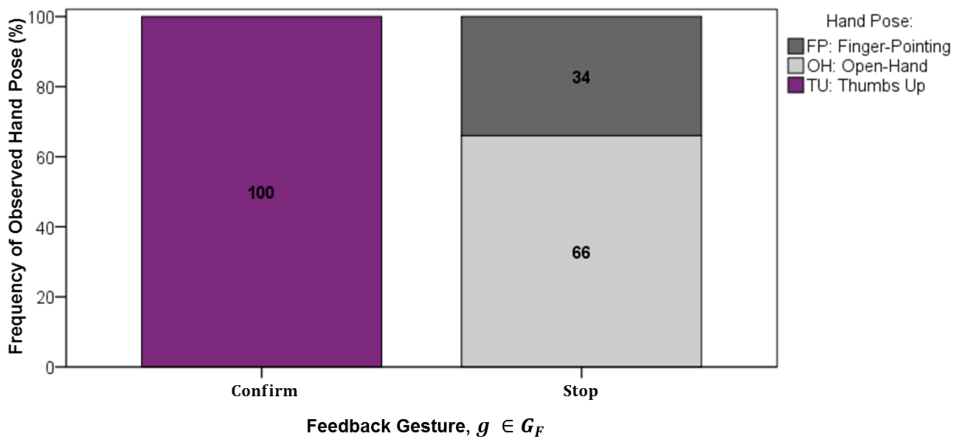

Figure 4.4: Most frequently observed hand poses for **Feedback Gestures** (G_F) for Study 1 ($N = 17$).

4.2 Study 2 and Study 3 Results: Analysing *Recognition Rate* and *Recognition Confidence* of Human and Robot Hand Gestures

Independent-samples t-tests were performed to the measures of *Recognition Confidence* (collected in Study 2) across the two commonly observed hand configurations for each human gesture. This analysis provides a comparison of whether participant confidence in recognizing the human gestures significantly varied across different hand configurations, as shown in Table 4.1.

For each robot gesture, one-way ANOVAs were applied to the measures of *Recognition Confidence* (from Study 3) across the three robot hand configurations: two human-inspired hand configurations for each gesture, and the Closed-Hand (CH) configuration (Table 4.2). Further, a Bonferroni post-hoc analysis was performed to determine whether participant confidence in recognizing robot gestures varied significantly across the three robot hand configurations. Exceptions to this analysis were gestures with only one commonly observed hand configuration; for those gestures, independent-samples t-tests were conducted across the observed human-inspired hand configuration and the CH configuration (Table 4.2).

The measures of *Recognition Confidence* and *Recognition Rate* from Study 2 and Study 3 are used together to evaluate how well the robot implementation of the same hand gestures and hand configurations/poses performed with respect to human-human gesture communication.[10]

In addition, for participants who did not understand the intended meaning of a robot gesture, other common interpretations of the gestures were analysed to determine whether there were other unpredicted-but-accepted meanings of the gestures. In this work, a misinterpretation was deemed "common" if at least 15% of participants had the same misinterpretation of the gesture, or if the same misinterpretation was repeated across different gestures within a gesture category. See Figure 4.7 for exemplars of all the other common misinterpretations of **Directional Gestures**.

Comprehensive analyses and results are presented throughout the remainder of this chapter, followed by a discussion for each gesture type.

[10]Further, the results of participant confidence in recognizing human gestures compared to robot expressions of the same gesture are provided in the Appendix C.

Table 4.1: Measures of independent-samples t-tests on the *Recognition Confidence* from Study 2.

Directional Gestures, G_D			
Gesture, $g \in G_D$	**Hand Poses**	t	p
Up	FP & OH	$t(86) = 2.34$	< 0.05
Down	FP & OH	$t(85) = 0.29$	0.77
Left	FP & OH	$t(51) = 1.01$	0.32
Right	FP & OH	$t(62) = 0.87$	0.40

Orientation Gestures, G_O			
Gesture, $g \in G_O$	**Hand Poses**	t	p
$<$ **45°**	HOH	N/A	N/A
90°	FP & HOH	$t(89) = 1.88$	0.06
180°	FP & HOH	$t(82) = 3.36$	< 0.01

Manipulative Gestures, G_M			
Gesture, $g \in G_M$	**Hand Poses**	t	p
Install	FP & OH	$t(75) = 2.15$	< 0.05
Remove	OH & HOH	$t(91) = 0.32$	0.75
PickUp	OH	N/A	N/A
Place	FP	N/A	N/A
Swap	FP & VS	$t(57) = -1.29$	0.20

Feedback Gestures, G_F			
Gesture, $g \in G_F$	**Hand Poses**	t	p
Confirm	TU	N/A	N/A
Stop	FP & OH	$t(94) = -0.28$	0.78

$p < 0.1$
$p < 0.05$
$p < 0.01$

Table 4.2: Measures of one-way (or Welch) ANOVA or independent-samples t-test on the *Recognition Confidence* from Study 3

Directional Gestures, G_D			
Gesture, $g \in G_D$	**Hand Poses**	F	p
Up	FP, OH & CH	$F(2,40) = 4.50$	< 0.05
Down	FP, OH & CH	$F(2,36) = 3.65$	< 0.05
Left	FP, OH & CH	$F(2,31) = 0.53$	0.59
Right[a]	OH, FP & CH	Welch's $F(2,11.58) = 16.93$	< 0.001
Orientation Gestures, G_O			
Gesture, $g \in G_O$	**Hand Poses**	F or t	p
$< \mathbf{45^\circ}$	HOH & CH	$t(40) = 1.49$	0.14
$\mathbf{90^\circ}$	FP, HOH & CH	$F(2,68) = 5.33$	< 0.01
$\mathbf{180^\circ}$	FP, HOH & CH	$F(2,72) = 5.14$	< 0.01
Manipulative Gestures, G_M			
Gesture, $g \in G_M$	**Hand Poses**	F or t	p
Install	FP, OH & CH	$F(2,41) = 5.40$	< 0.01
Remove	OH, HOH & CH	$F(2,56) = 2.77$	0.07
PickUp	OH & CH	$t(46) = 1.99$	0.05
Place	FP & CH	$t(72) = 0.39$	0.70
Swap	FP, VS & CH	$F(2,28) = 0.88$	0.42
Feedback Gestures, G_F			
Gesture, $g \in G_F$	**Hand Poses**	t	p
Confirm	TU	N/A	N/A
Stop	OH & FP	$t(60) = 0.24$	0.81

$p < 0.1$
$p < 0.05$
$p < 0.01$

[a] In Study 3, the *Recognition Confidence* of the **Right** gesture fails the assumption of homogeneity of variances. Therefore, a Welch ANOVA (rather than a one-way ANOVA) was performed.

4.2.1 Directional Gestures

The combined results of the human-human and human-robot gesture recognition studies (Study 2 and Study 3, respectively) for **Directional Gestures** (G_D = {**Up**, **Down**, **Left**, **Right**}) are shown in Figures 4.5 and 4.6. Figure 4.5 illustrates the percentage of participants who correctly identified each Directional Gesture (*Recognition Rate*). Figure 4.6 highlights the mean rating of confidence of interpretation for each Directional Gesture (*Recognition Confidence*). Figure 4.7 depicts the rates of common misinterpretations of each Directional Gesture from Study 3.

4.2.1.1 Directional Gesture: Up

In Study 2, when humans expressed the **Up** gesture, both FP and OH configurations were recognized accurately (82% and 96% respectively). In Study 3, when the robot expressed the **Up** gesture, people recognized the gesture better in the OH configuration (72%) than in the FP (46%) or CH (40%) configurations (Figure 4.5).

Participant *Recognition Confidence* of the **Up** gesture was significantly affected by the human hand configuration ($t(86) = 2.34$, $p < 0.05$) (Table 4.1). Participants felt more confident in understanding the gesture when expressed with the OH configuration than the FP configuration (Figure 4.6). Recognition Confidence was also significantly affected by robot hand configuration ($F(2, 40) = 4.50$, $p < 0.05$) (Table 4.2). Participants recognized the robot's gesture significantly more confidently in the OH configuration than in the FP configuration ($p < 0.05$). Statistical tests did not reveal a significant difference between the FP and CH configurations ($p = 1.00$) or the OH and CH configurations ($p = 0.18$) (Figure 4.6).

4.2.1.2 Directional Gesture: Down

When humans expressed the **Down** gesture, both FP and OH configurations were recognized accurately (86% and 90% respectively). When the robot expressed the **Down** gesture, people recognized the gesture better in the OH configuration (61%) than in the FP (46%) or CH (29%) configurations.

The results did not indicate any significant difference in the *Recognition Confidence* of the **Down** gesture expressed by a human using either the FP or OH configurations ($t(85) = 0.29$, $p = 0.77$); however, the results did reveal that *Recognition Confidence* was significantly affected by the robot hand configuration ($F(2, 36) = 3.65$, $p < 0.05$). Participants recognized the robot's gestures significantly more confidently in the OH configuration than in the CH configuration ($p < 0.05$). The results did not indicate a statistically significant difference between the FP and OH configurations ($p = 0.74$) or the FP and CH configurations ($p = 0.41$).

4.2.1.3 Directional Gesture: Left

Only 50% and 57% of the participants recognized the human **Left** gesture in the FP and OH configurations, respectively. When the robot expressed the **Left** gesture, people recognized the gesture better in the OH configuration (56%) than in the FP (43%) or CH (26%) configurations.

Human hand configuration had no statistically significant effect on participant *Recognition Confidence* of the **Left** gesture ($t(51) = 1.01$, $p = 0.32$). Likewise, the results did not reveal a statistically significant effect against the robot hand configurations (FP, OH and CH) on the *Recognition Confidence* of the gesture expressed by a robot hand ($F(2, 31) = 0.53$, $p = 0.59$).

4.2.1.4 Directional Gesture: Right

When humans expressed the **Right** gesture, both the FP and the OH configurations had moderate recognition rates (60% and 69% respectively). When the robot expressed the **Right** gesture, people recognized the gesture better in the FP configuration (55%) than in the OH (36%) or CH (43%) configurations.

The **Right** gesture expressed by a human hand using either the FP or OH configurations did not show a significant difference in participant *Recognition Confidence* ($t(62) = 0.87$, $p = 0.39$). *Recognition Confidence* was significantly affected by the robot hand configuration ($Welch's F(2, 11.58) = 16.93$, $p < 0.001$). The Games-Howell post-hoc test revealed that participants recognized the robot gesture more confidently in the FP configuration than in the CH configuration ($p < 0.001$). Tests did not reveal a statistically significant difference between the FP and OH configurations ($p = 0.12$) or the OH and CH configurations ($p = 0.82$).

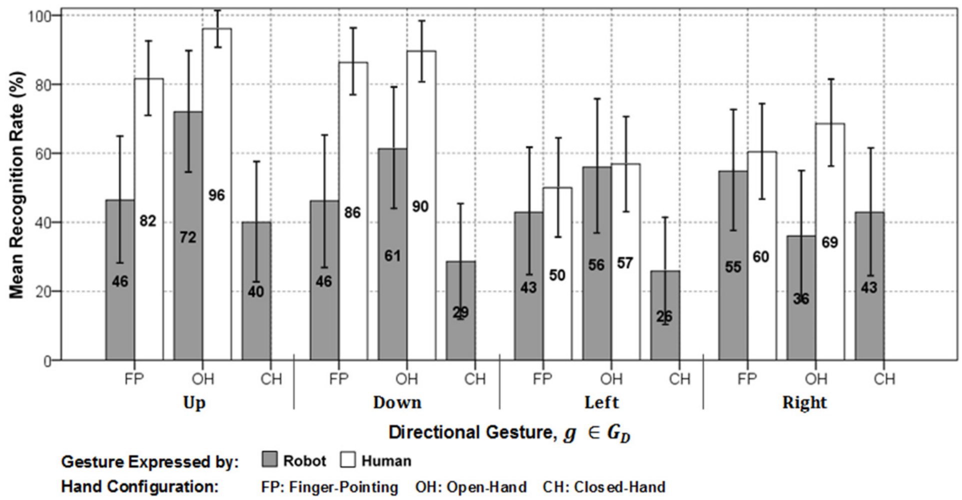

Figure 4.5: Human *Recognition Rates* for **Directional Gestures** (G_D) for both Study 2 (Human) and Study 3 (Robot). The error bars indicate the margin of error for a 95% confidence interval.

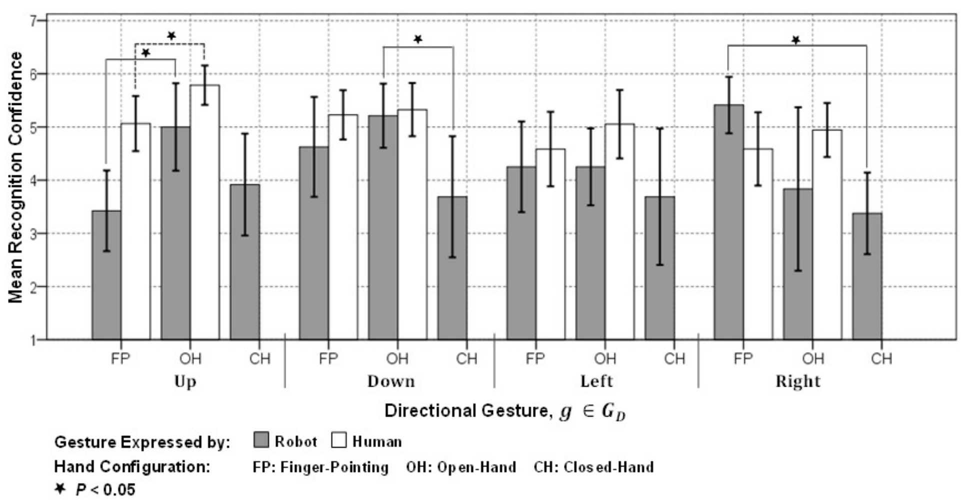

Figure 4.6: Human *Recognition Confidence* for **Directional Gestures** (G_D) for both Study 2 (Human) and Study 3 (Robot). The **Right** gesture failed the assumption of homogeneity of variances; therefore, the Games-Howell post-hoc test instead of the Bonferroni post-hoc test was performed for this gesture.

