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Analysis of Task-Based Gestures in Human-Robot Interaction

Amir Haddadi†, Elizabeth A. Croft†, Brian T. Gleeson‡, Karon MacLean‡, and Javier Alcazar*

***Abstract*— New developments, innovations, and advancements in robotic technology are paving the way for intelligent robots to enable, support, and enhance the capabilities of human workers in manufacturing environments. We envision future industrial robot assistants that support workers in their tasks, advancing manufacturing quality and processes and increasing productivity. However, this requires new channels of fine-grained, fast and reliable communication. In this research we examined the communication required for human-robot collaboration in a vehicle door assembly scenario. We identified potential communicative gestures applicable to this scenario, implemented these gestures on a Barrett WAM™[1] manipulator, and evaluated them in terms of human recognition rate and response time in a *real-time* interaction. Response time analysis reveals insights into the communicative structure of robot motions; namely, key short gesture segments include the bulk of the communicative information. These results will help us design more efficient and fluid task flow in human-robot interaction scenarios.**

I. INTRODUCTION

Over the past thirty years, robotic technology has been integrated into the manufacturing industry to advance efficiency, reduce worker ergonomic stress and workload, and maintain safety in the workplace [1]. Today, most industrial robots that interact with workers are assistive or supportive devices that require frequent and low-level human attention and intervention. Such devices often require initial extensive training to operate, and the use of these devices could require the worker to focus their attention on controlling the device instead of completing the task at hand.

However, as the manufacturing industry evolves, so too do demands for co-operative and collaborative robots that intuitively and effectively communicate with humans. Autonomous robots are used extensively in manufacturing, for activities such as painting, welding, lifting and inspection. However, these robots are completely isolated from humans by interlock barriers, carrying out fixed tasks in highly structured and controlled environments. These industrial robots are programmed in advance by specialized workers using complex teach pendants. There is no ongoing direct interaction; current safety practices require extensive lockout procedures and complete shutdown prior to human contact[2]. As a result, little to no interaction is allowed between self-guided or programmed robots and human workers in current manufacturing systems.

However, as researchers develop more adaptive and capable robot behaviours and systems, industrial robots will also benefit. These more communicative and collaborative robots are enabling a departure from separate interfaces and workflow, replacing them with more natural human-robot communication [2][3][4].

We envision robotic assistants (RAs) in future manufacturing industries that can collaborate directly and physically with human co-workers in their assembly tasks, as part of the production team. Our immediate aim is to advance methods for interaction between RAs and human co-workers through developments in communication and task-flow control, centred on supporting workers performing complex manufacturing tasks.

Industry is heavily dominated by single-arm robotic manipulators. Therefore, to bridge the gap between current systems and future robot embodiments, we focused on the development and evaluation of communicative robot gestures on single arm manipulators, such as the Barrett WAM™ arm. In this paper, we analyze communicative gestures, modeled on human-human collaboration in a real-time assembly scenario, in terms of recognition rate and human response time. This analysis enables us to i) identify a set of appropriate, task-based gestures understandable for humans when expressed by single arm robots, ii) evaluate these gestures for human recognition rate considering the effect of context and work flow in an assembly task, and more importantly iii) examine humans' response time to specific gestures. The results of these analyses permit us to understand the communicative content of human-like gestures and design more efficient and fluid human-robot interactions to control task flow.

Recently, researchers have studied human-like gestures in various contexts including: general human-like gestures within collaborative working processes [5][6][7], human-robot turn taking [8], and human-like hesitation gestures [9][10]. However, the focus of these works is often on human recognition and perception and the experiments are mainly video-based surveys rather than real-time human

†Amir Haddadi, haddadi@ieee.org, and Elizabeth A. Croft, ecroft@mech.ubc.ca, are with the Department of Mechanical Engineering, the University of British Columbia, 6250 Applied Science Lane Vancouver, BC V6T 1Z4 Canada;
‡Brian T. Gleeson, brian.gleeson@gmail.com, and Karon MacLean, maclean@cs.ubc.ca, are with the Department of Computer Science, the University of British Columbia, 201-2366 Main Mall, Vancouver, BC V6T 1Z4, Canada;
*Javier Alcazar, Javier.alcazar@ieee.org, is with General Motors Research and Development Center 30500 Mound Road Warren, Michigan, 48090, USA.

[1] WAM™, Barrett Technologies, Cambridge, MA, USA.

