

Human-Inspired Communicative Cues for Intent Expressive Motion Generation

by

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**Human-Inspired Communicative Cues for
Intent Expressive Motion Generation**

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and have found that it is complete and satisfactory in all respects,
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To beloved mom and dad

ABSTRACT

This thesis, inspired by the joint action literature, utilizes subtle, non-verbal kinematic changes that are not consciously recognizable in human motion called “communicative cues” to improve intent expressiveness of robot motion. Towards this end, this study first identifies two temporal and two spatial communicative cues through a human-human experiment ($n = 14$) and evaluates their utility in a simulated robot experiment ($n = 30$). After verifying the efficacy of communicative cues for generating intent expressive robot motion, an automated intent expressive motion generation framework is developed that handles the communicative cues through cue parameters. Via utilization of this motion generation framework, the communicative cues’ efficacy in real world human-robot interaction scenarios is verified and their robustness in different viewpoint and object configurations is evaluated in a human-robot experiment ($n = 34$). As the cue parameters are chosen manually in the human-robot experiment, an active reinforcement learning methodology is utilized to enhance the motion generation framework. Through a follow up human-robot learning experiment ($n = 30$), the proposed method is analyzed and it was seen that the robot can come up with user-specific cue parameters. Furthermore, a final human-robot experiment ($n = 11$) revealed that there might also be universal cue parameters that improve intent understanding for all users. This thesis contributes to the body of literature through investigation of human motion to identify the communicative cues, verification of the cues through a two-layer systematical analysis and evaluation of their robustness in different viewpoint and object configurations. Furthermore, an intent expressive motion generation framework is developed and it is enhanced with active reinforcement learning to achieve an improved intent expressive motion.

ÖZETÇE

Bu tez, ortak eylem psikolojisi literatüründen ilham alarak, “iletişimsel ipuçları” adı verilen, insan hareketinde ilk bakışta göze çarpmayan, sözsüz kinematik değişiklikleri robot hareketlerinde niyet belirtimini artırmak için kullanılmaktadır. Bu doğrultuda bu çalışma, ilk olarak iki zamansal ve iki uzaysal iletişimsel ipucunun saptandığı bir insan-insan deneyi ($n = 14$) gerçekleştirir ve bir simüle robot deneyi ($n = 30$) vasıtasıyla bu iletişimsel ipuçlarının kullanılabilirliğini sınar. Çalışma, iletişimsel ipuçlarının, robot hareketlerinde niyet belirtimini artırdığını doğruladıktan sonra, iletişimsel ipuçlarını, ipucu parametreleri aracılığıyla kullanan, otomatikleştirilmiş bir niyet belirtici hareket yaratım çerçevesi geliştirir. Bu hareket yaratım çerçevesini kullanarak, iletişimsel ipuçlarının, gerçek dünyada insan-robot etkileşimi senaryolarında da kullanılabilirliği bir insan-robot deneyi ($n = 34$) ile kanıtlanmış, farklı bakış açıları ve nesne düzenlerine karşı gürbüzlüğü de sınanmıştır. İnsan-robot deneyinde ipucu parametreleri elle seçilmiş, hareket yaratım çerçevesi bu eksikliği kapamak için bir aktif takviyeli öğrenme metoduyla güçlendirilmiştir. Bunu takiben, bir öğrenme deneyi ($n = 30$) ile önerilen yöntem incelenmiş ve robotun kullanıcıya özgü ipucu parametreleri öğrenebildiği görülmüştür. Son bir deney ($n = 11$), tüm kullanıcılarda niyet anlamayı güçlendiren, evrensel ipucu parametrelerinin varlığını ortaya koymuştur.

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Chapter 1

INTRODUCTION

Considering the robots' convergence to co-existence with humans, the area of robotics is at the verge of a paradigm shift: Now that the robots are slowly entering our homes, hospitals, schools and offices, they cannot be considered as sole industrial production tools. As the user preferences, expectations and tech comprehension differs, this ubiquitous presence of robots presents new aspects to investigate in human-robot interaction (HRI) and collaboration, one of which is intent communication in shared work spaces. In such scenarios, it is imperative that the human user(s) understand what their robotic partner is doing. This understanding will lead to fluency and thus, better efficiency and task outcome. Soon, many people will work alongside robots in shared work spaces, however very little of them will have knowledge in robotics. The aim of this thesis is to reduce the gap regarding intent communication between the humans and robots during collaborative scenarios, by improving intent expressiveness of the robot, for the humans to achieve a better understanding of the robot's intent¹.

Explicit verbal or visual cues can be very successful in communicating intentions. Consider the scenario of picking a hammer up. The intent communication can be done by explicitly saying "I am reaching for the hammer" to a partner, or by shining a laser on the hammer. However, verbalizing something is not time-efficient and may lead to misunderstandings if the environment is noisy. Providing an explicit visual cue requires extra hardware and may go unnoticed if the other partner is not looking at the right direction. Another option is to use the motion itself to express intent,

¹We define "intent" as the action that will be executed or the target object of such an action.

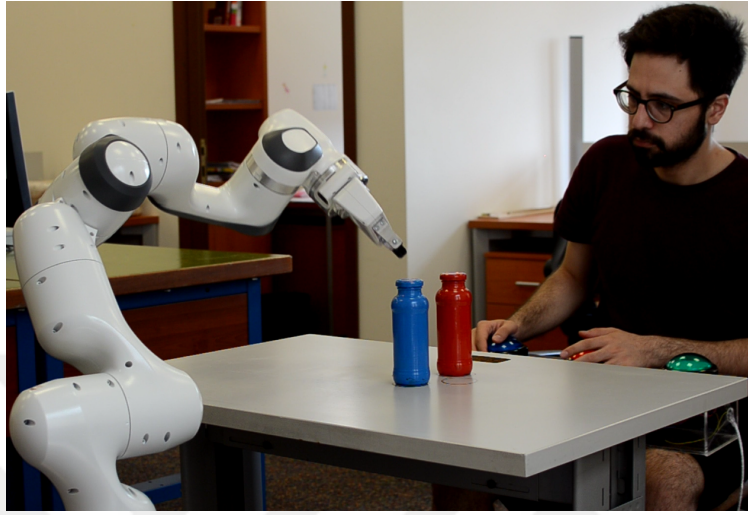


Figure 1.1: A participant guessing which object the robot is reaching towards. The participant makes his guess using the buttons located on his lap.

through subtle changes in the spatial, temporal, morphological or force related aspects of the motion. [Sebanz et al., 2006] argue that humans are very good at naturally and effortlessly generating intent expressive motion in the context of joint action. We argue that the robots should use the same channel to communicate their intent to their human partners.

Several human-robot interaction and joint action studies have investigated the problem of intent expression through motion kinematics, e.g, [Dragan et al., 2013] introduced the term “*legible motion*” which is widely used in the literature (see Ch. 2), [Donnarumma et al., 2017] utilizes “sensorimotor coarticulation” and “signaling” in the generated actions to improve intent recognition of an observer. In this thesis, we call all motions that facilitate the intent recognition process as “*intent expressive motions*” and we are interested in intent to act on and object vs. another as seen in Fig. 1.1.

Humans excel at recognizing underlying intentions of actions in human-human collaborative work spaces. However, there are very few studies that investigate what makes humans this good at intent expression and most of these studies belong to the joint action literature. Human-robot interaction studies rely on algorithms to

improve intent expression of the robots: They look at either engineered cost functions or different motion principles (e.g. straight vs. curved/exaggerated motions). These approaches are also tested in very constrained conditions such as a single observer viewpoint and a single object configuration. Furthermore, the existing studies disagree with each other in different testing conditions, different robot anthropomorphisms and the respective experimental setups. Instead of following a similar path, we follow the lead of joint action literature: We take human motion as a commencement point and test our approach in rigorous conditions (i.e. multiple observer viewpoints and multiple object configurations).