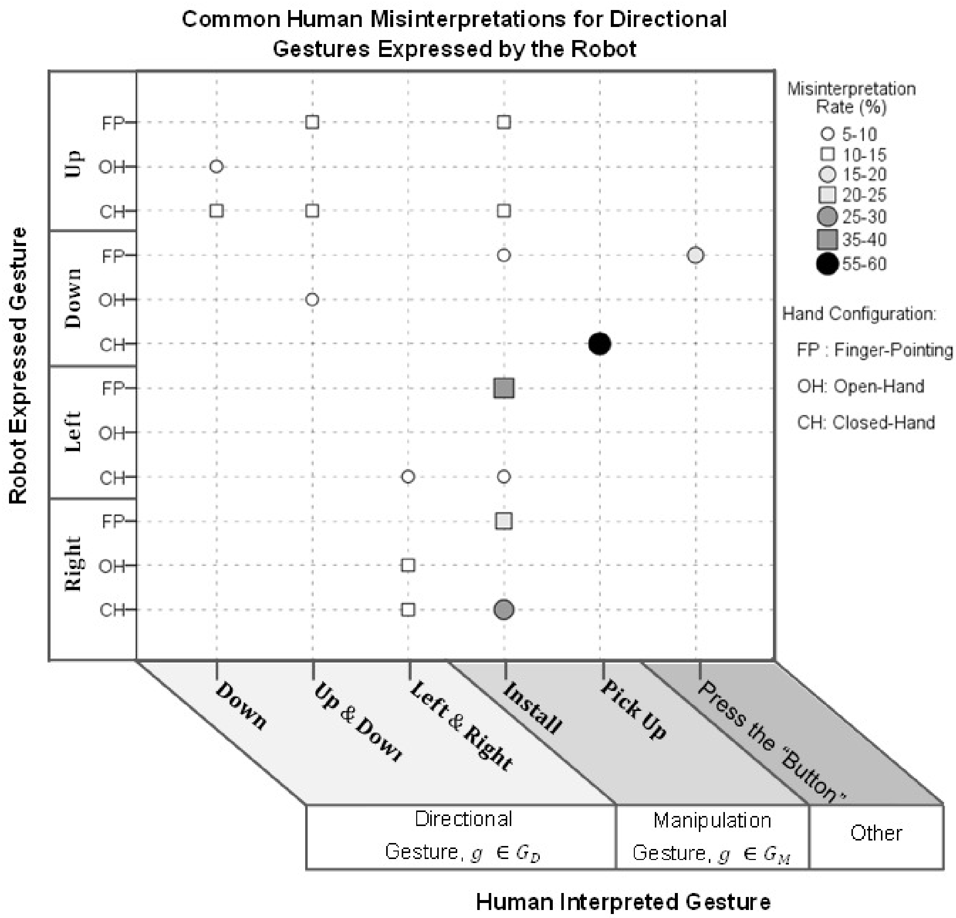

Figure 4.7: Common misinterpretations of Robot **Directional Gestures**, G_D.

4.2.1.5 Discussion

The best and most confidently recognized *human* hand pose for **Directional Gestures** was the OH pose. Similarly, the OH pose also often corresponded to the best and most confidently recognized *robot* hand pose. Comparing the approach of this work with [20], these results suggest that articulated fingers are not necessary for directional gestures, adding support to [15] that referential gestures can be well-recognized by non-anthropomorphic robotic hands; furthermore, it appears that fingers might not be needed at all, as there was often no statistically significant difference between OH and CH poses—a closed hand was just as effective as an open hand at communicating directionality. The exception to these results was with the **Right** gesture (Figure 4.6), for which an alternative robot hand pose (FP) outperformed the OH configuration; this is believed to be due to the fact that pointing gestures often anchor one referent (e.g., the car part) to another referent (e.g., the car door) [37], so the relative angle of the camera biased the perception of the gesture to relate these two referents in a rightward direction (i.e., the car part—the only referent on the left—to the car door—the only referent on the right).

As shown in Figure 4.7, many participants misinterpreted the intended direction of robot **Directional Gestures**; this confusion could be because the robot arm moved at a much slower speed than a human arm when repeating the motion for the gesture three times (to be consistent with observations from Study 1). Also, **Directional Gestures** were commonly misinterpreted as an **Install** gesture, which could be again due to the relative angle of the camera showing the robot arm closer to the car door than it actually was. Additionally, more than half of the participants misinterpreted a **Down** gesture when expressed with CH pose as a **PickUp** gesture (Figure 4.7); this could be because there were other parts on the table next to the car door and the motion of the gesture might have anchored participant perceptions to objects in the direction of motion (i.e., downward), resulting in a misinterpretation of the gesture as picking up those parts.

Based on these findings, the relationship between participant viewing angle (perspective) of the robot gesture and participant recognition rates for **Directional Gestures** deserves exploration in future work [28].

4.2.2 Orientation Gestures

Results of the *Recognition Rate* and *Recognition Confidence* analyses from both Studies 2 and 3 for **Orientation Gestures** ($G_O = \{< \mathbf{45}^\circ, \mathbf{90}^\circ, \mathbf{180}^\circ\}$) are shown in Figure 4.8 and Figure 4.9, respectively. No common misinterpretations were observed for **Orientation Gestures**.

4.2.2.1 Orientation Gesture: $< 45^\circ$

In Study 2, when humans expressed the $< \mathbf{45}^\circ$ gesture, the HOH configuration was recognized accurately (96%). When the robot expressed the $< \mathbf{45}^\circ$ gesture, people recognized the gesture better in the CH configuration (79%) than in the HOH (73%) configuration (Figure 4.8).

Robot hand configuration had no statistically significant effect on participant *Recognition Confidence* of the $< \mathbf{45}^\circ$ gesture ($t(40) = 1.49$, $p = 0.14$) (Figure 4.9 and Table 4.2).

4.2.2.2 Orientation Gesture: 90°

When humans expressed the $\mathbf{90}^\circ$ gesture, both the FP and HOH configurations were recognized accurately (85% and 98% respectively). When the robot expressed the $\mathbf{90}^\circ$ gesture, people recognized the gesture better in the HOH and CH configurations (87% and 85% respectively) than in the FP (79%) configuration.

Test results indicated a trend that the HOH configuration was more confidently recognized than the FP configuration for the $\mathbf{90}^\circ$ gesture expressed by a human, but this trend was marginally statistically significant ($t(89) = 1.88$, $p = 0.06$) (Table 4.1); however, test results indicated that the robot hand configuration had a statistically significant effect on how confidently participants recognize the gesture ($F(2, 68) = 5.33$, $p < 0.01$) (Table 4.2). People recognized the gesture significantly more confidently in the HOH configuration than in the FP configuration ($p < 0.01$). The results did not reveal a statistically significant difference between the FP and the CH configurations ($p = 0.30$), or the HOH and CH configurations ($p = 0.41$).

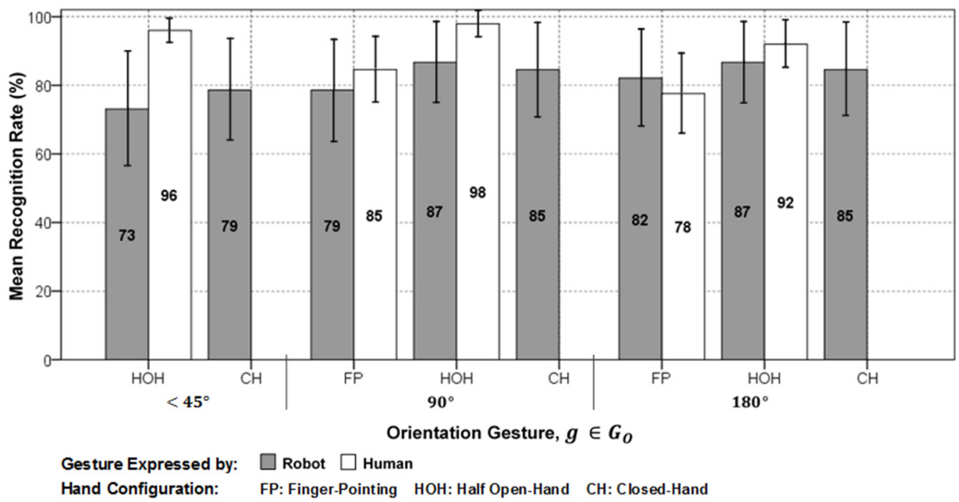

Figure 4.8: Human *Recognition Rates* for **Orientation Gestures**, G_O, for both Study 2 (Human) and Study 3 (Robot). The error bars indicate the margin of error for a 95% confidence interval.

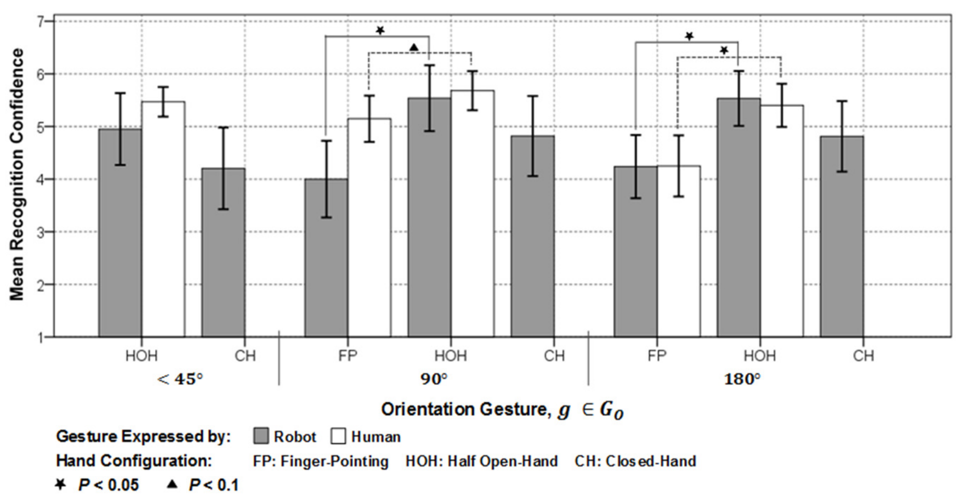

Figure 4.9: Human *Recognition Confidence* for **Orientation Gestures** (G_O) for both Study 2 (Human) and Study 3 (Robot).

4.2.2.3 Orientation Gesture: 180°

When humans expressed the **180°** gesture, the HOH configuration was recognized accurately (92%); however, the FP configuration had a relatively lower recognition rate (78%). When the robot expressed the **180°** gesture, all FP, HOH, and CH configurations were recognized accurately (82%, 87% and 85% respectively).

Participant *Recognition Confidence* of the **180°** gesture was significantly affected by the human hand configuration ($t(83) = 3.36$, $p < 0.01$). Participants recognized the gesture significantly more confidently when expressed with the HOH configuration than the FP configuration. *Recognition Confidence* was also significantly affected by the robot hand configuration ($F(2, 72) = 5.14$, $p < 0.01$). Participants recognized the robot gesture significantly more confidently in the HOH configuration than in the FP configuration ($p < 0.01$). The results did not reveal a statistically significant difference between the HOH and CH configurations ($p = 0.21$), or the FP and CH configurations ($p = 0.56$).

4.2.2.4 Discussion

Haddadi et al. [20] found that only 25% of people understood **Orientation Gestures** when expressed by a robotic manipulator with an un-actuated stuffed glove at the robot end-effector. In contrast, **Orientation Gestures** were found to be recognized very accurately in both human (Study 2) and robot (Study 3) studies (Figure 4.8). Haddadi et al. [20] utilized an Open-Hand pose for communicating orientation information, however, such hand poses were not observed in the human-human data collection (Sec. 3.1); thus, it is suspected that an Open-Hand pose might not be a natural configuration for this gesture. As shown in (Figure 4.8), the robot Closed-Hand (CH) pose was recognized as well, in some cases better than the human-inspired hand poses (i.e., Finger-Pointing and Half Open-Hand).

In both human and robot studies, the *Recognition Rates* of the **90°** and the **180°** gestures were consistent with the *Recognition Confidence* of the associated gestures, and both gestures were best and most confidently recognized with the Half Open-Hand (HOH) pose (Figures 4.8 and 4.9). Conversely, the robot < **45°** gesture was best recognized with the Closed-Hand (CH) configuration (Figure 4.8); however, within the participants who recognized the gesture correctly, they recognized it more confidently (though not significantly) with the HOH configuration than CH configuration (Figure 4.9). It is suspected that the reason HOH was less recognized in expressing the $< \mathbf{45^\circ}$ gesture is related to the angle of rotation, with smaller rotations having a lower recognition rate. For example, for the $< \mathbf{45^\circ}$ gesture, participants seemed to look confused about the intention of the robot, and sometimes did not observe the rotation of the hand at all. This could be because the Barrett Hand lacks an opposable thumb (discussed in Section 2.3), which could serve as a visual anchor or reference point to an observer [19, 2, 1]; thus, common non-anthropomorphic robot manipulators, such as Baxter's 1D gripper [16] and KUKA's two-finger gripper [4], are expected to be effective in communicating orientation information, though human observers might not feel as confident and comfortable in their assessments of the gesture's meaning—in short, for gestures indicating small changes in orientation, human coworkers will have to "trust their gut".

4.2.3 Manipulation Gestures

The measures of *Recognition Rate* and *Recognition Confidence* from both Study 2 and Study 3 for **Manipulation Gestures** ($G_M = \{\mathbf{Install}, \mathbf{Remove}, \mathbf{PickUp}, \mathbf{Place}, \mathbf{Swap}\}$) are shown in Figures 4.10 and 4.11, respectively. Figure 4.12 displays the rates of common misinterpretations of each Manipulation Gesture.

4.2.3.1 Manipulation Gesture: Install

In Study 2, when humans expressed the **Install** gesture, the Open-Hand (OH) configuration had a perfect recognition rate (100%); however, the Finger-Pointing (FP) configuration had a low recognition rate (57%). When the robot expressed the **Install** gesture, people recognized the gesture better in the CH configuration (68%) than in the OH (52%) or FP (35%) configurations (Figure 4.10).

Recognition Confidence of the **Install** gesture was significantly affected by the human hand configuration ($t(75) = 2.15$, $p < 0.05$) (Table 4.1). Participants felt more confident recognizing the gesture when expressed with the OH configuration than the FP configuration (Figure 4.11). Similarly, robot hand configuration significantly affected participant *Recognition Confidence* of the gesture ($F(2, 41) = 5.40$, $p < 0.01$) (Table 4.2). Participants recognized the robot's gesture significantly more confidently in the OH configuration than in the CH configuration ($p < 0.01$). No significant difference was observed between the FP and OH configurations ($p = 0.46$), or the FP and CH configurations ($p = 0.65$) (Figure **??**).