[2] ANSI/RIA R15.06-1999, and the original international safety standard ISO 10218

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robot interaction (HRI). In this work, we measure humans' response times to various task-base gestures in a real-time HRI and evaluate the results to understand the communicative and contextual content of gestural motions; i.e. segments of gesture motions that communicate essential information to a human partner. This analysis helps us understand the most critical elements of various gestures and design more fluid human-robot interactions. Although achieved in the context of assembly tasks, we believe that our results are generally applicable to other gesture-based HRI tasks.

II. Communication Design Approach

The manufacturing assembly environment imposes several challenges on HRI originating from the physical characteristics of the manufacturing environment and from the nature of the tasks involved in assembly. The environment imposes restrictions on which communication channels can be used. Assembly environments are often loud with noticeable variations in background noise - in some areas the use of earplugs is imposed - making auditory communication unreliable. When collaborating, workers are often observed to use hand signals to communicate information. This has led us to investigate gestural communication as a potential human-robot communication system appropriate to the industrial environment.

In our envisioned collaborative environment, the human operator and the RA operate on the same assembly: the human completes task elements requiring high manual dexterity while the RA provides support, e.g. fetches parts, directs/reminds the human of specialized task variations for a particular car model, and checks the assembly for correct completion. Focusing on task transition we i) propose a set of gestures, similar to those gestures that humans use to allow smooth flow of interaction in an assembly task, ii) determine the recognition rates and reliability of these gestures when expressed by single-arm industrial robots, iii) analyze humans' response time to these gestures and, iv) investigate what features make a cue meaningful and communicative.

III. Study Design and Methodology

A. Research Questions and Hypotheses

In the context of the gestural communication approach, described above, we need to identify and implement a set of gestures that can effectively communicate required information to the human partners, and design a more fluid interaction. For this purpose, we proposed the following research questions and corresponding hypotheses.

R_1*) Would humans understand specific human-like gestures expressed by a single arm manipulator during an assembly task?*

R_2*) Would humans respond to these robotic gestures at the same rate during a real-time interaction with the robot, or is human response time different for each gesture, according to the structure of the gesture?*

Figure 1. Assembly task designed for human-human study.

Answers to the first research question help us design an interaction with reliable sets of communicative gestures, while the second question enables us to understand the communicative content of human-like gestures and design for an effective task flow control.

Based on the research questions described above, we considered the following hypotheses:

H_1) *Some human-like gestures, expressed by the robot arm, are more likely to be recognized and understood by humans than others.*

H_2) *Humans respond to human-like gestures expressed by the robot arm at different rates (faster/slower) according to the context and/or gesture types.*

B. Methodology

Our approach for finding appropriate task-based gestures, implementing gestures on our robot arm, and designing the experiments is based on conventional user-centred design models commonly used in Human Computer Interaction (HCI) research [11] and maintains a human-centered focus at each stage of development. We transition the study through three phases: (1) Human-to-Human Communicative Behaviours, (2) Behavioural Description, and (3) Human-Robot Experiments. Our study focuses on a vehicle door assembly scenario in which participants place six different parts in appropriate locations and orientations on a car door. The three phases of our approach are discussed below.

B1. *Observations from Human-to-Human Communicative Behaviours*

To identify gestures appropriate for the door assembly task, we designed a pilot study with three subjects in which the subjects were asked to direct a worker (the experimenter) in an assembly task using single-handed gestures. As shown in Figure 1, the assembly task includes six different car door parts located on one side, and a vehicle door located on the other side, with seven spots available for the door parts to be attached using Velcro™ strips.

The subjects were instructed to direct the experimenter via gestures to place all six parts as they saw fit. They were, however, explicitly asked to use only one hand.