Based on the joint action literature, we argue that there are subtle, non-verbal kinematic changes that are not consciously recognizable in human motion that improve intent expressiveness. These kinematic changes can be in either temporal, spatial, morphological or force related aspects of motion. For the purposes of this thesis, we call these subtle kinematic changes in motion as “*communicative cues*” and we argue that once identified, the communicative cues can be injected in robot motion trajectories to improve intent expressiveness of the robot motion. We further argue that the communicative cues can both be calibrated to be universal for all users or be optimized for any user to achieve user-specific intent expressive motion through active reinforcement learning.

We start by investigating human-human interactions through a human-human experiment (HHE) to identify two temporal and two spatial communicative cues that can be incorporated in robot motion: (1) An increase in overall motion duration (OT), (2) An earlier maximum hand aperture relative to the motion duration (MA), (3) Exaggeration in motion (Exg) and (4) A change in grasp modality (GM). We follow this identification with a simulated robot experiment (SRE) to show that the communicative cues and their combinations facilitates the recognition of robot’s intention by human users. At this point, we develop a framework that automates intent expressive motion generation through parameterization of communicative cues. We make use of the motion generation framework in a follow-up human-robot interaction

experiment (HRE) and verify that a combination of the cues we have identified is robust to changes in object and viewpoint configurations. Seeing the cues' efficacy and motivated by the possibility of manually chosen cue parameters' sub-optimality, we enhance our intent expressive motion generation framework with an active reinforcement learning methodology based on Policy learning by Weighting Exploration with the Returns (PoWER, [Kober and Peters, 2009]). Augmented with learning capabilities, we enable the motion generation framework to come up with user-specific cue parameters. The success of this learning approach is evaluated through a two-phase human-robot learning experiment (LE): we verified that our robot can learn participant-specific cue parameters through the active reinforcement learning methodology in the first phase of the learning experiment, and in the second phase we reveal that the means of the learned participant-specific parameters also improve the intent expressiveness of robot motion. This second finding points towards the possibility that the universal cue parameters actually exist. Overall, 119 people have participated in five experiments we have conducted to identify, verify and utilize the communicative cues for intent expressive robot motion.

1.1 Thesis Statement

Human-inspired kinematic communicative cues can be used to learn and generate intent expressive robot motion that is robust to changes in object and viewpoint configurations, in turn improving intent recognition of human users compared to straight motions.

1.2 Summary of Contributions

This thesis introduces and evaluates the efficacy of “communicative cues” for intent expressive robot motion, making these contributions:

1. **Human-Inspired Communicative Cues for HRI:** Based on the joint action literature and inspired by humans, this thesis introduces the concept of

“communicative cues” for generating intent expressive robot motion to the field of HRI. Through *HHE* (conducted with 14 participants), we identify two spatial and two temporal communicative cues. We verify the cues’ utility through the *SRE* (conducted with 30 participants) and the *HRE* (conducted with 34 participants). Furthermore, we use the cues to come up with cue parameters that can be used to generate and learn intent expressive motion in the *LE* (conducted with a total of 41 participants in two separate phases). The human-inspired communicative cues have proven to be valuable for intent expression, passing through several stages of rigorous evaluation.

2. **Robustness of Cue-based Intent Expressive Motion:** The algorithmic intent expressive methodologies in the literature disagree with each other in different experimental setups. The robustness of our approach is tested in different object and viewpoint configurations through the *SRE* and the *HRE* to see that a combination of all cues is robust to changes in the environment.
3. **Automated Intent Expressive Motion Generation:** This thesis presents a communicative cue formulation that is based on cue parameters. Provided the (now parameterized) cues, our intent expressive motion generation framework automates the communicative cue based motion generation process and the utility of this framework is proven in the *HRE* and the *LE*.
4. **Learning Intent Expressive Robot Motion:** Our automated intent expressive motion generation framework requires cue parameters as input and choosing the input parameters by hand suffers from the presumption of suboptimality. In this thesis, we approach the cue optimization problem from a reinforcement learning perspective, utilizing one of the perks of the parameterized communicative cue formulation to our advantage: We consider the motion generation process as a policy that is based on the cue parameters. We search for optimal policy parameters through an extensive exploration in the parameter space and PoWER updates. The intent expressive robot motion is optimized through active feedback from the user, in turn, generating participant-specific intent

expressive motion. The usefulness of our approach is proven through the *LE*.

5. **User-Specific and Universal Cues:** This thesis further contributes to the literature through introduction of two types of communicative cues. We identify user-specific cues through active reinforcement learning, based on user feedback. Then, we further investigate for universal cues that improve intent expression of a robot for all users in the second phase of the *LE*. We see that the means of participant-specific parameters from the first phase of the *LE* provide an equivalent improvement in intent recognition of the participants signaling that there might be universal cues.

1.3 Outline

The remainder of this document is structured as follows:

- Ch. 2 explains the current state of intent communication by going over the literature on intent expressive motion generation, human-human experiments and the human-inspired approaches in intent communication.
- Ch. 3 describes our human-human experiment, its results and the identified communicative cues.
- Ch. 4 presents our simulated robot experiment, its results and utility of the identified communicative cues. Furthermore, this chapter presents an initial investigation on object configuration's effect on intent expression.
- Ch. 5 presents our intent expressive motion generation framework, how the communicative cues are parameterized and how this parameters are incorporated in motion generation.
- Ch. 6 describes the human-robot interaction experiment, how the cue parameters are selected to resemble human motion, the robustness of the combination of cues to object and viewpoint configuration and some other observations related to the field of human-robot interaction.

- Ch. 7 describes how the communicative cue formulation can be utilized in an active reinforcement learning methodology to achieve a method of user-specific intent expressive motion generation, how the PoWER updates are achieved and how the exploration is conducted.
- Ch. 8 explains the learning experiment, verification of the learning methodology, user-specific cue parameters, universal cue parameters and the experiment results.
- Ch. 9 concludes the document, explains the contributions, talks about the secondary observations we have made during the experiments and possible future directions.

Chapter 2

BACKGROUND

2.1 *Intent Communication in Robotics*

There are several studies regarding intent communication in the human-robot interaction literature. For the sake of this thesis, we divide the intent communication studies into intent expression and intent recognition.

Most of the intent expression literature is exploratory in nature, generally taking inspiration from or comparing against the animation methods where the influential *The Illusion of Life: Disney Animation* book by [Johnston and Thomas, 1995] is commonly referred to. [Dragan et al., 2013] define “legible” and “predictable” motion trajectories based on cognitive studies. In their work, they develop cost functions according to the predictability and legibility notions they have established. [Dragan and Srinivasa, 2013] optimize generated trajectories according to these developed cost functions for investigating optimal intent expressive motion generation. [Dragan et al., 2015] demonstrate how legible motion improves collaboration efficiency and how minimum effort motion may hinder fluency. [Busch et al., 2017] develop a model-free reinforcement learning methodology to generate legible motion trajectories and utilize two different policy representations to create legible motion. In both studies, the legibility notion ended up generating *exaggerated* motion trajectories. The principle of exaggeration is used extensively in animation to communicate a character’s intent or mood as described by [Johnston and Thomas, 1995]. However, how much exaggeration to produce is not clear in any of the aforementioned studies. Furthermore, the observer view-point is not taken into account. The question of whether humans actually use exaggeration to express intent or not is also an open one.