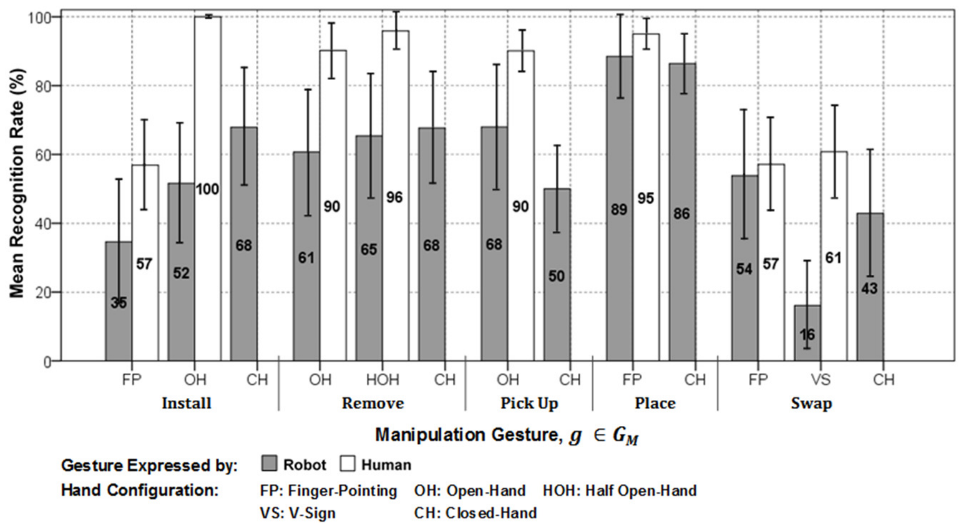

Figure 4.10: Human *Recognition Rates* for **Manipulation Gestures**, G_M, for both Study 2 (Human) and Study 3 (Robot). The error bars indicate the margin of error for a 95% confidence interval.

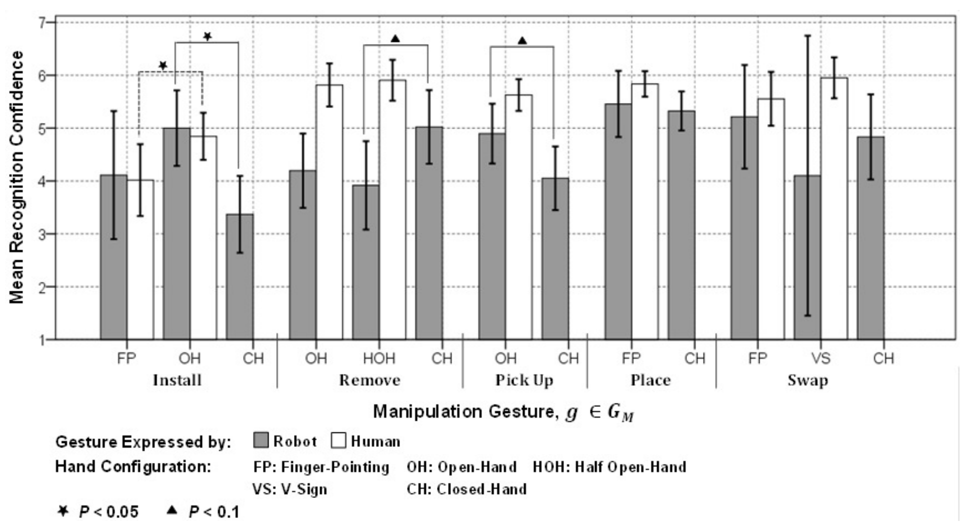

Figure 4.11: Human *Recognition Confidence* for **Manipulation Gestures**, G_M, for both Study 2 (Human) and Study 3 (Robot).

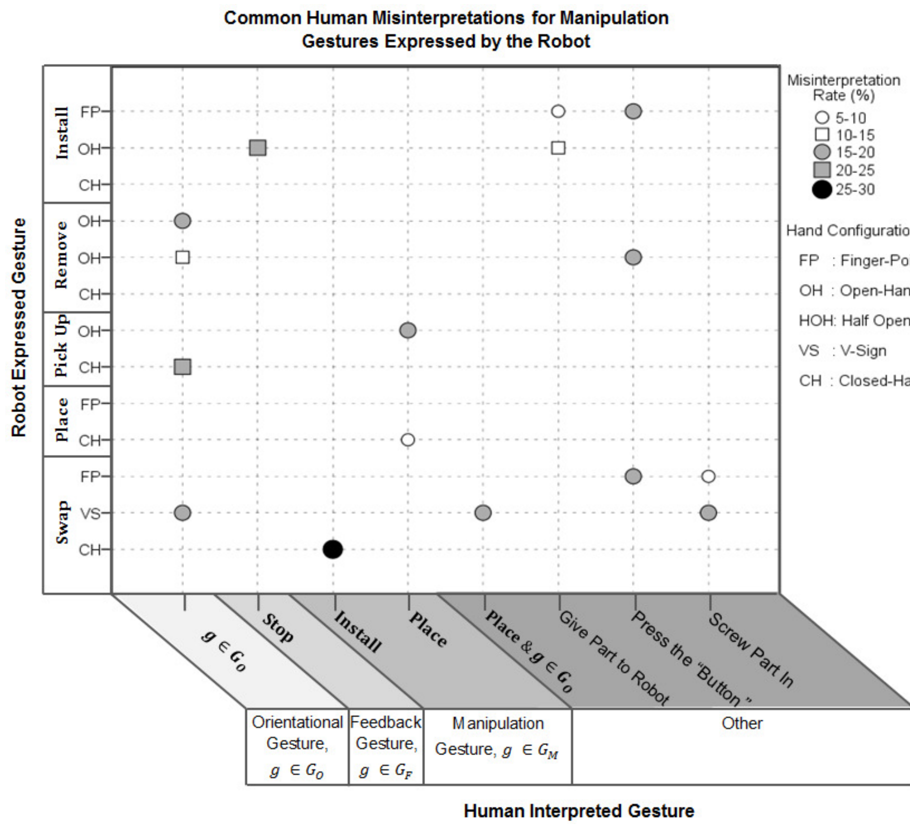

Figure 4.12: Common misinterpretations of Robot **Manipulation Gestures**, G_M.

4.2.3.2 Manipulation Gesture: Remove

When humans expressed the **Remove** gesture, both the OH and HOH configurations were recognized accurately (90% and 96%, respectively). When the robot expressed the gesture, people recognized the gesture slightly better in the CH configuration (68%) than in the OH (61%) or the HOH (65%) configurations.

The human hand configurations—OH and HOH—had no statistically significant effect on the *Recognition Confidence* of the **Remove** gesture ($t(91) = 0.32$, $p = 0.75$). Likewise, the results did not reveal a significant effect against the robot hand configurations (OH, HOH and CH) on the *Recognition Confidence* of the gesture ($F(2, 56) = 2.77$, $p = 0.07$). The results did not reveal a significant difference between the OH and HOH configurations ($p = 1.00$) or the OH and CH configurations ($p = 0.30$); however, there was a trend that the gesture was better recognized when expressed with the CH configuration than the HOH configuration ($p = 0.09$).

4.2.3.3 Manipulation Gesture: PickUp

When humans expressed the **PickUp** gesture, the OH configuration was recognized accurately (90%). When the robot expressed the **PickUp** gesture, the OH configuration was recognized more accurately than the CH configuration (68% and 50%, respectively).

The results show a strong trend that the HOH configuration was more confidently recognized than the FP configuration when the gesture is expressed by the robot, but this trend was only marginally significant ($t(46) = 1.99$, $p = 0.05$).

4.2.3.4 Manipulation Gesture: Place

When humans expressed the **Place** gesture, the FP configuration was recognized accurately (95%). When the robot expressed the gesture, both the FP and the CH configurations were recognized accurately (89% and 86%, respectively)

The **Place** gesture expressed by a robot hand using either the FP or the CH configuration did not show a statistically significant difference in the *Recognition Confidence* measure of the gesture ($t(72) = 0.39$, $p = 0.70$).

4.2.3.5 Manipulation Gesture: Swap

When the **Swap** gesture was expressed by a human, only 57% and 61% of the participants recognized the gesture in the FP and V-Sign (VS) configurations, respectively. Similarly, when the robot expresses the gesture, only 54%, 16%, and 43% of the participants recognized the gesture in the FP, VS, and CH configurations, respectively.

The human hand configurations (FP and VS) had no statistically significant effect on the participant *Recognition Confidence* of the **Swap** gesture ($t(57) = -1.29$, $p = 0.20$). Likewise, the results did not reveal a statistically significant effect against the robot hand configurations (FP, VS and CH, respectively) on the *Recognition Confidence* of the gesture expressed by the robot hand ($F(2, 28) = 0.88$, $p = 0.42$).

4.2.3.6 Discussion

Most of the human hand gestures were accurately recognized by the participants for all of the selected hand poses; the exceptions to this finding were the **Install** gesture and the **Swap** gesture (Figure 4.10). The **Install** gesture was perfectly recognized (i.e., the *Recognition Rate* was 100%) when expressed with an Open-Hand (OH) configuration; however, it had a much lower recognition rate (57%) when expressed with a Finger-Pointing (FP) configuration. Some participants misinterpreted the Finger-Pointing as "poking or pressing on the part" being installed on the car door (Figure 4.12). Overall, the **Swap** gesture had one of the lowest recognition rates of all human gestures when using either FP or V-Sign (VS) hand configurations with *Recognition Rates* of 51% and 61%, respectively (Figure 4.10); in Study 1, some participants indicated a preference to use two hands to execute a **Swap** gesture, stating that a one-handed **Swap** gesture was not as intuitive to them, which could explain the lower *Recognition Rates* of this one-handed **Swap** gesture.

As shown in Figure 4.10, no correlation was identified between the *Recognition Rates* of the human hand-configurations and the imitated robot hand-configurations. For example, the **Swap** gesture was best recognized in a VS hand configuration for the human case, whereas it was best recognized in a FP hand configuration for the robot case. This could have been partially due to the mechanical limitations of the robot hand (e.g., the VS pose did not look intuitive on the robot hand). In addition, two of the robot hand gestures—**Install** and **Remove**—were better recognized when expressed with an unposed, Closed-Hand (CH) configuration rather than a posed hand configuration, rejecting the assumption that human-inspired hand poses *always* outperform the unposed robot hand. As in the human case, approximately 16% of participants misinterpreted the robot **Install** gesture with a FP hand pose as "pressing on the part" (many thought the part was a button) (Figure 4.12). Furthermore, as shown in Figure 4.12, approximately 23% of participants misinterpreted the **Install** gesture with an OH pose as the robot indicating to "stop". For the **Remove** gesture, a Half Open-Hand (HOH) pose was commonly misinterpreted as "rotating the part", and OH pose was commonly misinterpreted again as "pressing on the part/button". Collectively, these results add support to and elaborate upon related work on differences in human anthropomorphic vs. robot non-anthropomorphic nonverbal communication [15, 18].

Haddadi et al. [20] found that people had difficulty recognizing many of the manipulation gestures investigated in Studies 1–3. In [20], the stuffed glove at the end of the manipulator consistently presented an Open-Hand pose, which was not necessarily the best hand pose for expressing many of the manipulation gestures, as identified by [20] and supported by the results of this work (Figures 4.10 and 4.11).

Referring to Figures 4.10 and 4.11, better recognized hand poses also had higher *Recognition Confidence* for both human and robot gestures, with the exception of the robot **Install** gesture. Note that while both human and robot expressions of the **Swap** gestures had low *Recognition Rates*, those participants who recognized the gesture *correctly* also recognized it *confidently*.

4.2.4 Feedback Gestures

Observations of human interactions in Study 1 yielded two gestures that were identified and categorized as **Feedback Gestures**, $G_F = \{$**Confirm**, **Stop**$\}$. **Feedback Gestures** differed from other identified gesture categories in that they were *symbolic* gestures (discussed in Section 2.1) used for reinforcing or interrupting the human movement rather than directing a part movement. For this category, only the human-inspired hand configurations identified in Study 1 were implemented on the robot; the Closed-Hand (CH) configuration was not used as a baseline, as this work was primarily interested in investigating if symbolic gestures could still deliver a clear communicative message when implemented on a non-anthropomorphic robotic hand. The **Confirm** gesture was most frequently expressed using a Thumbs-Up (TU) hand configuration shown in Figure 3.7e, and the **Stop** gesture was most frequently expressed using Open-Hand (OH) and Finger-Pointing (FP) hand configurations, shown in Figures 3.7a and 3.7b, respectively.

The combined results of Study 2 and Study 3 for **Feedback Gestures** are shown in Figures 4.13 and 4.14; Figure 4.13 illustrates the measures of *Recognition Rate* and Figure 4.14 illustrates the measures of *Recognition Confidence* for **Feedback Gestures**.

4.2.4.1 Feedback Gesture: Confirm

In Study 2, when humans expressed the **Confirm** gesture, the Thumbs-Up (TU) hand configuration was very accurately (98%) and confidently recognized; however, when the robot expressed the **Confirm** gesture, only 25% of participants recognized the gesture with a below average *Recognition Confidence* (see Figure 4.13 for the *Recognition Rate*, and Figure 4.14 for the *Recognition Confidence* measures of this gesture).

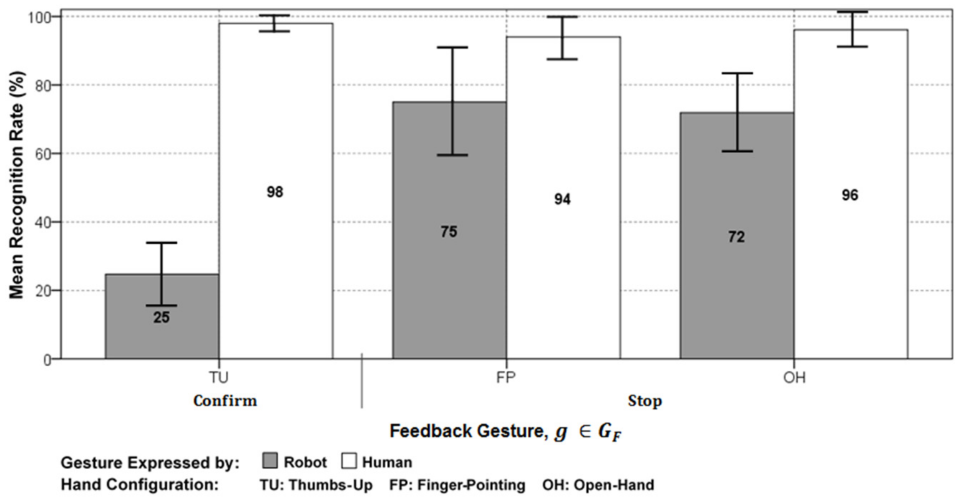

Figure 4.13: Human *Recognition Rates* for **Feedback Gestures** (G_F) gestures for both Study 2 (Human) and Study 3 (Robot). The error bars indicate the margin of error for a 95% confidence interval.