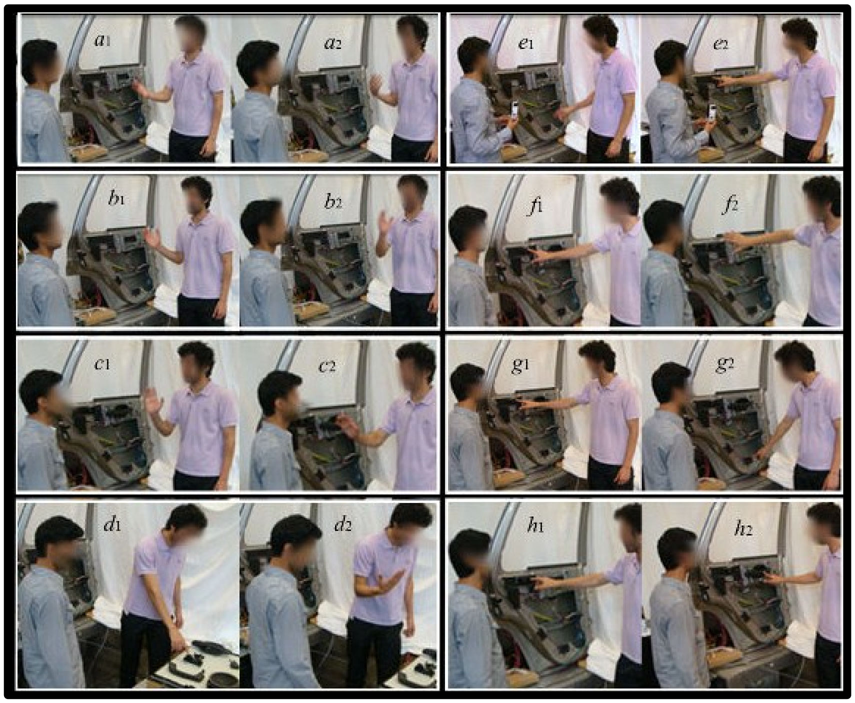

Figure 2. Task-based gestures found in human-human pilots – "Move Forward" (a), "Move Left" [and Right] (b), "Move Backward" (c), "Pick up" (d), "Place" (e), "Reorient" (f), "Reposition" (g), and "Swap" (h).

Among all gestures expressed by these subjects (15 in total), we selected nine essential gestures based on the following criteria: i) gestures were essential to task completion, and ii) gestures were repeatedly used by all three subjects. The selected gestures are:

a) gestures for directing the human movements (forward, backward, right and left), and

b) part related gestures; pick up, place, rotate, reposition, and swap, as shown in Figure 2.

These gestures can be categorized based on the nature of the gestures into A) Human motion gestures, B) Part displacement gestures, and C) Part re-orientation gestures.

*B*2. *Gesture Implementation and Behavioural Description*

Gestures identified in Section III.B1 were implemented on a 7-Dof Barrett WAM™ robot arm with its BarrettHand™ removed. We were interested in determining if gestures could be successfully generated without hand actuation, reducing the need for complex motion generation and control. Instead, we used an un-actuated stuffed glove at the robot end-effector to provide anthropomorphic context and to make the end effector highly visible in video recordings. For gestures in which human subjects used articulation of the fingers, such as pointing or indicating rotation, we used the entire hand with all fingers opened as shown in Figure 3. A recursive trial and error method was used in order to produce and improve the gestures as follows. First, the robot arm was manually moved to mimic a specific human gesture and then the trajectories were recorded, played back, and adjusted until the gestures became visually similar to those of the humans. Next, the selected trajectories were shown to the three subjects as well as a subject matter expert from our industrial collaborator, and they were asked to provide feedback on gesture improvement. We repeated this trial and error process twice and applied the feedback regarding the gestures, considering hardware limitations. These gestures are shown in Figure 3. One subject suggested that actuated fingers could improve the gestures. However, we observed that all subjects appeared able to understand the gestures made without finger motion, and thus elected to continue our study using the passive glove appendage.

*B*3. *HRI Experiment Design*

After producing trajectories for each gesture using the approach discussed above, we adapted these gestures for different parts and car door locations. These gestures were used to direct subjects in a real-time human-robot interaction experiment to measure human recognition rates and response times in an interactive task context.

Experimental Setup and Sensory Measurements

As shown in Figure 4, the experimental setup for our HRI study comprised six different parts located on a table on one side, a vehicle door on the other side, and a 7-DoF Barrett WAM robot arm located in front of the subject. Twelve QRD1114[3] reflective optical sensors were installed on the parts table and the car door for part tracking.

Two Xsens™[4] 3D real-time motion trackers, one attached to the robot arm and the other attached to the human's body (orange boxes in Figure 4), were used to detect the time between robot gesture onset and human movement - designated gesture response time (T_R).

[3] http://www.solarbotics.net/library/datasheets/QRD1114.pdf
[4] Xsens Technologies B.V., An Enschede, Netherlands.