The effect of exaggerated motion in intent expression is further analyzed by [Zhao

et al., 2016] and [Bodden et al., 2016]. [Zhao et al., 2016] generate three different trajectories; (1) “*simple*”, (2) “*curved*” and (3) “*straight*” for intent expressiveness and compare them. The first two of these motions are defined as “predictable” and “legible” respectively, by [Dragan et al., 2013]. At the end, [Zhao et al., 2016] demonstrate that “straight” motions improve intent expression more than their “curved” siblings. [Bodden et al., 2016] further questions the two studies by [Dragan et al., 2013] and [Zhao et al., 2016], and compare the motions defined in these studies. They conclude that there is no optimal solution to the intent expression problem yet; “simple” and “straight” motions may be as expressive as the “legible” motion depending on the robot’s anthropomorphism. We further argue that the observer view-point and the environment configuration is also relevant.

The aforementioned studies altered spatial aspects of motion to generate intent expressive motion. [Gielniak and Thomaz, 2011] demonstrate that both temporal and spatial aspects of motion might improve intent communication. They define spatio-temporal correspondence (STC) as a metric through observations of human motions. [Gielniak and Thomaz, 2011] also show that optimization of the temporal aspects of motions via STC improved (1) recognition of motion as a common human motion, (2) accuracy of intent identification, and (3) accuracy of mimicking compared to non-optimized motion. Throughout their study, human motion data is utilized to identify STC and their results indicate that an investigation of human motion can be helpful in designing intent expression.

There are similar studies in robot navigation, usually referred to as “socially acceptable navigation”, such as [Kruse et al., 2012] and [Avrunin and Simmons, 2014]. Both of these take inspiration from human-human interactions and will be mentioned again in Sect. 2.2.

There is also a large body of work in the field of intent recognition, see the survey presented by [Herath et al., 2017] for further details. This field spans multiple disciplines but it mainly concerns the computer vision community. The existing literature concentrates either on still images or videos, with the intent of recognizing actions

from a diverse set such as running and swimming. Although recognizing human intent would be valuable for robots and that our human-human interaction study (Ch. 3) gives us some insights, the presented work only focuses on intent expression by a robot.

2.2 Communicative Cues in Humans for HRI

The existing literature on human-human studies for robotic intent communication is sparse but it is especially so for arm motion generation compared to gaze, navigation and haptics. Most relevant studies about arm motions are from psychology (i.e. the joint-action literature).

Human-human interaction has been explored in the context of force based collaboration tasks, such as carrying and positioning a big object. [Reed et al., 2004] present one of the first studies in this area from a robotics perspective. There are studies that look into human-human haptic interactions specifically for studying intent in the context of HRI such as the work presented by [Groten et al., 2013]. They observe that humans heavily rely on the haptic channel for intent communication. A labeled HHI dataset for dyadic joint object manipulation, collected from a robotics perspective, is given by [Madan et al., 2015].

Gaze is another modality that is used for intent expression. [Mutlu et al., 2009] use gaze to “leak” information about robot’s intentions and show that humans can read the associated cues. [Moon et al., 2014] use robot’s gaze to communicate the hand-over location, their approach inspired by human-human hand-overs. These show that gaze can be a channel for intent communication and human data can be utilized to learn the necessary subtle cues.

Humans use gaze extensively to communicate. There are several studies that aim to recognize human’s intent from gaze. [Huang et al., 2015] trained an SVM to predict which ingredient a customer will order based on gaze. This can be extended to HRI to predict the object of an action. Gaze is an important modality in both HRI (see the review by [Admoni and Scassellati, 2017]) and Human-Computer Interaction (see

the review by [Poole and Ball, 2006]), and a lot of methods use human data to build models and make predictions.

The socially acceptable navigation studies mentioned in Sect. 2.1 look at human behavior to design robot navigation behavior; [Kruse et al., 2012] develop a cost model for navigation planning with inspiration from how humans behave when their paths cross and [Avrunin and Simmons, 2014] introduce an attractor model based on how people approach other people. The latter study uses “straight line” as a baseline and observe that this is not good for approaching people from behind. Their approaches are along the lines of our arguments; looking at human-human interaction to improve human-robot interaction.

[Nagai and Rohlfing, 2009] investigated human caregiver-infant interactions to identify the changed aspects of motions when teaching actions to infants. In their cognitive developmental study, they identified that the parental action demonstration incorporated higher roundness of movement, longer pauses and closer distance to the infant. [Nagai and Rohlfing, 2009] introduced this motion characterization as “*motionese*”. [Ugur et al., 2015] leaned towards the attention of infants to their caregivers’ highlights. They found out that the parents tend to modify their motions, i.e. parents utilized “*motionese*”, when their action is directed towards the infants. [Ugur et al., 2015] further showed that parental scaffolding is an important mechanism that speeds up the motion learning process not only in infants but in robots’ grasp and imitation learning.

Communicative motion cues in collaborative human-human interactions are analyzed in the joint action psychology literature. Several studies investigate and experiment with human reach-to-grasp motions. [Becchio et al., 2008] investigate the effect of social intent on motion, [Becchio et al., 2012] demonstrate that the information encoding motion intent is available in motion kinematics, and [Sartori et al., 2011] argue that this information can be inferred from certain communicative cues in motion. [Donnarumma et al., 2017] provide evidence that these motion cues are automatically generated in sequential actions such as a reach-to-grasp followed by a

grasp-to-pour. [Donnarumma et al., 2018] show that communicative signaling can increase the quality of human-robot interactions.

More specifically, [Sartori et al., 2009] analyze the conscious, non-exaggerated efforts in motion that make the actions intent expressive. They claim that, this effort would amplify the subtle cues in motion, making them more observable. They conduct two separate experiments with a marker-based motion capture setup to identify the subtle cues in intent expressive reach-to-grasp motions. They observe deviation from the non-communicative trajectory, time of maximum hand aperture and time of peak closing velocity as communicative cues.

Reaching to an object is a common component in many actions. In a shared workspace with many objects, it is important to understand which object is being reached to. For example the interaction partner can help, get out of the way or infer the next steps. These reasons prompted us to do a similar experiment from an HRI perspective to the one [Sartori et al., 2009] did, as a starting point. Our aim is to replicate some of their results and to identify additional cues that robots can utilize. We modify [Sartori et al., 2009]’s experiment to be conducted in a less intrusive environment for the participant by removing marker-based motion tracking in our human-human experiment.

Chapter 3

HUMAN-HUMAN EXPERIMENT

In joint tasks, human-robot interactions are not as fluent as human-human interactions yet, since robots are not as effective in intent expression as humans. Our claim is that, this hurdle can be overcome by investigating human-human interactions and implementing a methodology that somewhat recreates human-like intent expression. As demonstrated by several joint action studies (see Sect. 2.2), motion intent is hidden in motion kinematics and there are some subtle *communicative cues* that are conducted by humans when expressing intent.

In this experiment¹, we aim to identify communicative cues in human reach-to-grasp motions, looking from an HRI perspective. We investigate how humans reach-to-grasp a cylindrical bottle from a table when there is another bottle in close vicinity. Several studies in both robotics and joint-action literature, such as the ones done by [Dragan et al., 2013] and [Sartori et al., 2009], analyze a similar scenario. In this experiment, we modify [Sartori et al., 2009]’s experiment to be conducted in a less intrusive manner, by removing the marker based motion tracking. Our experiment has two conditions; With (test) and without (control) an observer present. We follow a within-subject design through a counter-balanced order; all the participants perform the experiments in both conditions.

This experiment was approved by the Internal Review Board (IRB).

3.1 Participants

The experiment was conducted on 7 male and 7 female participants. The median age was 21.5. All of the participants were Turkish citizens from a university campus

¹The details of this experiment was also published in [Kebüde et al., 2018].



Figure 3.1: Human-human experiment setup as viewed from the video camera.

community. The robotic experience of the participants varied: 9 of them stated that they had no experience, 4 of the participants have watched robot videos online or had minor interactions with robots, and 1 of them stated that he has worked with robots but the nature of that work was not research related.