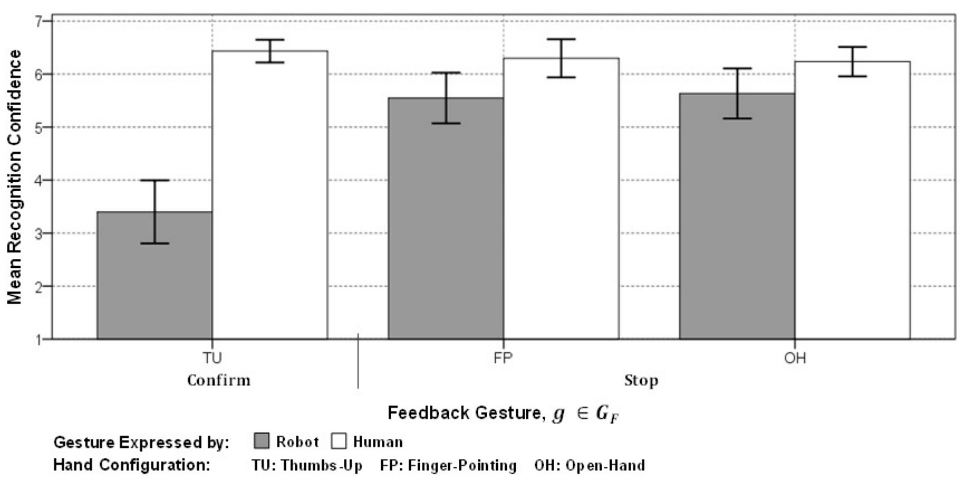

Figure 4.14: Human *Recognition Confidence* for **Feedback Gestures** (G_F) gestures for both Study 2 (Human) and Study 3 (Robot).

4.2.4.2 Feedback Gesture: Stop

When humans expressed the **Stop** gesture, both the Finger-Pointing (FP) and Open-Hand (OH) configurations were recognized accurately (94% and 96% respectively). Similarly, when the robot expressed the **Stop** gesture, both the FP and OH had high *Recognition Rates* (75% and 72%, respectively), though these rates were lower than those of the human gestures (Figure 4.13).

For both the human-human and human-robot cases, hand configuration had no statistically significant effect on the participants *Recognition Confidence* of the **Stop** gesture ($t(94) = -0.28$, $p = 0.78$ and $t(60) = 0.24$, $p = 0.81$, respectively) (Figure 4.14).

4.2.4.3 Discussion

The selected feedback gestures—**Confirm** and **Stop**—are symbolic gestures [1] and, as such, are strongly influenced by contextual factors [5, 26]. Discussed below are the results of human observations of these feedback gestures and the contextual factors that might contribute to perceptual differences.

The robot's **Confirm** gesture had a very low performance, which is suspected to be due to the mechanical limitations of the robot hand—the robot hand has no thumb, and the TU pose looked more like the robot was displaying an inappropriate "middle finger" (as repeatedly and humorously noted by participants) [41]. As discussed in Section 2.3, related non-anthropomorphic robot manipulators, such as Baxter's 1D gripper [16] and KUKA's two-finger gripper [4], are expected to be interpreted in a similar manner; thus, it is recommended that robotic manipulators used in collaborative environments have a level of anthropomorphism such that there is a clear opposable thumb, as confirmatory information conveyed through a TU pose was shown to be one of the most important gestures for such a robot to communicate.

Recognition Confidence of the **Stop** gesture was consistent with the *Recognition Rate* of the gesture for both human and robot gestures (Figure 4.14). These results add further evidence to the related work of [15], which reported that terminating gestures, such as "Stop" or "No", are well recognized on both anthropomorphic and non-anthropomorphic robotic hands.

Overall, the findings of this work suggest that even a mechanically limited robotic hand can still express certain symbolic gestures [1, 5, 26], such as the **Stop** gesture [15]; however, it is warned that presenting a Thumbs-Up (TU) hand configuration without the use of an opposable thumb should be used with caution or not at all, as it can be perceived as inappropriate [41].

4.3 Summary

An objective of this work was to investigate a collection of intuitive and human-recognizable hand gestures and accompanying hand poses that can be implemented on industrial, non-anthropomorphic robotic hands to nonverbally communicate with co-located human coworkers. The results indicated that most of the human gestures were well recognized (*Recognition Rate* greater than 90%) by the participants with at least one of the two selected hand poses observed in a human-human nonverbal scenario discussed in Study 1. Similarly, most of the robot gestures were relatively well recognized (*Recognition Rate* greater than 60%) by the participants with at least one of the three robot hand poses—two human-inspired hand poses and the Closed-Hand (CH) pose.

However, the following gestures were exceptions to these results, yielding lower Recognition Rates:

1. **both human and robot expressions of Left and Right Directional Gestures**, possibly due to the relative angle of the camera with which the gestures were recorded, as well as the relative location of the robot, the car part, and the car door in the work space;

2. **both human and robot expressions of the Swap Manipulation Gesture** (Figure 4.10), possibly because **Swap** is a complex gesture that participants indicated would be better performed when expressed with two hands, unlike other identified gestures.

3. **robot expressions of the Confirm Feedback Gesture**, which was likely due to the mechanical limitation of the robot hand and its lack of having a thumb (Figure 4.13).

In the human-human study (Study 2, Section 3.2), participant *Recognition Rates* of human hand gestures were consistent with participant *Recognition Confidence* of the gesture. In the human-robot study (Study 3, Section 3.3), the best and most confidently recognized human hand poses typically corresponded to the best and most confidently recognized robot hand poses for **Directional**, **Orientation**, and **Feedback Gestures**, with the exception of the **Right** Directional Gesture and the $<$ **45°** Orientation Gesture (though the differences were not statistically significant). For **Manipulation Gestures**, robot hand poses imitated from human hand poses were not always better recognized than non-posed (i.e., Closed-Hand (CH)) configurations; for example, the robot **Remove** gesture had the highest *Recognition Rate* and *Recognition Confidence* when expressed with the CH pose.

Together, these studies provide insights into how humans produce and perceive nonverbal communication to interact with other human co-workers in assembly tasks, inform how robots should communicate to human co-workers in the same settings, and how human co-workers might interpret these nonverbal signals from their robot counterparts.

The next chapter expands upon these results to provide a set of guidelines for the mechanical design of robotic hands.

Chapter 5

Guidelines for the Design of Expressive Robotic Hands

The results of this work combined with experimenter observations in Studies 1–3 yielded insights and guidelines for the design of individual regions and features of a robotic hand. These region and feature considerations are illustrated in Figure 5.1 and described below in Section 5.1. The application of these principles to the design of real robot hands is presented in Section 5.2. Further steps to formalize these guidelines are proposed in Section 5.3.

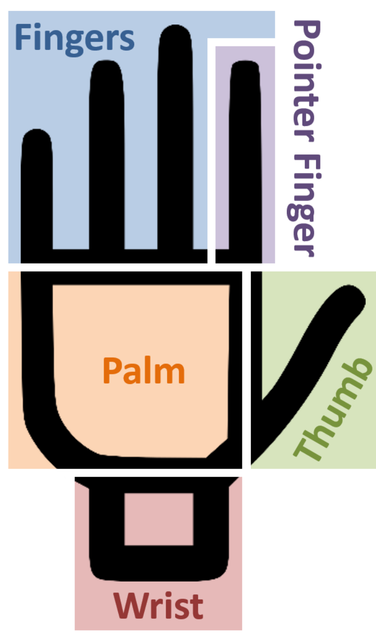

Figure 5.1: Significant regions for consideration when designing a robotic hand, including the wrist, palm, fingers, pointer finger, and thumb.

5.1 Regions and Features of a Robotic Hand

The analysis of Study 1 suggested a specific set of common hand gestures that were represented by one or more hand configurations/poses (Section 4.1). The implementation and subsequent analysis of these gestures on a robotic hand provided insights on particular regions of the hand that would impact human perceptions of the intended communicative meaning (Section 4.2). Definitions and considerations for each of the regions shown in Figure 5.1 and discussed in the follow subsections.

5.1.1 Wrist

The wrist is the anchor point for the robot hand, and connects to the base of the palm (Figure 5.1). The side of the hand opposite the wrist (i.e., the palm, extended fingers, or the pointer finger) enables the robot to produce hand gestures in the set of **Directional Gestures**, G_D [37]. Furthermore, the results of this thesis indicate benefit from the wrist providing or permitting some form of tilt movement (side-to-side) and/or twist movement (forward-and-backward), as all of the selected gestures (with the exception for the **Confirm** gesture) involved some sort of movement of the wrist or forearm. Tilting of the wrist allows the robot to better produce hand gestures in the set of G_D, as well as the **Stop** gesture (in the set of **Feedback Gestures**, G_F; Figure 3.5bc). Twisting of the wrist allows the robot to better produce hand gestures in the set of **Orientation Gestures**, G_O.

5.1.2 Palm

The palm serves as the main region from which other regions of the hand extend (Figure 5.1). The palm of a robotic hand should take one of two forms: planar or volumetric. A *planar* palm has two clear "sides"—the "back of the hand" and the "front of the hand"—which allow it to produce hand gestures with Open-Hand poses (e.g., Figure 3.7a); an example of a simple planar palm design might be a semi-circular disk like a ping-pong paddle. A *volumetric* palm has no clear directionality—similar to a balled up fist—which allows it to produce hand gestures with Closed-Hand poses (e.g., Figure 3.8); an example of a simple volumetric palm design might be a sphere or cube.

5.1.3 Fingers

The fingers—pointer, middle, index, and/or pinky—extend out from the palm on the side opposite the wrist (Figure 5.1). These fingers can be spread apart or closed (touching each other), and can be unarticulated or articulated at the proximal knuckle point. While fingers that are spread apart might allow the robot to produce a V-Sign hand pose (Figure 3.7d), the results in Section 4.2.3.5 suggest that the V-Sign pose might not be as effective as other hand poses in human-robot communication; thus, the design choice of fingers spread apart or touching is not essential for the gestures identified in this study. Based on the study results, unarticulated fingers are suggested to be posed in one of three ways: Open-Hand, Half Open-Hand, or Closed-Hand. Articulated fingers can permit transitional hand poses somewhere between the range of Open-Hand and Closed-Hand poses, and can be articulated either separately (decoupled) or together (coupled); based on insights from Study 1 (Section 4.1); however, the only recommended decoupling is the pointer finger, discussed below. For both unarticulated and articulated fingers, the selected hand pose dictates the effectiveness of hand gestures as perceived by the human observer. Because the fingers might naturally add “sides” to the palm, they will override any perceptions yielded by the palm alone; furthermore, the number and layout of fingers might be aesthetically linked to the size and shape of the palm, so at least three fingers are suggested to establish clear “sides” of the palm.

5.1.4 Pointer Finger

An extended pointer finger separated from other fingers in a Closed-Hand pose (either unarticulated or articulated) allows the robot to produce Finger-Pointing poses (Figure 3.7b) to communicate very specialized hand gestures (Figure 5.1). For example, as illustrated in Study 1, the **Place** gesture (in the set of **Manipulation Gestures**, G_M; Figure 3.4f) was only expressed using the Finger-Pointing pose in human-human interactions (Section 4.1).

5.1.5 Thumb

The thumb often assists in one of two purposes: physical manipulation or social expressiveness; each of these purposes often dictates the location of the thumb on the robot hand (Figure 5.1). For effective *physical manipulation*, the thumb on a robot hand is often located near the wrist and on the "front" of the palm; this allows the robotic manipulator to apply forces from opposing directions between the fingers and thumb (e.g., for grasping an object). For effective *social expressiveness*, the results of this work suggest that the thumb should be near the wrist and to the side of the palm (i.e., as with a Thumbs-Up hand pose); this allows the robot to produce unique *symbolic* hand gestures, such as the **Confirm** gesture (in the set of **Feedback Gestures**, G_F; Figure 3.5a), and adds a reference point to hand poses to improve the recognition of **Orientation Gestures** (G_O), especially for small orientations (i.e., $<$ **45°** gesture). Thus, to support both physical and social purposes, it is recommended that the thumb be able to roll from below the palm to the side of the palm.

5.2 Applications of Design Guidelines

The section reviews robotics hands that were used by, or related to, this thesis work, and applies the design principles described above to evaluate (for the Barrett Hand; Section 5.2.1), predict (for the Seed Robotics RH4D Aries Hand; Section 5.2.2), and improve (for the Seed Robotics RH7D Eros Hand; Section 5.2.3) the social expressiveness of robot hands.

5.2.1 Barrett Hand

The implementation challenges and subsequent Study 3 experimental results using the Barrett Hand (Figure 5.2) revealed the foundational insights for the design guidelines proposed above. The hand can be evaluated by the regions and features proposed above, which dictate its social expressiveness.

The wrist of the Barrett Hand is fixed; however, it is mounted to a forearm that can both tilt and twist at an elbow in the arm, enabling fundamental movements for the production of **Directional Gestures** (Section 4.2.1) and **Orientation Gestures** (Section 4.2.2), respectively. The perception of a palm is formed by the mechanism coupling the wrist to the fingers, which forms two clear sides of the hand, classifying it as a planar palm. While the fingers dictate the effectiveness of Open-Hand vs. Closed-Hand poses, this planar palm is effective at communicating **Orientation Gestures**, as evidenced by the positive results of Study 3 (Section 4.2.2). The fingers are separately articulated, enabling the robot to effectively produce hand configurations in the range between Open-Hand and Closed-Hand poses. In addition, the articulated pointer finger enables the Barrett Hand to produce specialized hand gestures, such as the **Place** gesture (Figure 3.4f). However, the lack of a thumb makes it impossible for the Barrett Hand to approximate *symbolic* hand gestures, such as the **Confirm** gesture (Figure 3.5a) with the Thumbs-Up pose, which is crucial for affirmative communication.