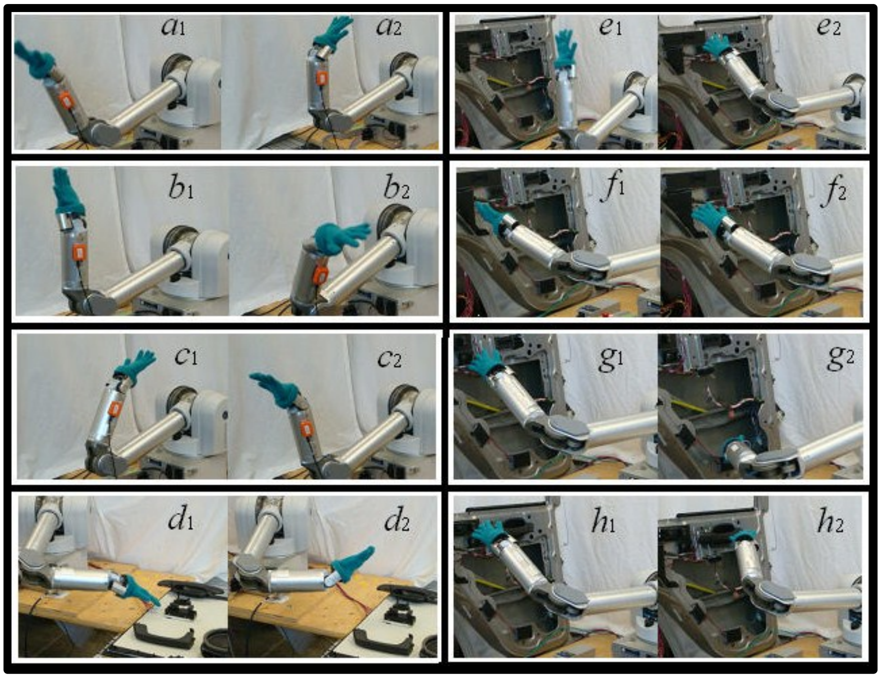

Figure 3. Gestures implemented on the Barrett WAM arm – "Move Forward" (a), "Move Left" [and Right] (b), "Move Backward" (c), "Pick up" (d), "Place" (e), "Reorient" (f), "Reposition" (g), and "Swap" (h).

The Xsens sensors capture 3-D linear accelerations. We compared the magnitude of the acceleration to a threshold, equal to 10% of the maximum acceleration measured signal (from the robot arm and each individual subject), to detect the motion start times and thus measure T_R.

An example of this procedure is shown in Figure 5 for the "Move Left" gesture. Explicit rules for the experiment restricted subjects from making random movements; however, we video recorded all sessions and evaluated the response times to handle cases where multiple movements or no movements were apparent in the Xsens data. Subjects were instructed as follows:

1- Stay at your current position and do not move unless instructed by the robot (by expressing communicative gestures).
2- Start doing your task as soon as you know what the robot is telling you; you don't need to wait for the robot to stop moving.
3- You can only make one motion at a time. You can only hold one part at a time.

These rules were imposed in order to i) limit human motions to the task-related motions, and ii) detect the exact moment when humans understand and respond to each robot gesture. Signals from all sensors were synchronized in real time on a Windows machine using Quanser QuaRC™[5] and MATLAB Simulink™ with 100 Hz sampling rate. The Barrett WAM arm was operated by an external Linux machine running Xenomai[6] and the btclient[7] library.

[5] Quanser Inc., Markham, Ontario, Canada.
[6] www.xenomai.org/
[7] Barrett's robot control client software.

HRI Experimental Task and Procedure

In total, 12 participants (3 female, average age 23.9) volunteered for the study. Prior to interacting with the robot, the subjects were asked to fill out a questionnaire regarding their demographic information (e.g., age, gender, etc.), as well as their familiarity in interacting with robots (average reported familiarity with robots was 1.8 out of 5). Participants had no previous experience with robotic gestures. Although our participants had no experience with industrial assembly technology, we expect that our results can be generalized to assembly workers, as our study focused on gestural interaction and not on the details of the assembly task.

Real-time human-robot interaction task

The subjects' primary task was to place parts onto a car door while the robotic arm used communicative gestures to give instructions and directions. This task had two steps.

Phase 1, *Gesture introduction*: Each subject was familiarized

Figure 4. Experimental setup for human-robot interaction study.