3.2 Experimental Setup

The experimental setup consists of two cylindrical bottles on a table for the participant to reach to grasp, and a camera (Fig. 3.1). The experimenter and the participant are positioned on opposite sides of the table and the entire experiment is recorded. The camera is placed diagonally to avoid influencing the participant with a direct facing camera. The location of the camera depends on participant's handedness, i.e., if the participant is right-handed, the camera is placed on their right diagonal and vice versa. Two cylindrical bottles, one filled with water and the other with tea, are placed on the table 5 cm apart within the participant's reach, in different configurations.

There are four different bottle configurations for the participant to reach, grasp, take and put back: (1) Side-by-side (Fig. 3.2a), (2) diagonal, to partially block participant's reaching motion (Fig. 3.2b), (3) one-in-front, to partially occlude one of

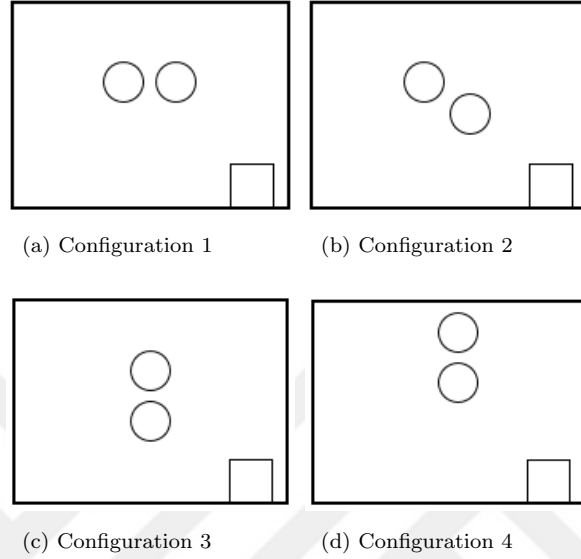


Figure 3.2: Top-view for the configurations of the objects when the participant is right handed and sits facing the bottom edge of each figure. Square at the bottom right shows the initial hand position.

the objects (Fig. 3.2c), (4) one-in-front, the object at the back placed at the edge of participant's reach, to investigate the effects of extra effort on communicative cues (Fig. 3.2d).

3.3 Experimental Protocol

Before the experiment, the participants are given the informed consent form and enough time to go over it. The experiment begins after they sign the form.

The experiment starts with informing the participants regarding the experimental setup and what the experiment requires them to do. The participants are then asked about their handedness to construct the environment and they were also explicitly instructed to always start from a pre-determined initial position at each iteration (see Fig. 3.2), and to always reach with the same hand. For each configuration, we told the participant to repeat the action twice per object, resulting in a total of $4 \times 2 \times 2 = 16$ motions per participant, for a total of 224 for the experiment. The participants follow the order of objects to reach to, based on a list provided on a piece of paper. The

experiment proceeds based on the counterbalance order between the control (without the observer) and test (with the observer) conditions: Half of the participants start with the control case and the other half with the test case.

3.3.1 Control Case

The experimenter is positioned at the opposite side of the participant at the table, pretending to work on his laptop. He does not engage with the participant in any way. The participant signals the experimenter when they are done with a specific configuration. The experimenter switches to the next configuration and keeps on pretending to work on their laptop.

3.3.2 Test Case

The experimenter actively acts as an observer, paying attention to participant's actions. The participants are explicitly asked to communicate their intent as clear as possible with their motion itself, without utilizing their gaze, hand pointing or verbal communication. Experimenter does not provide any feedback to the participant, leading to a completely non-verbal interaction.

3.4 Communicative Cues and Data Collection

The human-human experiment was designed to identify communicative cues hidden in intent expressive reach-to-grasp motions. This identification requires a priori knowledge on changes between non-communicative and communicative human motions. We conducted a pilot experiment to gather information regarding these changes and to verify whether we can observe the cues explained in joint-action literature. We then collected data at the experiment phase about the communicative cues. We also conducted a survey to gather participants' opinion on intent expressive motion generation. The experimental protocol, apart from the survey, was the same between the pilot and the main experiment.

3.4.1 Pilot Phase

The pilot experiment was conducted on 5 participants (4 male and 1 female), two of whom were already aware of the nature of the study and previous work. This led to an observation of communicative reach-to-grasp motions similar to “legible” motions defined by [Dragan et al., 2013], i.e, these two participants exaggerated their motions due to their bias. The pilot phase still generated useful information regarding identification of subtle communicative cues in reach-to-grasp motions. We have observed an increase in overall duration, an earlier maximum hand aperture timing and a change in grasp modality between the control and test cases. We decided to use these as our communicative cues in addition to exaggeration.

3.4.2 Experiment Phase

The pilot phase helped us identify which communicative cues to collect data for. We have conducted a frame-by-frame analysis on the recorded videos by annotation and labeling for data collection. The frames of interest were defined as follows for each reach-to-grasp motion:

- Beginning of motion, t_{start}
- Beginning of hand aperture, t_{open}
- Time to reach maximum hand aperture, $t_{aperture}$
- Time to reach the object ($\sim 40\%$ of opposing digits pass object centroid), t_{reach}
- Time of hand starting to close, t_{close}
- Time of grasping the object, t_{grasp}

As we desired the experiment to be less intrusive, this process is not as accurate as the marker-based motion capture data gathered in [Sartori et al., 2009]. The time frames are still accurate to ± 33 ms (± 1 frame).

Following the observations in the pilot phase, the gathered time stamps were used to calculate three variables:

Overall motion duration, t_{total} : The time frame at which the motion started is subtracted from the time frame at which the hand reaches the object.

$$t_{total} = t_{reach} - t_{start} \quad (3.1)$$

Time to reach maximum hand aperture, t_{max} : The time frame at which the motion started is subtracted from the time frame at which the hand reaches the maximum hand aperture.

$$t_{max} = t_{aperture} - t_{start} \quad (3.2)$$

Relative time to reach maximum hand aperture, r_{max} : As the overall duration of motion was observed to change between control and test cases, time of maximum hand aperture does not seem to be a good variable to be considered as a communicative cue. Instead, we investigate relative time of maximum hand aperture, i.e., at which point of motion the hand reaches its maximum aperture. Hence, a ratio of time of maximum hand aperture and overall motion duration is calculated.

$$r_{max} = \frac{t_{max}}{t_{total}} \quad (3.3)$$

In addition to these temporal aspects of motion, two spatial aspects were investigated qualitatively, following the pilot phase observations. The reason for the qualitative nature of this investigation is the fact that we are not using a marker-based system and as a result a quantitative investigation would not be accurate.

Exaggeration: [Dragan et al., 2013]’s “legible” motion tends to generate exaggerated motions for intent expression. We have also observed during the pilot phase that, the participants who had intimate knowledge of the study exaggerated their motions significantly, while others only did so slightly in the edge cases. [Sartori et al., 2009] also stated a deviation from the straight trajectory to be a good intent indicator. However, the deviation they identified via marker based motion capture data was at most 1.6 cm, which is not measurable through our video recordings. Hence, we looked at qualitatively noticeable ($\sim 15cm$) deviations from the regular human motion

trajectories through experiment videos, i.e., whether *there is* qualitatively noticeable exaggeration or not.

Grasp Modality: As we have observed changes in grasp modality in the pilot phase, we decided to consider this as another potential communicative cue for intent expressive motion. Therefore, we looked at changes in how the object is grasped between the control and test cases, e.g., if the participant grasped the bottle from the side at the control case, they might grasp to bottle from the front or top at the test case.

The identified cues mentioned above can be watched in the annotated video recording of a participant of the experiment, presented in Extension 1 (see App. A).