The Barrett Hand is similar to (but not actually used as) morphologies of robotic hands common in industry (see Section 2.3), it follows that such robot hands might not be sufficient for supporting fluent human-robot gestural interactions. More anthropomorphic robotic hands that closely resemble human anatomy might produce better approximations of human gestures; however, such hands are typically much more expensive and less effective in the industries. The next section describes an example of an inexpensive and robust robotic hand designed to address the future industrial needs *with respect to social expressiveness.*

Figure 5.2: The Barrett Hand.

5.2.2 Seed Robotics RH4D Ares Hand

Seed Robotics (http://www.seedrobotics.com) designs and develops tendon-based robotic hands for advanced manipulation. Their designs are highly customizable using 3D printed modular components, and the developed product tend to be significantly less expensive than other robotic manipulators on the market. Currently, their robot hands are too small for manipulation in industrial settings; however, the flexibility in design is appealing for purposes of review in this thesis, as the design can be adapted for social expressiveness. This section discusses their base model hand—the RH4D Ares (Figure 5.3)—and *predicts* how well people might interpret gestures produced by it. The next section presents a redesign of the hand informed by this thesis work.

The Ares robotic hand features four actuated degrees of freedom: two in the wrist, one in the coupled fingers, and one in an opposable thumb. The wrist enables both twist rotation (for **Orientation Gestures**) and forward/backward rotation; however, the forward/backward wrist rotation does not add much social expressiveness to the hand, as none of the gestures identified in Study 1 (Section 4.1) or implemented in Study 3 (Section 3.3) warranted this movement. Thus, as with the Barrett Hand (Section 5.2.1), the Ares hand must be mounted to a higher-DOF arm to support the range of motion necessary for **Directional Gestures**. The palm is formed by the space between the two fingers and the thumb. The two fingers are visibly separate, but actuated together (i.e., coupled); while this configuration could produce Closed-Hand poses and the less important V-Sign pose (Figure 3.7d), the Ares is unable to produce the Finger-Pointing pose (Figure 3.7b), which is beneficial for some **Directional Gestures** and the **Place Manipulation Gesture**. The articulated opposable thumb is ideally located for grasping objects; however, its range of motion is limited to supporting only Half Open-Hand or Closed-Hand poses, and its positioning suggests that any displays of a Thumbs-Up pose would be deemed inappropriate. In summary, the Ares hand is effective for physical manipulation of small objects, but its effectiveness in socially expressivity is limited to gestures expressed using Half Open-Hand poses (e.g., **Orientation Gestures**) and Closed-Hand poses (e.g., some **Manipulation Gestures**).

Based on the above predictions, the Ares hand does not fully address the needs identified in this thesis for gestural communication in HRI. These predictions serve as hypotheses about how people might perceive hand gestures with the Ares hand, which could be formally tested in future work. For now, these predictions alone were enough for Seed Robotics, who subsequently worked with the thesis author to change the design of the Ares hand to better support social expressiveness (described in the next section).

Figure 5.3: The Seed Robotics RH4D Ares hand.
(http://www.seedrobotics.com/rh4d-ares-hand.html)

5.2.3 Seed Robotics RH7D Eros Hand

To enhance the social expressiveness of the RH4D Ares hand (Section 5.2.2), the founders of Seed Robotics met with the thesis author to discuss the design considerations proposed in Section 5.1. This discussion informed the development of a new Seed Robotics hand—the RH7D Eros (Figure 5.4). This section presents the design characteristics that make the Eros one of the most socially expressive robotic hands available, as illustrated in Figure 5.5.

The Eros hand features seven actuated degrees of freedom: three in the wrist, two for the fingers, and two for the thumb. As with the Ares, the Eros wrist features both twist rotation (for **Orientation Gestures**) and forward/backward rotation; however, side-to-side tilting rotation has been added and the forward/backward rotation has been moved to where the wrist and palm meet, adding strong support for **Directional Gestures**. A planar palm is very clearly formed between the recommended three fingers and the thumb. To maximize expressivity while minimizing actuation costs, two of the three fingers (the "non-pointer fingers") are articulated together and one of the fingers (the pointer finger) is articulated separately; this articulated configuration supports the full range of Open-Hand to Closed-Hand poses (Figure 5.5ab), and allows the hand to produce Finger-Pointing poses (Figure 5.5c) to support some **Directional Gestures**, the **Place Manipulation Gesture**, and the **Stop Feedback Gesture**. The thumb has been relocated from the front of the palm (Figure 5.3) to the side of the palm (Figure 5.4). As with the Ares, the thumb can bend; however, the Eros adds a rolling motion enabling the thumb to transition between the front of the palm (for physical manipulation) and the side of the palm (for social expressiveness), supporting a strong Thumbs-Up pose for better **Orientation Gestures** and the **Confirm Feedback Gesture** (Figure 5.5d).

Based on the experimental results (Section 4.2) and the proposed data-driven design guidelines (Section 5.1) of this thesis work, the Eros hand represents a significant improvement over both the Ares (Section 5.2.2) and the Barrett Hand (Section 5.2.1) in terms of social expressiveness; however, as with the Ares, these predicted improvements are as hypotheses to be investigated in future studies. The Eros is currently too small for industrial manipulation tasks, though its 3D-printable design suggests that it could be made larger and stronger for manufacturing applications such as picking and placing workpieces in assembly lines. In an ultimate combination of physical and social, the Eros hands have been used for performing human-robot handshakes, representing the synergy between anthropomorphism and engineering for a future in which both humans and robots collaborate.

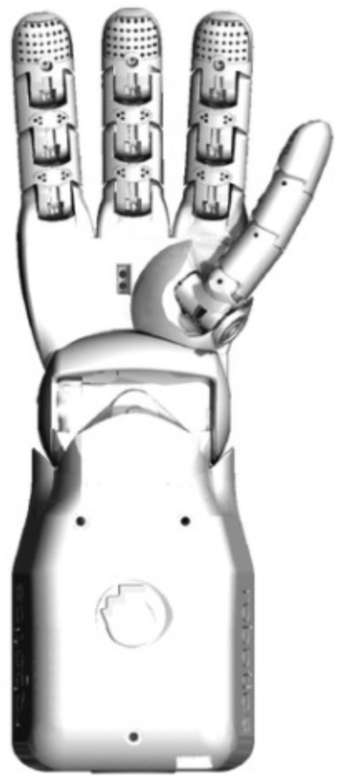

Figure 5.4: The Seed Robotics RH7D Eros hand.
(http://www.seedrobotics.com/rh7d-eros-hand.html)

5.3 Next Steps

The design guidelines proposed in Section 5.1 are informed by human-human gestural communication (Section 4.1) and their subsequent implementations for human-robot interactions (Section 4.2); however, these guidelines come from a single robot hand (the Barrett Hand) within a particular scenario (collaborative industrial manufacturing), so the significance and impact of the principles is currently limited to these domains. Thus, further exploration of the space of robot hands—as well as their associated regions, features, and applications—is needed to formalize principles for the design of physically and socially effective robotic hands. The formalization of these guidelines will enable a researcher to quickly evaluate (Section 5.2.1), predict (Section 5.2.2), and improve (Section 5.2.3) a robot hand with respect to requirements identified for both physical manipulation and social expressiveness in a target application domain.

The final chapter provides conclusions and future directions of this work.

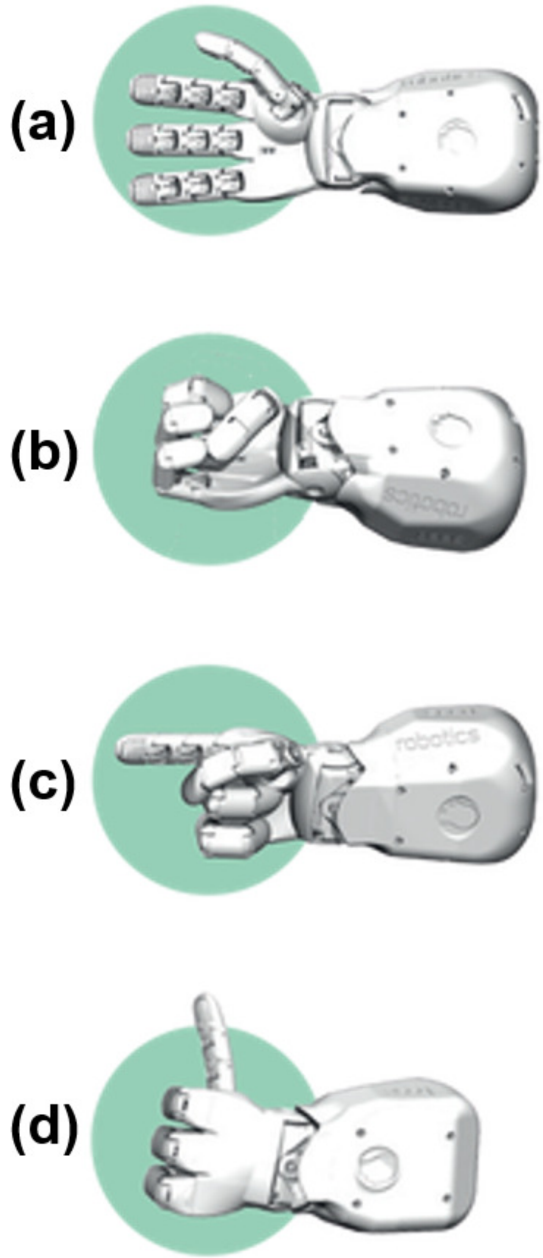

Figure 5.5: A selection of configurations/poses expressed by the Seed Robotics RH7D Eros hand, including (a) Open-Hand, (b) Closed-Hand, (c) Finger-Pointing, and (d) Thumbs-Up.
(http://www.seedrobotics.com/rh7d-eros-hand.html)

Chapter 6

Conclusions

In noisy industrial settings, spoken communication is unreliable and even impractical for human-robot coworkers. This work addressed nonverbal gestural expressions as a means of reliable human-robot communication. The aim of this work was (1) to study the communicativeness of a common three-finger robotic hand in industrial scenarios, and (2) to investigate human recognition of robot hand gestures in a collaborative human-robot task. The results highlight the efficacy of using a common non-anthropomorphic robotic manipulator—the Barrett Hand—to communicate with human observers (e.g., coworkers) using hand gestures.

Humans generally recognize *human* hand gestures accurately and confidently in human-human interactions (discussed in Section 2.1); however, human recognition of *robot* hand gestures has not been adequately explored in human-robot interactions (Section 2.2). Although typical industrial robotic grippers are non-anthropomorphic and have limited dexterity (Section 2.3), the results demonstrate that such devices are capable of expressing **Directional**, **Orientation**, **Manipulation**, and **Feedback** gestures (defined in Sections 3.1) in a human-recognizable manner. Three studies (Sections 3.1 – 3.3) were performed to explore and inform the use of such robot hands for human-robot communication in collaborative settings, the results of which are presented in Sections 4.1 and 4.2.

According to the results presented in this work, most gestures are better and more confidently recognized when displayed with a posed robot hand rather than an unposed, closed hand; however, hand poses used by humans when expressing a gesture are not necessarily ideal for a robot to use when expressing the same gesture. These results suggest principles and guidelines for the mechanical design of expressive robot hands and robot hand gestures in co-present human-robot interactions, including human-robot collaboration; these guidelines are presented in Section 5.1 and applied in Section 5.2.

An overview of the contributions of this work is summarized below in Section 6.1. A discussion of limitations and future work are provided in Section 6.2, followed by concluding remarks in Section 6.3.

6.1 Contributions

This work developed and evaluated a cardinal set of user-generated gestures applicable to industrial scenarios in which the robot must intuitively and effectively provide a set of instructions to a co-located person while collaborating on a shared task. The key contributions of this work are:

- a methodology for designing and implementing task-based communicative gestures to be expressed by a robot in HRI;
- a cardinal set of user-generated task-based communicative hand gestures and accompanying hand poses for human-robot co-working tasks;
- an evaluation and validation of the identified gesture set with respect to human *Recognition Rate* and *Recognition Confidence* within a human-robot collaboration scenario; and
- a set of guidelines for the mechanical design of robot hands.

6.2 Limitations and Future Work

These thesis investigations revealed considerations and limitations in the methods utilized that could be addressed more exhaustively in related or future work.

In Study 1, when identifying the gestures that were utilized in human-human collaborative assembly scenario, the **Up**-and-**Down** and **Left**-and-**right Directional Gestures** (G_D) were analyzed together based on the assumption that these gestures were symmetric; however, in subsequent analyses, it was determined that these directional gestures were best recognized with different hand poses—thus, the assumption of symmetry in the analysis of Study 1 might not hold and requires further investigation. Informed by this observation, Study 2 and Study 3 both treated the Up-and-Down and Left-and Right gestures separately.

In this work, the Closed-Hand (CH) pose was utilised as a baseline for analysing participant *Recognition Rates* and *Recognition Confidence* of robot hand gestures. An extension to this work would be to have a person also gesture with the CH pose to serve as a baseline for the human-human study (Study 2), and to evaluate how well people perceive the human CH gesture compared to the robot CH gesture (as with other gestures in Section 4.2).

The objective of this work is to gain preliminary insights into the transfer of natural human hand gestures to non-anthropomorphic robot hand gestures; however, restrictions on participants in Study 1 (described in its methodology, Section 3.1) might have resulted in human hand gestures that were less natural than what would be observed in an actual assembly scenario. Future work would investigate human hand gestures and speech utterances produced in natural collaborative industrial settings, and model these gestures for non-anthropomorphic robot hands common in these settings.

Sections 5.2.2 and 5.2.3 applied the design guidelines outlined in Section 5.1 to predict how people would recognize robot gestures produced by the Seed Robotics Ares and Eros hands, respectively. These predictions serve as hypotheses to be tested in formal studies. Future work would employ the same procedure performed in Study 3 (Section 3.3), implementing the same hand gestures and configurations/poses on both the Ares and Eros hands. Participant *Recognition Rates* and *Recognition Confidences* for each of these robotic hands could be compared to the Barrett Hand, as well as the human-human production of the same gestures, as in Section 4.2. The results of such a study would provide further insights and support for the data-driven design of expressive robotic hands.