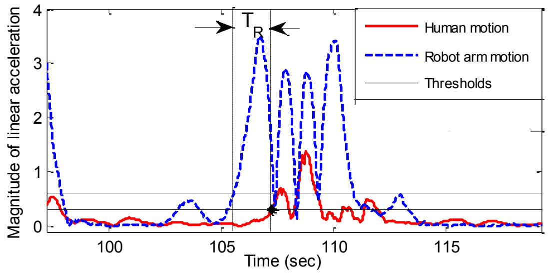

Figure 5. Response time (T_R) detection based on the robot and human movements – example for the "Move Left" gesture.

with the task through a real-time scenario during which all nine gestures were used in the same order. This introduction was used to evaluate human recognition rates for all gestures in the same ordered task context, as well as introducing subjects to the gestures for the next phase of the task. If the participants responded with an incorrect action or did not understand the meaning of a gesture, the experimenter described the meaning of the gesture and corrected any errors.

Phase 2, *Gesture utilization*: the experimenter ran a set of scripted real-time tasks, randomly utilizing all nine gestures, five times each. It was expected that after the introductory task, subjects would be able to identify each gesture. We measured human response times to all gestures during the experiment. In scenarios where a subject was too close to the robot or to one of the sides of the work area, incompatible gestures were not shown for safety reasons and context compatibility, resulting in some gestures being presented only four times.

Posthoc Survey Questionnaire

After the two phases of the real-time HRI task, one instance of each gesture was replayed on the robot, and the subjects were asked to answer the following questions: 1) "What did you think the robot was trying to indicate"; if the subjects misunderstood a gesture during the introductory scenario, they were asked to provide us with what they originally thought it meant, and 2) "How easy was it for you to understand the robot (on a scale from 1(easy) to 5 (difficult))". Subjects were also asked to provide suggestions on how to improve the gestures and describe any confusion they may have experienced.

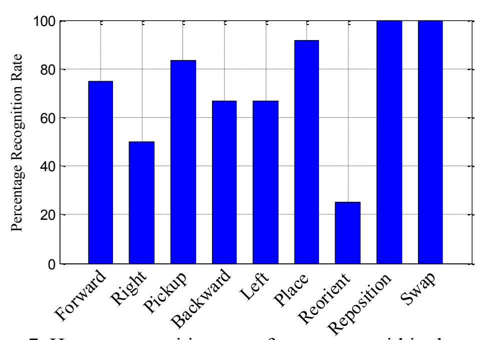

Figure 7. Human recognition rates for gestures within the task context (In order of appearance).

IV. Experimental Results

A. *Results from Statistical Analysis*

A1. Recognition rates and difficulty levels

Figure 7 shows recognition rates for each gesture in the introductory task. Gestures that required fingers for pointing, i.e. "Part Pick up", "Place Part", "Reposition" and "Swap", are well understood by the subjects even though no finger actuation was used. However, the "Re-orient" gesture was understood in only 25% of cases. "Move Right" and "Move Left" are symmetric gestures but had different recognition rates. We surmise that the difference in initial recognition rates between these two identical gestures is due, in part, to the gesture presentation order ("Move Right" appeared before "Move Left" in the introductory section). The scope of this confounding factor is limited to only the recognition rates of these two symmetric gestures. In addition, the task itself and context are contributory; the "Move Right" gesture was either not understood at all or completely understood; in the latter case, participants moved towards the parts table and waited for the robot to show them the right part.

A few subjects, however, interpreted the "Move Left" gesture as "Part Placement" on a space on the door close to the robot arm; this confusion could be due to the relative location of the robot and the car door in the work space. In general, the participants' gesture difficulty ratings (Figure 6) were consistent with gesture recognition rates (Figure 7), with high recognition rates corresponding to low average difficulty ratings. A repeated measures ANOVA shows that at least two of the gestures are different in terms of difficulty level ($p<0.001$). Pairwise comparisons between different categories of gestures shown in Figure 8 (A: Human motion gestures, B: Part displacement gestures, and C: Part re-orientation gestures), reveal that part displacement gestures (B) are recognized significantly easier than human motion (A) and part reorientation (C) gestures ($p<0.05$). However, the `difference between recognition rates for A and C gestures is not statistically significant[8].