Survey: In addition to the aforementioned five variables, we collected data from the participants through a survey, conducted at the end of the experiment. We asked two questions:

1. How much did you change your motion during the communicative case? (5 degrees Likert scale question)
2. If you have changed your motion, what were the key aspects you have put importance to? (Open-ended)

3.5 Hypotheses

Being led by the observations made in the pilot phase, we established our hypotheses as follows:

1. Overall motion duration increases in the test case.
2. Maximum hand aperture occurs earlier in the test case.
3. Participants might exaggerate their motion in the test case.
4. Grasp modality might change between the control and the test cases.

Table 3.1: Mean variable values along with t -values and significance results for the left tailed t -tests. Degrees of freedom is 446 for all.

Variables	Ctrl Mean	Test Mean	t	p-values
t_{total}	0.65	0.75	-4.47	$< 5e - 6$
t_{max}	0.47	0.43	1.92	< 0.05
r_{max}	0.70	0.57	8.08	$< 5e - 15$

3.6 Statistical Analyses

We conduct three cumulative left-tailed (due to one-way hypotheses) t -tests on three variables, described in Sect. 3.4, between control and test cases: (1) t_{total} , (2) t_{max} , and (3) r_{max} . These analyses helped us evaluate hypotheses, described in Sect. 3.5, 1 (**H1**) and 2 (**H2**). In addition, we present 95% confidence intervals for the differences between the control and test cases, for the three variables mentioned above. Hypotheses 3 (**H3**) and 4 (**H4**) were evaluated quantitatively through number of times exaggeration and changes in grasp modality was observed.

The results of the t -tests are shown in Tbl. 3.1 and the confidence intervals in Fig. 3.3.

3.7 Hypotheses Evaluation

Overall motion duration t_{total} : We observe a statistically significant increase in the overall motion duration with mean 650 ms in the control case vs 750 ms in the communicative case with $p < 1e - 5$, as presented in Tbl. 3.1. This result supports the first hypothesis in Sect. 3.5. Fig. 3.3 present the 95% confidence interval, confirming this increase as shown in Fig. 3.3.

Time to reach maximum hand-aperture t_{max} : Our results show a weak significance for a decrease in time to reach maximum hand-aperture between the control case and the test case with mean 467 ms. for the control case vs. 430 ms. for the communicative case. The difference between two cases is 37 ms which is nearly

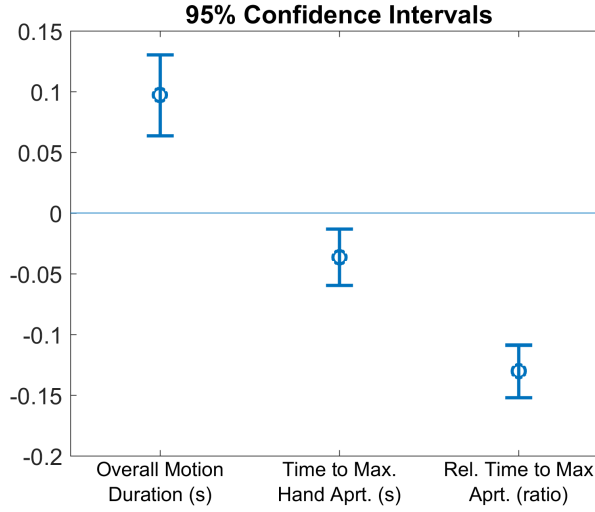


Figure 3.3: 95% confidence intervals for differences between overall motion durations (s), differences between time to maximum hand aperture (s) and differences between relative time to maximum hand aperture ratios.

within one time frame error. Due to the weak significance and the error being nearly within one time frame, we do not consider time to reach maximum hand aperture by itself to be a useful communicative cue.

We test this variable as it was used by [Sartori et al., 2009]. [Sartori et al., 2009]’s findings showed that the maximum hand aperture is achieved later in the test case, as opposed to our results. This discrepancy might be caused by cultural differences between the participants or the differences between the experimental task and setup (markerless vs marker-based data collection).

Relative time to reach maximum hand aperture r_{max} : We argue that the relative time to maximum hand aperture is a more robust clue as to whether hand aperture timing is a communicative cue or not. Our experimental results show that there is a significant decrease in the relative hand aperture timing between the control case with mean 71% and the test case with mean 59% with $p < 1e - 5$ (see Tbl. 3.1). In other words, the maximum hand aperture occurs earlier when there is an observer present. This decrease in relative timing is also confirmed in the Fig. 3.3.

Exaggeration: We did not observe many cases where the participants exagger-

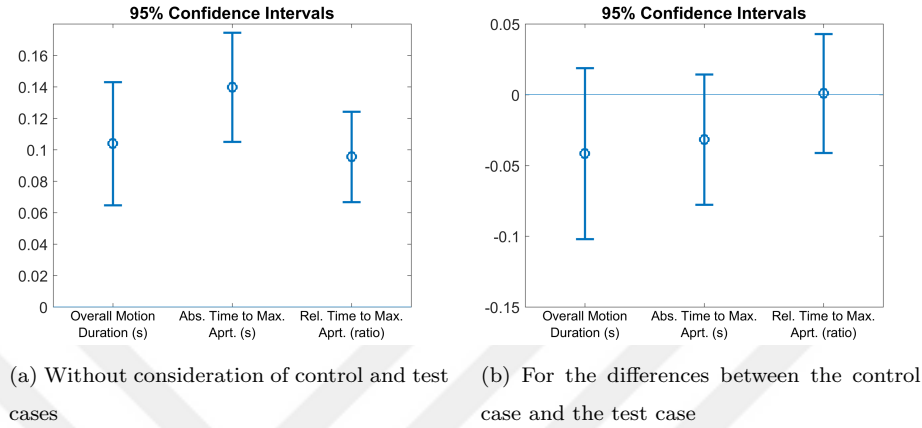


Figure 3.4: 95% confidence intervals for differences between males and females considering three metrics.

ated their motions. There might be less than 1.6 cm of deviation as measured by [Sartori et al., 2009], which is not observable from the video recordings. This is in contradiction with the third hypothesis presented in Sect. 3.5. Still, we observed some exaggeration for some participants in certain edge cases. Exaggeration happened in configurations 2, 3 and 4, in which one of the bottles partially block the other one visually/motion-wise (Fig. 3.2). The lack of exaggeration in human intent expressive motion does not imply that exaggeration is not a useful communicative cue for robots. Several studies in robotics, as presented in Sect. 2.1, showed that it is a useful communicative cue for robots under certain configurations. In addition, exaggeration is used extensively to communicate intent in as described by [Johnston and Thomas, 1995].

Grasp Modality: Some participants changed the way they grasped the objects between the control and the test cases. Out of the total 224 motions (112 per case), we have observed 103 grasp modality changes between the control and test cases. Most of the participants decided that the object that is closest to their hand should be grasped from the front or the side while the object that is further to them should be grasped from either the top or the opposite side.

Gender’s Effect: Even though we did not have a specific hypothesis for the

gender's effect on intent expression, we evaluated it through paired two-tailed t-tests and 95% confidence intervals. The comparisons are made by looking at the differences in overall motion duration, absolute time to maximum hand aperture and relative time to maximum hand aperture between the genders (1) for without the consideration of control and the test case, and (2) for the differences between the control case and the test case. We achieved a very significant effect with $p < 1e - 5$ for all metrics in (1) and Fig. 3.4a provides 95% confidence intervals for the differences between males and females. Fig. 3.4a shows that males are slower than females in task execution for reach-to-grasp motions. However, when we look at (2), we observed no effect of gender on intent expression with $p > 0.1$ for all metrics and Fig. 3.4b presents 95% confidence intervals for the differences between males and females considering the difference between the control and the test case. Through Fig. 3.4b, it can be seen that there is no difference in cue execution between genders and hence, we do not evaluate gender's effect on cues further.