In future work, the implemented robot hand gestures could be compared to other communication modalities—such as teaching pendants, touch interfaces, or speech (even though speech might not be an option in the target domains)—with respect to common metrics in human-robot collaboration, such as human response time and overall task performance. As noted in the results (Section 4.2), the camera angle from which the studies were evaluated might have impacted participant *Recognition Rates* and *Recognition Confidence*; further studies will investigate how observer perspective influences the clarity of gestural communication [14]. Finally, the gesture communication system will be integrated into a decision-making mechanism to enable the robot to predict and select the most appropriate communicative action to maximize interpretability by a human co-worker.

6.3 Concluding Remarks

Collaborative robots are transforming the way in which people work in industrial settings, and will continue to disrupt manufacturing for years to come. As such, it is important for robots to understand how to effectively communicate with their human co-workers. This thesis provides the groundwork for these collaborative robots, upon which further work can be built.

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Appendix A

Study 1 Instructions

Study one presented in section 3.1 had two phases:

A.1 Study1-Phase1 Instructions

In phase 1 of Study 1 (Section 3.1), participants were asked to use hand gestures to instruct a human confederate, referred to as the "worker", to assemble six car door parts on a car door. Figures A.1 shows the proper location and orientation of each of the six parts.

As shown in Figure A.2, the participant stood in front of the car door (at a distance of 2ft), and the experimenter stood to the right of the car door (at a distance of 1ft). The car door parts were placed on a table between the experimenter and the human volunteer. This setup allowed the experimenter and the human volunteer to easily access the car door as well as the car door parts.

To provoke a wider range of natural and intuitive gestures in each round of the experiment, the worker would intentionally and as naturally as possible make mistakes at assembling the parts on the car door. During assembling each part, the worker would:

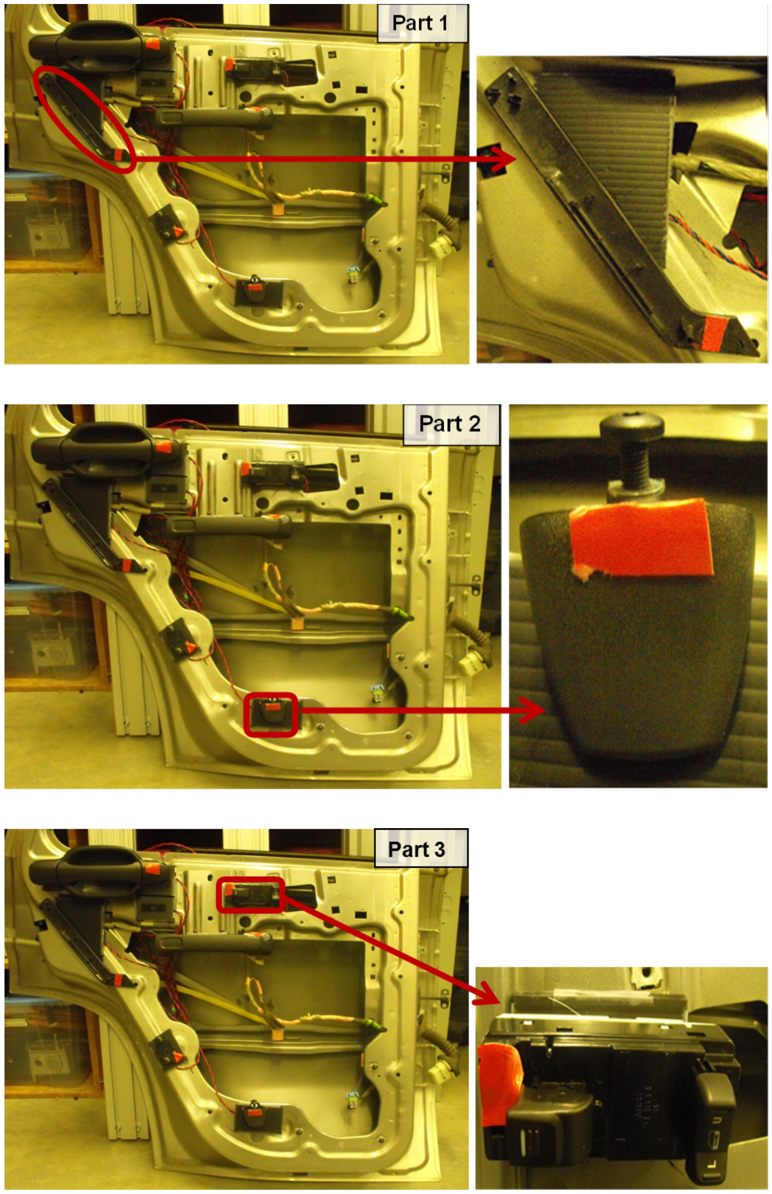
- part 1:
  - Hold part 1 below and to the left of its final location on the door, and slightly tilted to the right; and
  - Rotate part 1 more than needed (to have it tilted to the left).
- part 2:
  - Take part 5 instead of part 2 from the table; and
  - Attach part 2 with a wrong orientation (**90**° clockwise).
- part 3:
  - Attach part 3 to a wrong spot on the car door; and

  - Attach part 3 to its correct spot on the car door but with a wrong orientation (**180**°).

- part 4:
  - Hold part 4 below its final location on the door and slightly tilted to the left; and
  - Rotate part 4 more than needed (to have it tilted to the right).

- part 5:
  - Attach part 5 with a wrong orientation (**90**° counter-clockwise); and
  - Rotate part 5 **180**° clockwise (i.e. reattach part 5 in **90**° clockwise orientation with respect to its correct orientation).

- part 6:
  - Hold part 6 above and to the left of its final location on the door; and
  - Attach part 6 with a wrong orientation (**180**°).



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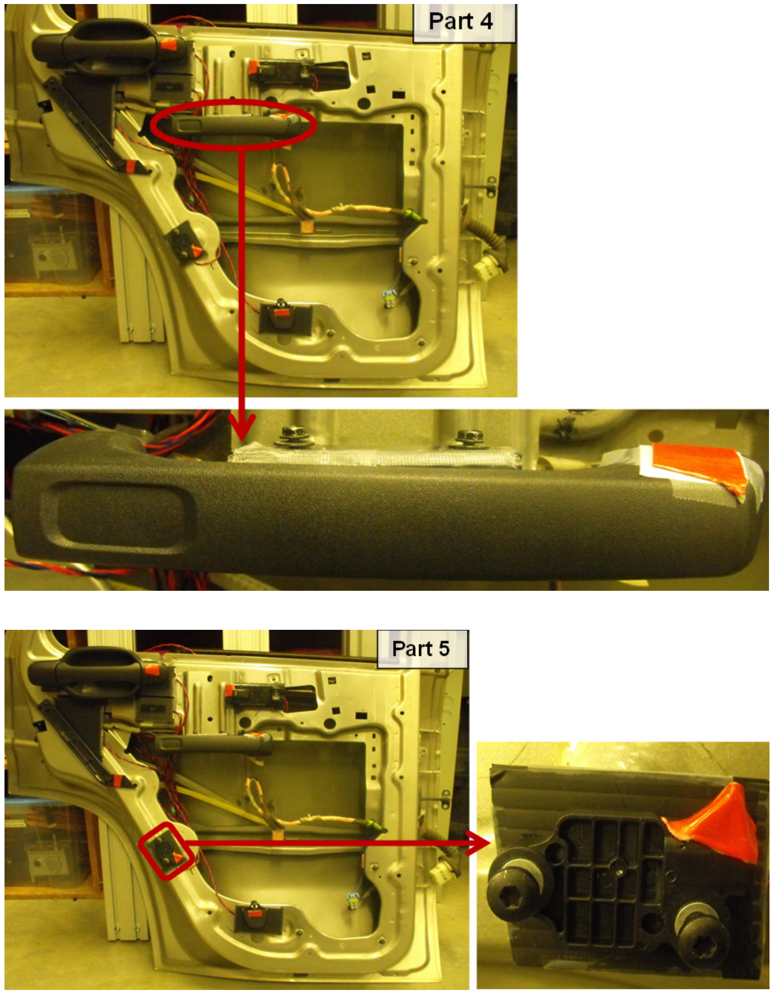

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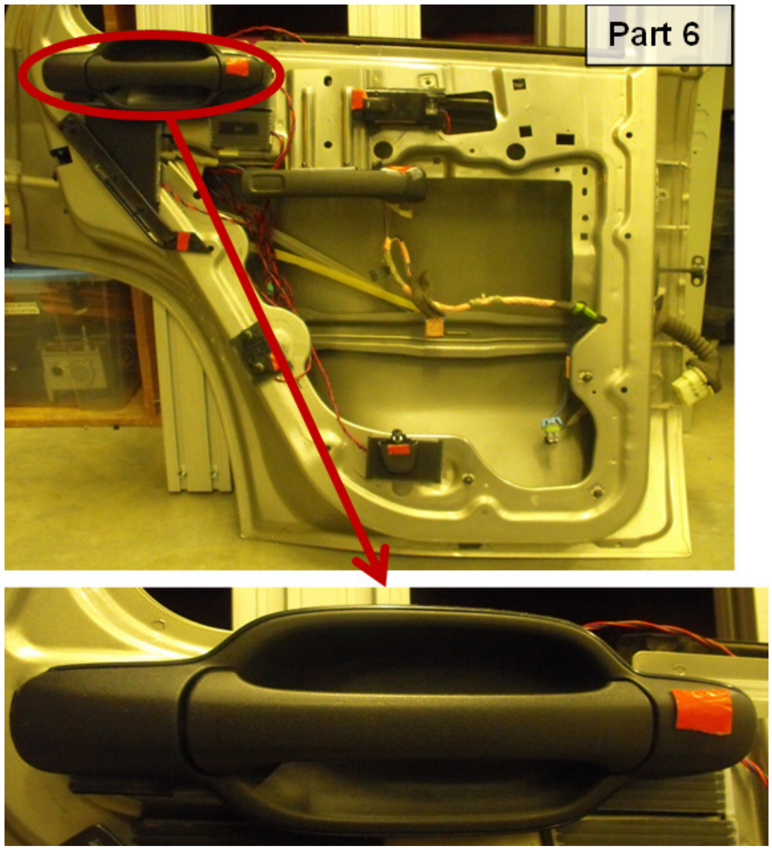


Figure A.1: Proper location and orientation of each of the six parts on the car door

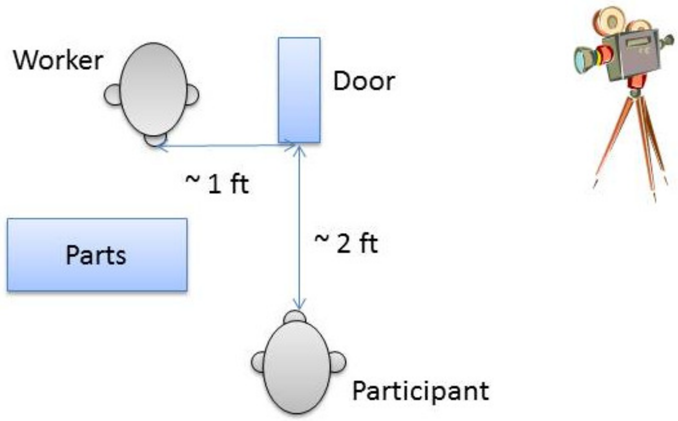


Figure A.2: Experimental setup for human-participants pilot experiment (Study1-Phase1).

A.2 Study1-Phase2 Instructions

In this phase, a new picture of the assembled vehicle door containing changes in the orientation or location of three of the six parts now assembled on the vehicle door was given to the participants (Figure A.3). Participants are asked to direct the worker to rearrange the parts on the door to achieve the new assembly arrangement.

Similar to Study 1, Phase 1, the vehicle door was in front of the human volunteer (2ft), and the experimenter stood to the right of the vehicle door (1ft) facing towards the human volunteer (Figure A.4).

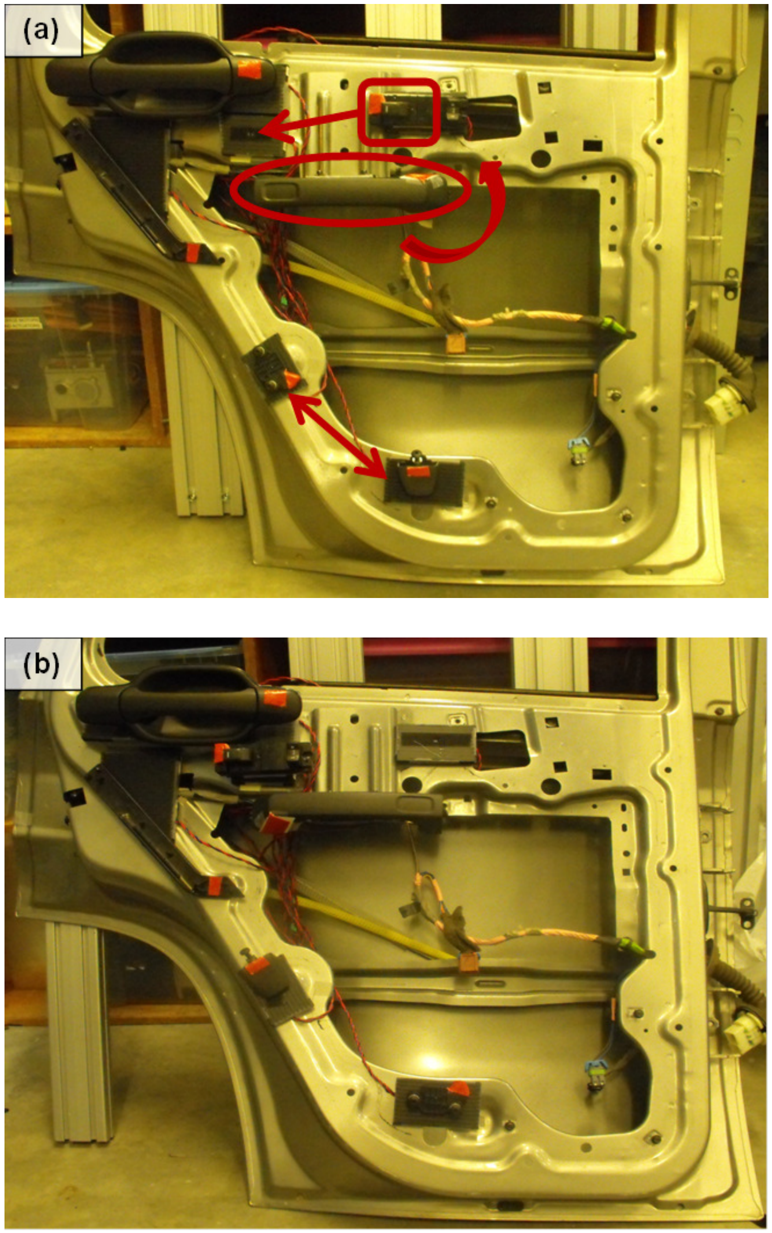


Figure A.3: Highlighted changes in the orientation or location of three of the six parts assembled on the vehicle door

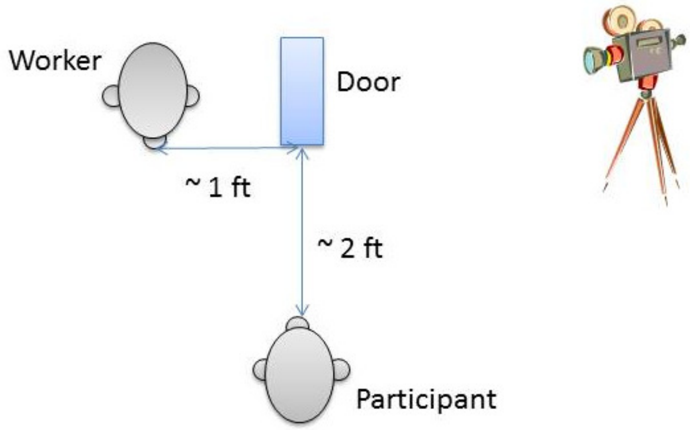


Figure A.4: Experimental setup for human-participants pilot experiment (Study1-Phase2).