A2. Response Time Measurements

In this section, we report on the relationship between the response times to specific gestures and gesture motion segments, revealing the communicative content that helps

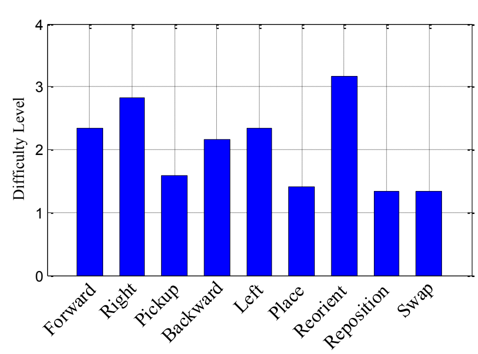

Figure 6. Difficulty level scaled from 1(easy) to 5(difficult) for each gesture aquired from posthoc surveys (In order of appearance).

[8] Statistical significances of all pairs were tested using a Wilcoxon signed rank test as well as a t-test paired sample test.

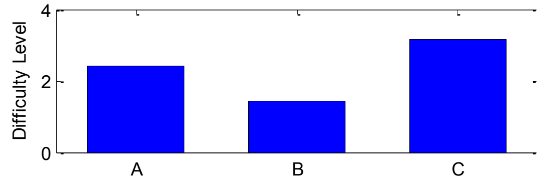

Figure 9. Reported difficluty level for different categories of gestures. A) Human motion gestures, B) Part manipulation which involve part movement, and C) Part manipulation gestures which involve part re-orientation.

humans understand, recall, and respond to each gesture. In particular we investigated which segments of a gesture have the greatest communicative content. We measured response times of all subjects to different gestures, randomized through the second phase of the real-time interaction scenario after the initial introductory task[9], as discussed in Section III-B3. This extensive response time study, which consists of more than 500 response times in total, revealed that humans respond to different gestures at different rates depending on i) gesture type, and ii) context.

Based on initial observations, we segmented gesture motions into *acceleration ramps* demarcated by acceleration extrema, which we call *pauses* in this paper. Each pause represents a trajectory point with minimum velocity. Figure 9 shows an example of gesture segmentation for the "Move Left" gesture. In order to find whether a particular pause or segment of a motion included the most communicative part of a gesture, we studied the distribution of response times with respect to the gesture pauses over the period of each gesture.

Figure 10 shows the distribution of the response times for all participants. As can be observed from this figure, response times are mostly distributed around one or two consecutive pauses of each gesture. For some gestures, such as the "Move Backward" gesture, the first pause of the gesture (Figure 3-c1) is of most importance, and response times of all subjects are mainly distributed around this pause. This demonstrates that participants were able to remember and recognize this gesture from its first few segments. Once humans recognize a gesture, they respond to it after about 300 *msec*, average human reaction time to an expected stimulus [12]. This clear relation, however, is not observed for some other gestures including the "Move Forward" and "Re-orient" gestures. Our findings suggest that some gestures, such as the "Move Backward" gesture, are more discriminable by their initial segments. Future work will focus on discriminability analysis, similar to [13], to optimize differentiability between the desired cues, and to provide a set of distinct, recognizable gestures.

Analysis of response times revealed that most of the subjects tend to "follow" robot movements; meaning that they respond to a gesture when the robot arm is moving in the direction which is the objective of robot command. For instance, participants typically responded to the "Move Backward", "Move Left", and "Move Right" gestures when the robot arm was moving towards the same direction, that is, during the second segment of these gestures.

Therefore, our analysis shows that specific segments of a gesture include most communicative information about that gesture, and thus, are essential while the remainder of the

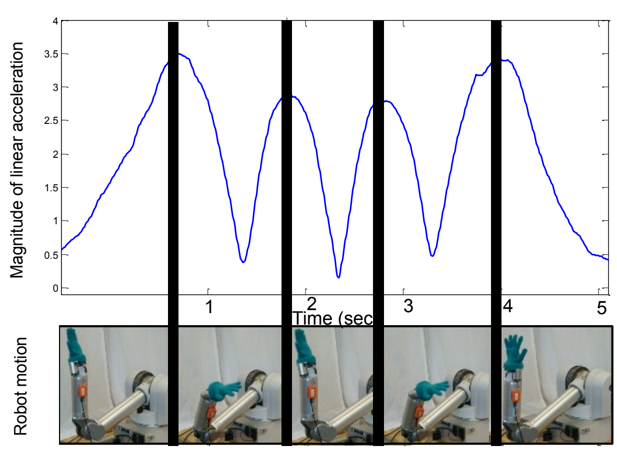

Figure 8. Gesture segmentation – example for the "Move Left" gesture. Each frame shows the robot pose at the end of the corresponding segment.