3.8 Responses to Survey Questions

For the first question about the motion change, only a single participant responded as "changed significantly", 6 participants responded as "changed a little", 6 others responded as "did not change much" and one participant responded as "did not change at all". These responses confirm that most of the participants were not trying to generate highly exaggerated motions.

An interesting observation about these responses is that the decrease in relative time to reach maximum hand aperture, which was significantly different between the control and the test cases, was not a conscious change. This implies that the hand aperture timing, overlooked by the robotics studies, might be a key communicative cue in human-human interactions.

For the second open-ended question about their motion change, most of the participants provided responses that support the observed communicative cues in this study. Some of the participants stated that they decreased their motion speed, while

some others said that they changed the way they grasped the objects.

Four of the participants stated that they changed their body posture and oriented their chest towards the object they were reaching towards. These interesting responses hint that body posture and orientation may be an important communicative cue for intent expressive motion generation and thus should be taken into account in addition to the arm motion. This has implications both for intent expressive motion generation (for robots that have a torso) and for recognizing human intent.

3.9 Summary

Humans are very good at collaboratively working on a task, whereas robots still have a long distance to go. We wanted to look at what makes people good at this and whether we apply what we learn to robots. We concentrated on expressing intent through motion with an eye towards improving collaboration fluency and task efficiency as [Becchio et al., 2012] suggest that the motion intent is hidden in the motion itself. We have designed a human-human reach-to-grasp experiment, similar to the one by [Sartori et al., 2009], from an HRI perspective with the aim of identifying communicative cues that can be readily utilized by robots.

This experiment led us to identify four communicative cues (Sect. 3.6): (1) An increase in overall motion duration, (2) a decrease in the relative time to reach maximum hand aperture, (3) exaggeration of motion (in rare cases), and (4) grasp modality change between object configurations. An interesting finding is that humans actually use little or no exaggeration whereas it is used widely in animation which inspired several robotics researchers to do the same. Another interesting finding is about grasp-modality and hand-aperture timing which have been overlooked in the literature.

The participants were not aware that their relative time to reach to maximum hand aperture differed between the cases. This implies hand aperture timing might be one of the key aspects of non-verbal intent expression for humans. As found out by the following experiments, however, this does not help identify the object of the action.

As a result, we hypothesize that it is a useful communicative cue for expressing the action itself. Another outcome of the survey was that several participants reported conscious change in their body posture to signal the object that they were reaching to.



Chapter 4

SIMULATED ROBOT EXPERIMENT

The human-human experiment (Ch. 3) reached its aim of identifying communicative cues in human motion that can be incorporated into robot motion. The next step is to verify that these cues can help robot motion become intent expressive. We first start with a simulated robot experiment to be able to systematically test a large set of cues and cue combinations before moving onto an experiment with a real-robot.

This experiment¹ is conducted with a graphical user interface (GUI) and videos recorded from simulation using a setup very similar to the one in the human-human experiment. During the experiment, the participants would watch a video of the robot reaching to one of the objects, stop the video and make their object guess. In this chapter, we provide additional results and discussion about the effect of object configurations.

This experiment was approved by the Internal Review Board (IRB).

4.1 Cues and Motion Generation

This experiment is utilizing multiple cues and all of their possible combinations, and as a result its design is relatively complex. The cues that are used in this experiment are: relative time to reach maximum hand aperture (MA), overall motion duration (OT), exaggeration (Exg) and grasp modality (GM). Every combination of these cues, based on them being present or not, is tested. Thus, the resulting experiment is a $2 \times 2 \times 2 \times 2$ multi-factorial design. The case when no cue is present corresponds to the no intention case (Non).

¹The details of this experiment was also published in [Kebüde et al., 2018].

One of the first experiment participants' motions that has shown all of the identified communicative cues were investigated to decide on how to generate motion trajectories on the robot. We have chosen various way points in the robot's end-effector space to generate similar spatial cues of motion (i.e. *Exg* and *GM*) to this participant and used different time constraints to inject temporal cues (i.e. *OT* and *MA*) like the participant did in HHE. A cubic-spline describing the end-effector trajectory was generated using the chosen way points and time constraints. In each configuration (see Sect. 4.3), the robot reached both objects, resulting in 2^4 cue combinations $\times 3$ bottle configurations $\times 2$ objects = 96 robot reach-to-grasp motion trajectories.

4.2 Participants

The experiment had 20 male and 10 female participants. The median age was 22 and all of the participants were from a university campus community. 25 of the participants stated that they have watched robot videos online or had minor interactions with robots, 3 of them had moderate knowledge in robotics but did not have any hands-on experience and 2 of them had worked with robots but not in a research related endeavor. The experiment was gamified. To motivate the participants, a gift card of 50 TRY (~ 8 USD) for a local coffee shop was promised to one of the participants selected randomly from the top three scorers. This score was based on the accuracy and speed of their guess, as estimated by Eq. 4.4.

4.3 Experimental Setup

The experimental setup consists of a simulated 6-DOF manipulator with a three-finger gripper, reaching to grasp one of two cylindrical objects of different color residing on a table in three different configurations, as depicted in Fig. 4.1. The participants watch the motions through a graphical user interface (GUI) to make their guesses regarding which object the robot is reaching towards.

4.3.1 Simulation

The 96 motion trajectories mentioned in Sect. 4.1 were generated using the Gazebo simulation environment, first introduced by [Koenig and Howard, 2004], with the Universal Robots UR5 robot arm model attached with a Robotnik Automation’s Barret Hand BH8-282 three-finger gripper. Trac-IK, developed by [Beeson and Ames, 2015], was used to calculate joint trajectories from end-effector trajectories. ROS, first presented by [Quigley et al., 2009], was used as the middle-ware between all the software components.

The simulation environment consists of the arm positioned on top of a platform, in front of a table that has one red and one blue cylindrical objects on top. The camera is placed such that the participant will see the robot from the opposite side of the table, similar to HHE (Fig. 4.1).

The cue combinations (Sect. 4.1) were used to generate robot motion for three object configurations (Fig. 3.2a, 3.2b, and 3.2c) of the first experiment (see Sect. 3.2). The fourth one (Fig. 3.2d) was not investigated since no specific change between the third and fourth configurations was observed in the first experiment.

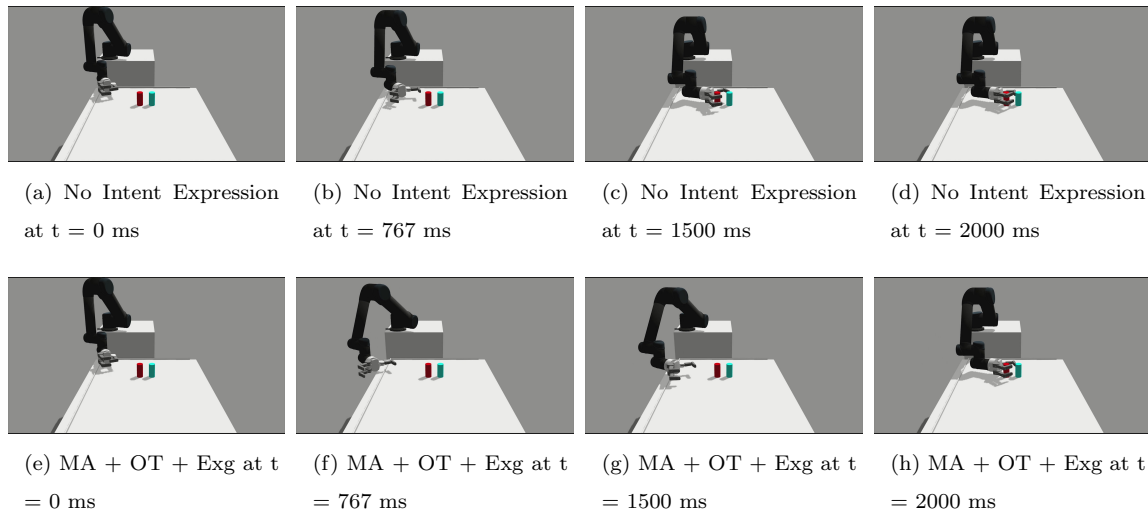


Figure 4.1: Comparison of no intention case vs. maximum aperture + overall time + exaggeration case.