Appendix B

Advertisements, Online Surveys, and Consent Forms

This appendix outlines the details of the online surveys used for Studies 2 and 3. Consent forms and advertisement materials used for the studies are also presented in this appendix. This appendix is divided into two sections: Section B.1 presents the consent form and the online survey used for Study 2; and Section B.2 presents the consent form and the online survey used used for Study 3.

B.1 Study 2 Advertisements, Online Surveys, and Consent Forms

In Study 2, two versions of the same online survey was used, each containing a different pseudo-random order of video-clips, each of a person exhibiting one of the identified hand gestures in Study 1 to direct a worker in an assembly task analogous to Study 1 (Chapter 3, Section 3.1). All versions of the survey used a single consent form. This consent form is presented in Figure B.1. The study was advertised via online media tools including twitter, facebook, and the Collaborative Advanced Robotics and Intelligent Systems (CARIS) Laboratory website and distribution of advertisements to university students. The advertised material is presented in Figure B.2 and Figure B.3.

Each survey contained 14 pages, each page containing a video and the same three survey questions discussed in Study 2 (Chapter 3, Section 3.2). A sample page is shown in Figure B.4.

Gesture Survey

Thank you for volunteering to participate in the survey.

The University of British Columbia
Collaborative Advanced Robotics and Intelligent Systems (CARIS) Laboratory
Department of Mechanical Engineering, UBC
6250 Applied Science Lane, Vancouver, BC V6T 1Z4
Tel: (604) 822-3147 Fax: (604) 822-2403
Web site: http://caris.mech.ubc.ca

Gesture Survey Consent Form

Project Title: Exploring the Effect of Robotic Articulated Hands in Task Based Gestures in Human-robot Interaction
Principal Investigator: Dr. Elizabeth Croft
Research assistant and contact person: Sara Sheikholeslami

Funding: This research is funded by the Collaborative, Human-focused, Assistive Robotics for Manufacturing.

Purpose:
The purpose of this project is to evaluate hand and arm gestures as a communication medium in human-robot interaction. The ultimate goal of our research is to explore whether human-like gestures expressed using a poseable robot hand are better recognized by humans than those expressed with a non-poseable robot hand. Results from this study will help determine how robots can better communicate with humans using hand gestures.

Procedures:
The study is being conducted via an online survey. It consists of short videos of people assembling a car door with different parts to be placed/rearranged on the car door. You will be asked to answer short questions about each of the videos. The survey should take no longer than 15 minutes to complete.

This project is part of an ongoing research in human-robot interaction which will be published in peer reviewed journals and conferences. You will not be compensated for your participation.

Potential Risks: None.

Confidentiality: This online survey is hosted by the UBC subscribed Enterprise Feedback Management tool (EFM). Enterprise Feedback Management (EFM) is a Canadian-hosted survey solution complying with the BC Freedom of Information and Protection of Privacy Act. All data is stored and backed up in Canada (Sydney BC). No identifying information

Last revised: July 31, 2013 Gesture Survey Consent Form.docx

(Figure continued on next page)

about your computer will be collected.

This consent form is the first page of the survey. You are required to give your consent by pressing the "consent to participate" button below in order to participate in the study. If you do not wish to participate, simply press the "no thank you" button below and you will be redirected out of the survey form.

If you have any concerns about your treatment or rights as a research subject, you may telephone the Research Subject Information Line in the UBC Office of Research Services at the University of British Columbia, at (604) 822-8598.

Revision 01

- Consent: By pressing this button, you consent to participate in this study, and acknowledge you have reviewed this consent form. Continue to survey.
- No thank you, I do not wish to participate in the survey.

Last revised: July 31, 2013 Gesture Survey Consent Form.docx

Figure B.1: Screen capture of the consent form used for the human-human interaction online surveys conducted in Study 2 (Chapter 3, Section 3.2).

Re: [Call for Volunteers] Robot becoming good teammates – A Human-Robot Interaction Study

The CARIS lab is conducting a fascinating online survey in human-robot interaction to understand human robot relations better. With the rapid advancements and innovations in the realm of robotic technology, soon there will be robot assistants capable of supporting humans in their daily tasks. However, this requires effective and reliable human-robot communication.

We aim to use non-verbal robot gestures that enable smooth flow of interaction between humans and robots. The primary criterion in selecting these gestures is their intuitiveness. We would like to invite you to participate in our fun human-human collaboration online survey. It will take no more than 15 minutes of your time, and you will be asked to watch and comment on short videos of two people working together on a vehicle door assembly task.

With your help, we will be able to design robots capable of having natural interaction with their human teammates in the near future.

Visit http://bit.ly/caris_study to take the survey. You will be required to complete an online consent form in order to begin the survey. For information/concerns regarding the survey please contact:

Sara Sheikholeslami

Or visit:
http://bit.ly/caris_study

Thank you very much for your help.

Sara Sheikholeslami, Undergrad Researcher, UBC Mechanical Engineering
AJung Moon, Ph.D. Student, UBC Mechanical Engineering
Elizabeth Croft, Professor, UBC Mechanical Engineering

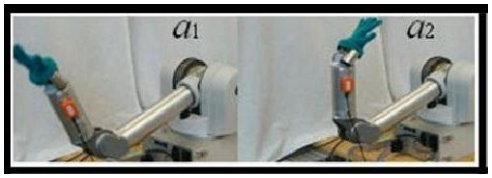
Last Revised: August 1, 2013 Call for Volunteers HH Interaction

Figure B.2: Contents of the online advertisement used to recruit participants for Study 2. The study was advertised on the CARIS Laboratory website. Links to this advertisement was distributed via other online media tools, including twitter and facebook.

Collaborative Advanced Robotics and Intelligent Systems Laboratory

Wishing to have robot partners? Participate in our online survey today!

Come help me be a good teammate!



The UBC CARIS Lab is looking for volunteers to participate in a fun human-human collaboration online survey. (About 15 minutes).

You will be asked to watch and comment on short videos of two people working together on a vehicle door assembly task. With your help, we will be able to design robots that can better communicate with their human teammates in the near future.

Visit http://bit.ly/caris_study to read the instructions and watch the videos, OR Contact Sara at to participate.

The Human-Robot Experiment @CARIS Lab
ICICS x527 http://bit.ly/caris_study

The Human-Robot Experiment @CARIS Lab
ICICS x527 http://bit.ly/caris_study
sarash.ubc@gmail.com 604-822-3147

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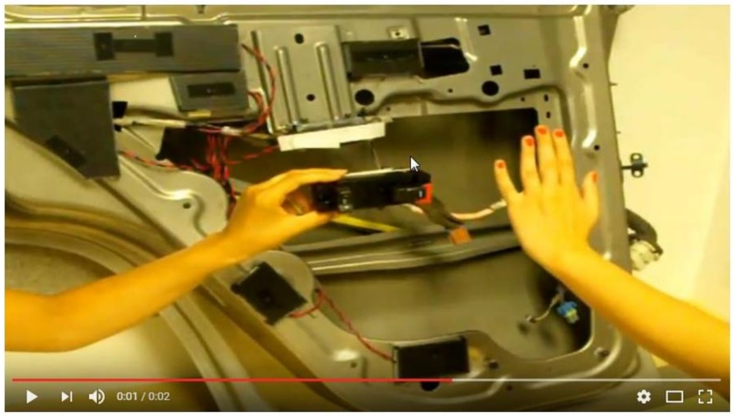
Last revised: August 6, 2013 Call for Volunteers ICRA HHI tear.doc Page 1 of 1

Figure B.3: Contents of the paper advertisement used to recruit participants for Study 2. The advertisement was distributed to university students.

Please watch the video paying attention to the hand motions of the "director" on **the right**.

LEFT RIGHT



1) What do you think the worker should do with the part?

____

2) How easy was it for you to understand the meaning of this gesture?

❍ 1- Very difficult
❍ 2
❍ 3
❍ 4
❍ 5
❍ 6
❍ 7- Very easy

3) How certain are you of your answer to Q1?

❍ 1-Very uncertain
❍ 2
❍ 3
❍ 4
❍ 5
❍ 6
❍ 7-Very Certain

Previous Page Next Page

Thank you for participating in the survey.

Figure B.4: An example of one of the 14 pages of the Study 2 online survey. All pages of the survey contained the same questions in the same order; however, the video content of each page was randomly selected.

B.2 Study 3 Advertisements, Online Surveys, and Consent Forms

In Study 3, two versions of the same online survey was used, each containing a different pseudo-random order of video-clips, each of a person exhibiting one of the identified hand gestures in Study 1 to direct a worker in an assembly task analogous to Study 1 (Chapter 3, Section 3.1). All versions of the survey used a single consent form. This consent form is presented in Figure B.5. The study was advertised via online media tools including twitter, facebook, and the Collaborative Advanced Robotics and Intelligent Systems (CARIS) Laboratory website and distribution of advertisements to university students. The advertised material is presented in Figure B.6 and Figure B.7.

Each survey contained 14 pages, each page containing a video and the same three survey questions discussed in Study 3 (Chapter 3, Section 3.2). A sample page is shown in Figure B.8.

Gesture Survey

Thank you for volunteering to participate in the survey.

The University of British Columbia
Collaborative Advanced Robotics and Intelligent Systems (CARIS) Laboratory
Department of Mechanical Engineering, UBC
6250 Applied Science Lane, Vancouver, BC V6T 1Z4
Tel: (604) 822-3147 Fax: (604) 822-2403
Web site: http://caris.mech.ubc.ca

Gesture Survey Consent Form

Project Title: Exploring the Effect of Robotic Articulated Hands in Task Based Gestures in Human-robot Interaction
Principal Investigator: Dr. Elizabeth Croft
Research assistant and contact person: Alex Reddy

Funding: This research is funded by the Collaborative, Human-focused, Assistive Robotics for Manufacturing.

Purpose:
The purpose of this project is to evaluate hand and arm gestures as a communication medium in human-robot interaction. The ultimate goal of our research is to explore whether human-like gestures expressed using a poseable robot hand are better recognized by humans than those expressed with a non-poseable robot hand. Results from this study will help determine how robots can better communicate with humans using hand gestures.

Procedures:
The study is being conducted via an online survey. It consists of short videos of a robot hand using communicative gestures to give instructions to a person to assemble a car door with different parts to be placed/rearranged on the car door. You will be asked to answer short questions about each of the videos. The survey should take no longer than 15 minutes to complete.

This project is part of an ongoing research in human-robot interaction which will be published in peer reviewed journals and conferences. You will not be compensated for your participation.

Potential Risks: None.

Confidentiality: This online survey is hosted by the UBC subscribed Enterprise Feedback Management tool (EFM). Enterprise Feedback Management (EFM) is a Canadian-hosted survey solution complying with the BC Freedom of Information and Protection of Privacy Act. All data is stored and backed up in Canada (Sydney BC). No identifying information

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about your computer will be collected.

This consent form is the first page of the survey. You are required to give your consent by pressing the "consent to participate" button below in order to participate in the study. If you do not wish to participate, simply press the "no thank you" button below and you will be redirected out of the survey form.

If you have any concerns about your treatment or rights as a research subject, you may telephone the Research Subject Information Line in the UBC Office of Research Services at the University of British Columbia, at (604) 822-8598.

Revision 02

Consent: By pressing this button, you consent to participate in this study, and acknowledge you have reviewed this consent form. Continue to survey.

No thank you, I do not wish to participate in the survey.

Last revised: June 25, 2014 Gesture Survey Consent

Figure B.5: Screen capture of the consent form used for the human-robot interaction online surveys conducted in Study 3 (Chapter 3, Section 3.3.

Re: [Call for Volunteers] Robot becoming good teammates – A Human-Robot Interaction Study

The CARIS lab is conducting a fascinating online survey in human-robot interaction to understand human robot relations better. With the rapid advancements and innovations in the realm of robotic technology, soon there will be robot assistants capable of supporting humans in their daily tasks. However, this requires effective and reliable human-robot communication.

We aim to use non-verbal robot gestures that enable smooth flow of interaction between humans and robots. The primary criterion in selecting these gestures is their intuitiveness. We would like to invite you to participate in our fun human-robot collaboration online survey. It will take no more than 15 minutes of your time, and you will be asked to watch and comment on short videos of a human and a robot arm working together on a vehicle door assembly task.

With your help, we will be able to design robots capable of having natural interaction with their human teammates in the near future.

Visit http://bit.ly/caris_study to take the survey. You will be required to complete an online consent form in order to begin the survey. For information/concerns regarding the survey please contact:

Alex Reddy

Or visit:
http://bit.ly/caris_study

Thank you very much for your help.

Alex Reddy, Undergrad Researcher, UBC Mechanical Engineering
Sara Sheikholeslami, MASc. Studet, UBC Mechanical Engineering
AJung Moon, Ph.D. Student, UBC Mechanical Engineering
Elizabeth Croft, Professor, UBC Mechanical Engineering

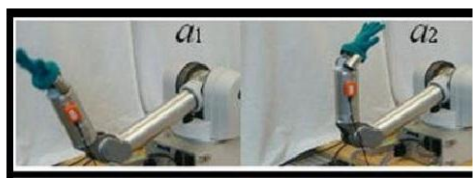
Last Revised: June 25, 2014 Call for Volunteers HR Interaction rev2.doc

Figure B.6: Contents of the online advertisement used to recruit participants for Study 3. The study was advertised on the CARIS Laboratory website. Links to this advertisement was distributed via other online media tools, including twitter and facebook.