[9] Three scenarios were observed in which subjects did not remember the meaning of a gesture during Phase 2 of the real-time task; these cases were removed from the response time analysis.

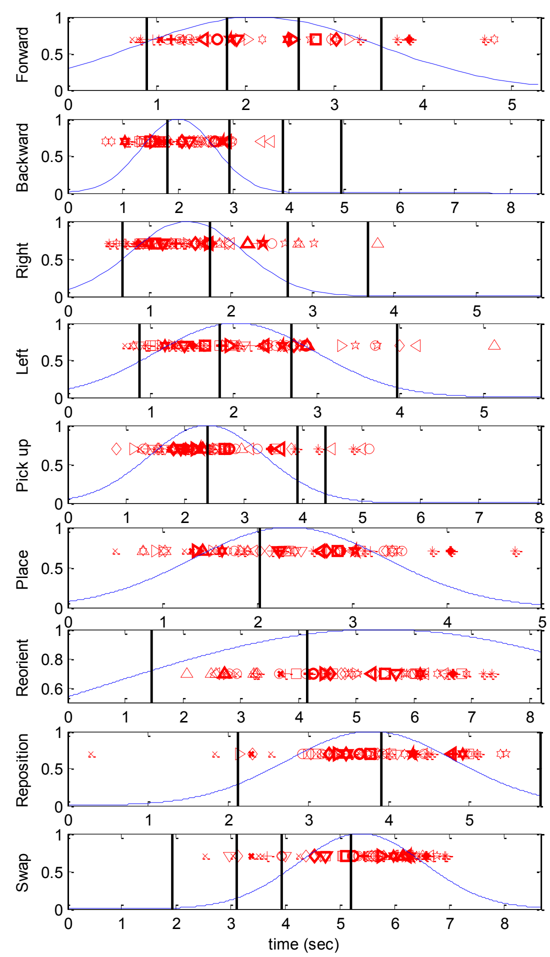

Figure 10. Scatter plot and Gaussian distribution of response times to all gestures with respect to the motion segments and pauses. Vertical lines indicate pauses in the gesture trajectories. Response times for different subject are represented by different shapes.

motion could be truncated, if necessary, to allow the robot to move on to its next action and reduce execution time, improving task effectiveness [14]. This knowledge of critical and less important gesture elements can help us design for better task flow and smoother interaction in the future, although the effects of gesture truncation on recognition rates and operator training will require additional study.

B. Results from Interviews and Observations

Interviews with participants elicited important information regarding different gesture types. As reported by Ende et al. [6], context and task flow are important factors that affect gesture recognition by humans. Two of the participants were not able to understand the "Part Placement" gesture during the post-hoc survey, when the gesture was presented out of context, although they recognized and responded to it correctly during the real-time introductory assembly task. The analysis of response time also confirms this finding: although "Move Left" and "Move Right" are symmetric gestures, the response times of humans are different for these two gestures. The assembly was taking place on the left side and hence the "Move Left" gesture was, sometimes, misinterpreted as part-related gestures.

From our observational evidence we also noted that people tend to follow robot movements; this is supported by findings from our analysis of response times, as described previously. Although we explicitly asked the subjects not to move unless instructed by the robot, most of the participants moved back to the start point located in front of the robot and assumed a neutral pose after finishing their task. In other words, subjects may have interpreted the robot's movement to the neutral pose as a motivation for moving back to the start point themselves. Also, the angle at which a specific gesture is viewed is important. Two of the participants explicitly mentioned that they might have recognized a gesture if they had seen it from a different point of view.

Another important finding of the study was that, although people tend to use fingers in part displacement cues, they could understand corresponding robot gestures with no finger actuation, e.g. when robot points to an object with the entire hand.

V. Conclusions and Future Work

In this paper we studied the effect of human-like gestures in a real-time vehicle assembly scenario and investigated human recognition rates and response times.

Task-based human-like gestures were implemented on a single-arm robotic assistant. Given an assembly scenario, our study shows that humans can recognize and understand part displacement gestures more easily compared to human motion gestures and part re-orientation gestures. Analysis of human response times to various gestures revealed that specific segments of a gesture motion include the greatest communicative content. People are able to interpret gestures from these critical segments alone, without waiting for the gesture to be completed. Future work will use this information in order to design for enhanced task flow.

Acknowledgment

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The study was approved by the University Behavioural Research Ethics Board, approval number H10-00503-A020.

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