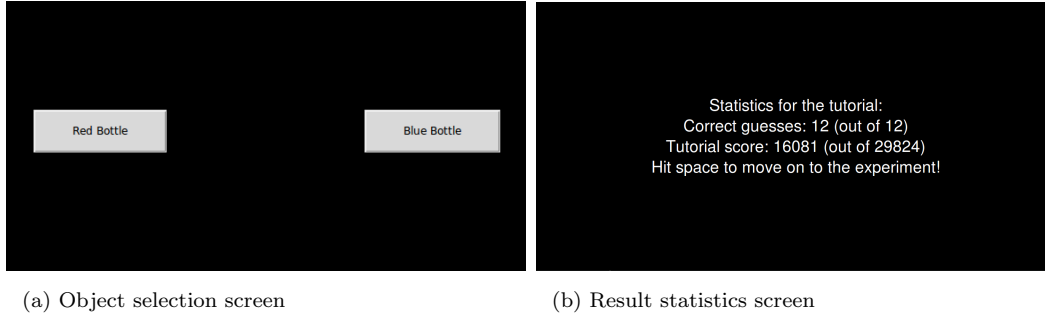


Figure 4.2: GUI screens at different phases of the experiment.

The simulated motion trajectories were recorded to be shown the participant via the GUI. Screenshots from two example trajectories for the same configuration and the same object can be seen in Fig. 4.1. The top row depicts a trajectory with no cues (*Non* case) and the bottom depicts a trajectory with *MA*, *OT* and *Exg*. The latter takes longer and reaches its maximum aperture earlier relative to the overall duration. Furthermore, the changes between configurations and cue combinations are demonstrated in the videos given in the Extensions 2 and 3 (see App. A).

4.3.2 Graphical User Interface

The experiment is conducted through a GUI developed using the TkInter Python package and the GStreamer video player. The main function of the GUI is to display the simulated robot videos to the participants and record their object guesses (Fig. 4.1 and 4.2). All the participants use the same computer and the monitor.

4.4 Experimental Protocol

Before the experiment, the participants are given the informed consent form and enough time to go over it. The experiment begins after they sign the form.

The experiment starts with informing the participants regarding the basics of the experiment and their role. The participants are told that they are going to see robot videos reaching towards two objects and that they are going to be asked to guess

which object as quickly and as accurately as possible. Then they are shown the GUI which starts with a form to collect participant information, i.e., name, ID, gender, age and robotic experience. After the participants fill out this form, the experiment is carried out in three steps:

1. **Preview Phase:** Six videos of the simulated robot executing trajectories with no intent expression (No cues case, *Non*) were shown to the participants. This step is for the participants to get accustomed to the robot's movement, so they can focus on the robot's intent in the later steps. The participants were not asked to understand the robot's intent at this step.
2. **Tutorial Phase:** Six videos from the *Non* case and six videos from the *MA + OT + Exg* case (i.e., when the three cues were injected to robot motion) were shown to the participant. The participants were asked to hit the space bar to play the next video and hit the space bar again to stop it when they are sure about the robot's target intent. This brings up the object selection screen (Fig. 4.2a) with two buttons for the participant to make their guess. This step is conducted, so the participant gets accustomed to the GUI and the experimental process. The calculated guess score (Eq. 4.4) for this step is shown at the end (Fig. 4.2b), to motivate the participant for the upcoming experiment phase.
3. **Experiment Phase:** 96 motion trajectories that depict different cue combinations were shown at this phase. The participants were asked again to hit space bar to play the next video, hit space bar again to stop it and to make their guess on the object selection screen. This is the step where the participant data was collected (see Sect. 4.5 and 4.7).

A brief introduction text is provided before each phase of the experiment. The GUI also displays statistics at the end of the tutorial and the experiment phases as depicted in Fig. 4.2b.

4.5 Data Collection and Metrics

The following data is recorded for each participant and for each video during the experiment phase:

1. Object configuration
2. Object that the robot is reaching towards (*target*)
3. Active communicative cues (see Sect. 4.1)
4. Time the participant stopped the video (t_{guess})
5. Duration of the video (t_{dur})
6. The participant's object guess (*guess*)

The recorded data is used to calculate the following for each participant and each video:

Correctness (C): The correctness of participant's target guess. Using an Iverson bracket:

$$C = [guess = target] \quad (4.1)$$

Guess rating (r_{guess}): The relative point of the video the participant has made the guess. It is a ratio between the time the video was stopped to make a guess and the whole video duration.

$$r_{guess} = \frac{t_{guess}}{t_{dur}} \quad (4.2)$$

The recorded data along with the correctness and the guess rating are used to calculate the following metrics to motivate the participant (see Fig. 4.2b);

Number of correct guesses ($n_{correct}$): Defined as a cumulative summation of correctness values per video. n is the number of videos watched.

$$n_{correct} = \sum_{i=1}^n C_i \quad (4.3)$$

Participant score (S): This measure is for motivating the participant to make fast and accurate guesses. Quicker and more accurate guesses result in higher scores.

It is a cumulative summation of the remaining motion durations of the videos where the participant guessed correctly. A wrong guess does not contribute to the sum.

$$S = \sum_{i=1}^n (C_i(t_{i,dur} - t_{i,guess})) \quad (4.4)$$

Finally, we calculate a guess score to evaluate the hypotheses with, as follows:

Guess score (J_{guess}): Participant's guess score. It is equal to r_{guess} if $C = 1$ for that video and 1 if $C = 0$ (i.e. it is the same as not being able to make a guess during the whole duration of a video). Note that lower is better.

$$J_{guess} = \begin{cases} r_{guess}, & \text{if } C = 1 \\ 1, & \text{otherwise} \end{cases} \quad (4.5)$$

4.6 Hypotheses

We expect the communicative cues observed in the HHE experiment (Ch. 3) to have an effect on the intent expressiveness of robot motion. We want to evaluate the cues both individually and in combination. We base the first three hypotheses based on these ideas. They were previously analyzed by [Kebüde et al., 2018]. On top of the results presented in that work, we investigate the effect of the object configuration on the intent expressiveness of the communicative cues. This forms the basis of our fourth hypothesis. Hence, our hypotheses for the SRE are as follows:

1. The individual communicative cues (MA , OT , Exg , GM) affect the intent expressiveness of the robot motion compared to the no cue (Non) case.
2. Some cue combinations have unique effects on the intent expressiveness of the robot motion compared to the no cue case.
3. All the cue combinations affect the intent expressiveness of the motion compared to the no cue case.
4. Object configuration affects the intent expressiveness of the motion.

4.7 Statistical Analyses

To evaluate the hypotheses 1 (**H1**) and 2 (**H2**), we conduct a multi-factorial repeated measures analysis of variance, with all possible interactions across factors using the guess score (J_{guess} , Eq. 4.5) as the dependent variable. The results of this ANOVA is presented in Tbl. 4.1.