Collaborative Advanced Robotics and Intelligent Systems Laboratory

Wishing to have robot partners? Participate in our online survey today!

Come help me be a good teammate!



The UBC CARIS Lab is looking for volunteers to participate in a fun human-robot collaboration online survey. (About 15 minutes).

You will be asked to watch and comment on short videos of a human and a robot hand working together on a vehicle door assembly task. With your help, we will be able to design robots that can better communicate with their human teammates in the near future.

Visit http://bit.ly/caris_study to read the instructions and watch the videos, OR Contact Alex at to participate.

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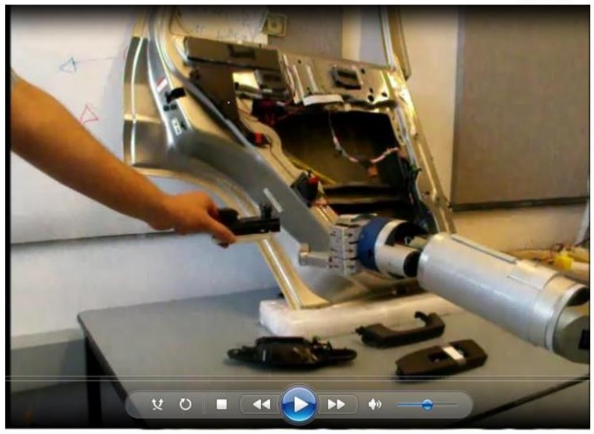
ICICS x527 http://bit.ly/caris_study

Figure B.7: Contents of the paper advertisement used to recruit participants for Study 3. The advertisement was distributed to university students.

Please watch the video paying attention to the hand motions of the robot arm ("director") on **the right**.

LEFT RIGHT



1) What do you think the "worker" should do with the part?

____

2) How easy was it for you to understand the meaning of this gesture?

- ❍ 1- Very difficult
- ❍ 2
- ❍ 3
- ❍ 4
- ❍ 5
- ❍ 6
- ❍ 7- Very easy

3) How certain are you of your answer to Q1?

- ❍ 1-Very uncertain
- ❍ 2
- ❍ 3
- ❍ 4
- ❍ 5
- ❍ 6
- ❍ 7-Very Certain

[Previous Page] [Next Page]

Thank you for participating in the survey.

Figure B.8: An example of one of the 14 pages of the Study 3 online survey. All pages of the survey contained the same questions in the same order; however, the video content of each page was randomly selected.

Appendix C

Participants' confidence in recognizing human gestures compared to robot expressions of the same gestures

The following section provides the results of participant confidence in recognizing human gestures compared to robot expressions of the same gesture. While this analysis is beyond the scope and the objectives of this thesis, we added this section for completeness.

Independent sample t-tests were applied to measures of *Recognition Confidence* across the robot and human expressions of each hand configuration for all gestures (Table C.1, and Figures C.1 for the **Directional Gestures**, C.2 for the **Orientational Gestures**, C.3 for the **Manipulation Gestures**, and C.4 for the **Feedback Gestures**).

Most of the gestures were interpreted with higher *Recognition Rates* when performed by a person rather than when performed by the robot. The exceptions to these results are:

1. Finger-Pointing (FP) configuration of the **Right** Directional Gesture ($t(43.99) = 1.97$, $p = 0.06$) (Figure C.1),
2. both FP and Half Open-Hand (HOH) configurations of the **180°** Orientational Gesture ($t(57) = -0.03$, $p = 0.98$ and $t(74) = 0.40$, $p = 0.69$, respectively) (Figure C.2), and
3. both FP and Open-Hand (OH) configurations of the **Install** Manipulation Gesture ($t(36) = 0.14$, $p = 0.89$ and $t(62) = 0.36$, $p = 0.72$, respectively) (Figure C.3),

though the differences were not statistically significant.

Gestures that are recognized significantly more accurately when performed by a person rather than when performed by the robot include:

1. both FP and OH configurations of the **Up** Directional Gesture ($t(50) = -3.36$, $p < 0.01$ and $t(65) = -2.04$, $p < 0.05$, respectively),
2. FP configuration of the **90°** Orientational Gesture ($t(65) = -2.91$, $p < 0.01$),
3. both OH and HOH configurations of the **Remove** Manipulation Gesture ($t(62) = -4.21$, $p < 0.001$ and $t(63) = -5.02$, $p < 0.001$, respectively),
4. OH configuration of the **PickUp** Manipulation Gesture ($t(116) = -2.00$, $p < 0.05$),
5. V-Sign (VS) configuration of the **Swap** Manipulation Gesture ($t(34) = -3.12$, $p < 0.01$),
6. Thumbs-Up (TU) configuration of the **Confirm** Feedback Gesture ($t(116) = -11.17$, $p < 0.001$), and
7. both FP and OH configurations of the **Stop** Feedback Gesture ($t(66) = -2.43$, $p < 0.05$ and $t(66.21) = -2.21$, $p < 0.05$, respectively).

Table C.1: Measures of independent samples t-test on the to measures of *Recognition Confidence* across the robot and human expressions of each hand configuration for all gestures. Note that FP configuration of **Right** Directional Gesture and OH configuration of **Stop** Feedback Gesture failed the assumption of equality of variances, and therefore, the reported results for these two gestures do not assume equal variances.

Directional Gestures, G_D			
Gesture, $g \in G_D$	**Hand Poses**	t	p
Up	FP	$t(50) = -3.36$	< 0.01
	OH	$t(65) = -2.04$	< 0.05
Down	FP	$t(54) = -1.22$	0.23
	OH	$t(60) = -0.27$	0.78
Left	FP	$t(34) = -0.60$	0.55
	OH	$t(41) = -1.57$	0.12
Right	FP	$t(43.99) = 1.97$	0.06
	OH	$t(42) = -1.86$	0.07
Orientational Gestures, G_O			
Gesture, $g \in G_O$	**Hand Poses**	t	p
$< \mathbf{45}°$	HOH	$t(115) = -1.50$	0.14
90°	FP	$t(65) = -2.91$	< 0.01
	HOH	$t(71) = -0.42$	0.67
180°	FP	$t(57) = -0.03$	0.98
	HOH	$t(74) = 0.40$	0.69
Manipulative Gestures, G_M			
Gesture, $g \in G_M$	**Hand Poses**	t	p
Install	FP	$t(36) = 0.14$	0.89
	OH	$t(62) = 0.36$	0.72
Remove	OH	$t(62) = -4.21$	< 0.00
	HOH	$t(63) = -5.02$	< 0.00
PickUp	OH	$t(116) = -2.00$	< 0.05
Place	FP	$t(118) = -1.31$	0.19
Swap	FP	$t(40) = -0.71$	0.48
	VS	$t(34) = -3.12$	< 0.01
Feedback Gestures, G_F			
Gesture, $g \in G_F$	**Hand Poses**	t	p
Confirm	TU	$t(116) = -11.17$	< 0.00
Stop	FP	$t(66) = -2.43$	< 0.05
	OH	$t(66.21) = -2.21$	< 0.05

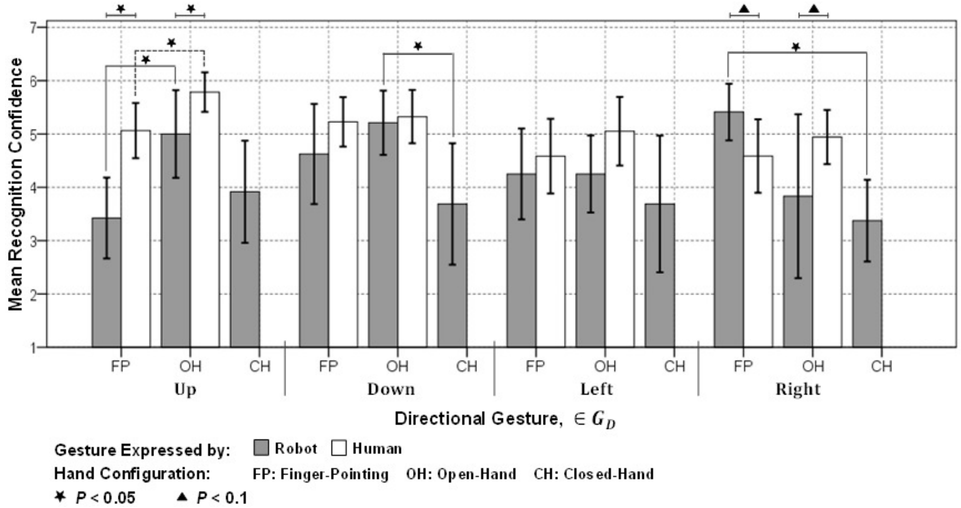


Figure C.1: Measures of *Recognition Confidence* across the robot and human expressions of each hand configuration for **Directional Gestures**, G_D.

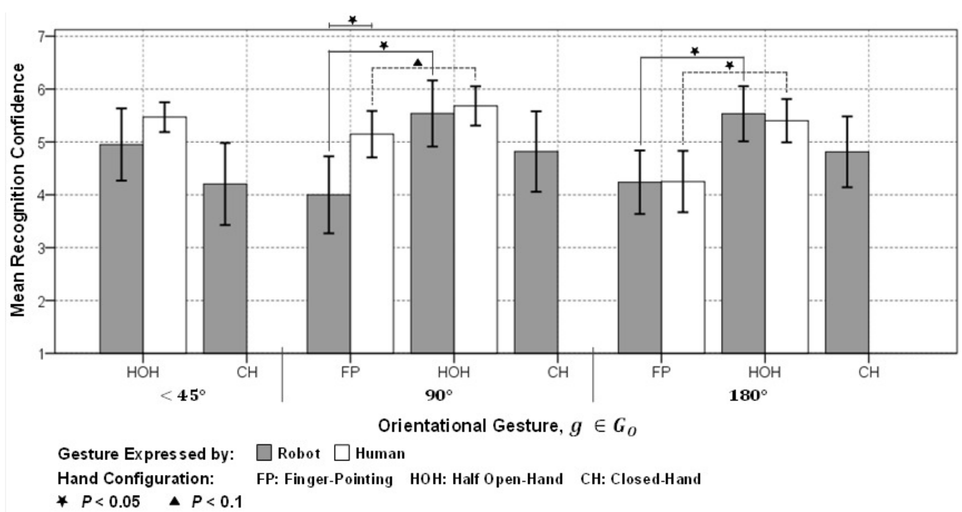


Figure C.2: Measures of *Recognition Confidence* across the robot and human expressions of each hand configuration for **Orientational Gestures**, G_O.

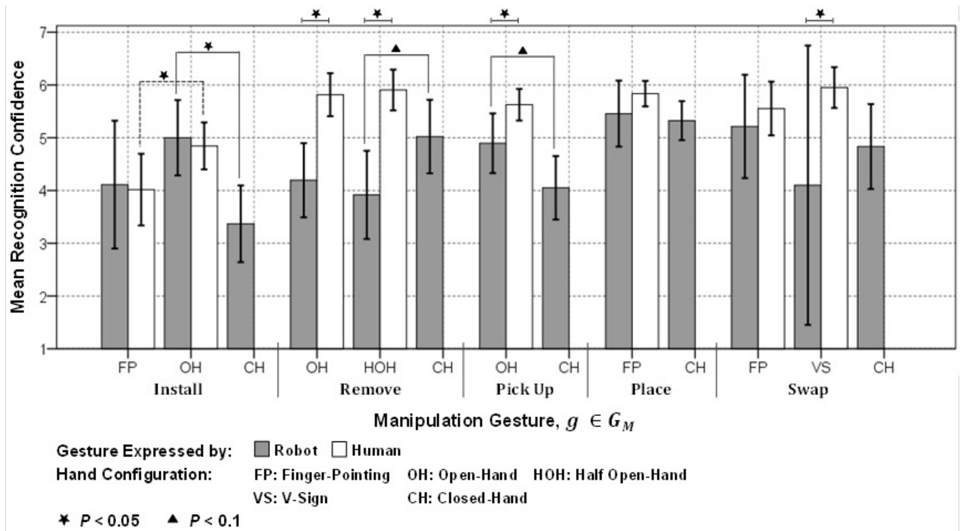


Figure C.3: Measures of *Recognition Confidence* across the robot and human expressions of each hand configuration for **Manipulation Gestures**, G_M.

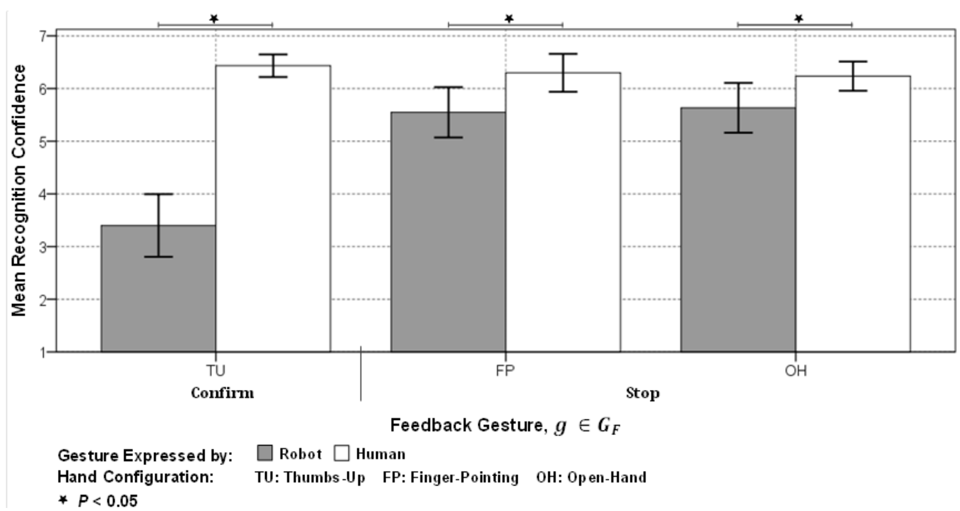


Figure C.4: Measures of *Recognition Confidence* across the robot and human expressions of each hand configuration for **Feedback Gestures**, G_F.