Hypothesis 3 (**H3**) is evaluated by paired t-tests between the *Non* case and all other cue cases, for a total of 15 comparisons. The results of these t-tests is presented in Tbl. 4.2. In addition, we present the 95% confidence intervals for the differences between the cue cases and the *Non* case, see Fig. 4.3. Since this analysis suffers from the multiple comparisons problems, we checked our results with the Benjamini-Hochberg procedure, described by [Benjamini and Hochberg, 1995] using a false discovery rate of 0.05^2 . We did not see any loss of significance and as a result present uncorrected values to be able to plot confidence intervals.

Hypothesis 4 (**H4**), is evaluated by a repeated measures ANOVA with the object configuration as the independent variable (Tbl. 4.3), followed up by analyzing the confidence intervals (Fig. 4.4) between the guess score means.

4.8 Hypotheses Evaluation

H1: The individual cues affecting the expressiveness of the motion as measured by the guess score (J_{guess} , Eq. 4.5), is evaluated based on the main effect results of the ANOVA. Tbl. 4.1 shows that all the cues but *MA* had a significant effect on the guess score. It can be concluded that this hypothesis is partially satisfied.

Although we expected *MA* to be a significant cue for intent expression, as we have discussed in Ch. 3, this was not the case. This is actually not surprising given the fact that reaching any object would have this component. We argue in Sect. 4.9 that, *MA* might be an important cue to express the action that is being executed (reach-to-grasp in our case) rather than the target of the action.

²Lower rates imply a more stringent correction. Our chosen rate is very common in practice.

Table 4.1: Multi-factor Repeated Measures ANOVA results.

Source	SS	df	MS	F	p-value
MA	0.05	1	0.05	1.50	> 0.05
OT	0.73	1	0.73	20.38	< 1e - 5
Exg	1.02	1	1.02	23.07	< 1e - 5
GM	4.72	1	4.72	101.11	< 1e - 6
MA+OT	2e-3	1	2e-3	0.05	> 0.05
MA+Exg	0.04	1	0.04	1.30	> 0.05
OT+Exg	0.02	1	0.02	0.61	> 0.05
MA+GM	8e-4	1	8e-4	0.02	> 0.05
OT+GM	0.14	1	0.14	4.17	< 0.05
Exg+GM	2.07	1	2.07	61.51	< 1e - 6
MA+OT+Exg	9e-3	1	9e-3	0.22	> 0.05
MA+OT+GM	0.06	1	0.06	1.49	> 0.05
MA+Exg+GM	4e-3	1	4e-3	0.11	> 0.05
OT+Exg+GM	0.06	1	0.06	1.93	> 0.05
MA+OT+Exg+GM	9e-4	1	9e-4	0.02	> 0.05
Error	109.84	2864			
Total	118.75	2879			

H2: The unique effects of cue combinations is evaluated based on the interaction effects of the ANOVA. Tbl. 4.1 shows that there are two cue combinations that result in an interaction among cues: *OT+GM* and *Exg+GM*. It can be concluded that this hypothesis is satisfied.

It should be noted that the non-significant effects of the other cue combinations do not demonstrate they cannot be used in intent expressive motion. The results solely suggest that there is no interaction between those cue combinations to influence the intent expressive effect directly.

H3: The cue combinations affecting the intent expressiveness of all the combinations is evaluated by the the multiple t-tests since the ANOVA did not show the non-unique effects of the combinations. With the multiple paired t-tests, we can see the effect of individual cues and combinations, at the cost of losing statistical

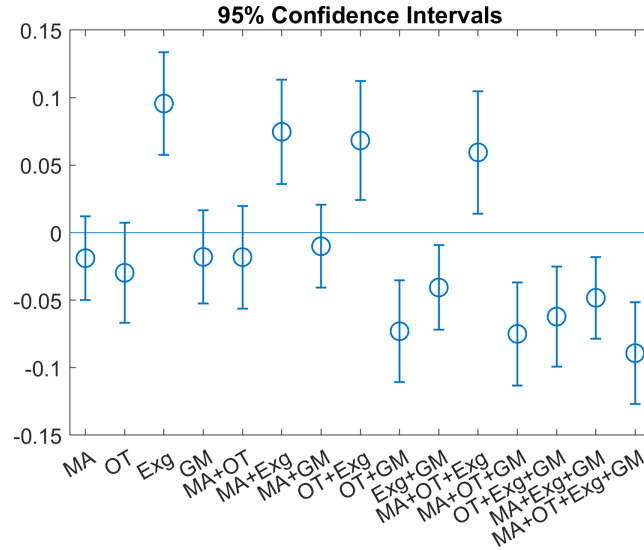


Figure 4.3: 95% Confidence Intervals for the differences between cue combinations vs. *Non case*.

power since each comparison will now have one eighth of the data to work with. Furthermore, we plot the 95% confidence intervals to show whether the cues and their combinations had a positive or a negative impact.

We can see that 10 out of 15 cases to be significantly different than the *Non* case by looking at the confidence intervals (Fig. 4.3) and the t-test results (Tbl. 4.2). There seems to be a discrepancy between the ANOVA and t-test results regarding the cues *OT* and *GM*, as they were found to be significant in the former but not in the latter test. This is due to the lower statistical power of the t-test as it was done with one eighth of the data. If the results of both analyses are combined, the number of significant cases become 12. The remaining 3 cases all have *MA* in common (see **H1**). We conclude that H3 is partially satisfied.

Since the main aim of this research is to figure out the communicative cues that aid in intent expressive motion generation, we look at whether these cues and their combinations improve the guess score. The Fig. 4.3 shows that only 8 out of the 12 significant cases resulted in a better (lower) guess score. An interesting observation is that the 4 negative cases all have *Exg* in common. This cue only results in better scores in combination with *GM*.

Table 4.2: Mean guess scores along with significance results for the paired tests. Red box is the worst and green box is the best guess score. Degrees of freedom is 358 for all.

Cue Combinations	Mean	t	p-values
No Intention	0.5334	N/A	N/A
MA	0.5145	1.0956	> 0.05
OT	0.5036	1.5884	> 0.05
Exg	0.6290	-4.6423	< 1e - 4
GM	0.5154	1.0203	> 0.05
MA + OT	0.5152	0.8661	> 0.05
MA + Exg	0.6081	-3.6584	< 1e - 3
MA + GM	0.5233	0.5727	> 0.05
OT + Exg	0.6016	-2.9788	< 1e - 2
OT + GM	0.4603	3.8245	< 1e - 3
Exp + GM	0.4927	2.4692	< 0.05
MA + OT + Exg	0.5928	-2.6275	< 1e - 2
MA + OT + GM	0.4584	3.7746	< 1e - 3
OT + Exg + GM	0.4712	3.3094	< 1e - 3
MA + Exg + GM	0.4851	2.9786	< 1e - 3
MA + OT + Exg + GM	0.4441	4.6579	< 1e - 4

The case of all four cues combined ($MA+OT+Exg+GM$) results in the best guess scores among all the cases. *Exg* by itself causes the worst results and all other combinations that have *Exg* without *GM* present negative effects on intent expression, i.e., they are worst than the *Non* case. This suggests that *Exg* is a bad intent indicator. As this cue was utilized extensively by other studies, we think that this result might be caused by having only a single view point with bad depth perception (through videos on a monitor) and/or a single direction of exaggeration on the horizontal plane.

H4: Tbl. 4.3 shows that there is a significant difference in the guess scores between the object configurations. The follow-up confidence interval analysis, using the Fig. 4.4, confirms this. There is a statistically significant decrease (non-overlapping intervals), in the mean guess score moving away from the side-by-side configuration; Participants were able to achieve the best scores in the side-by-side configuration

Table 4.3: Repeated Measures ANOVA results for the Object Configurations

Source	SS	df	MS	F	p-value
Configuration	2.58	2	1.2875	88.1521	$< 1e - 30$
Error	42.02	2877			
Total	44.50	2879			

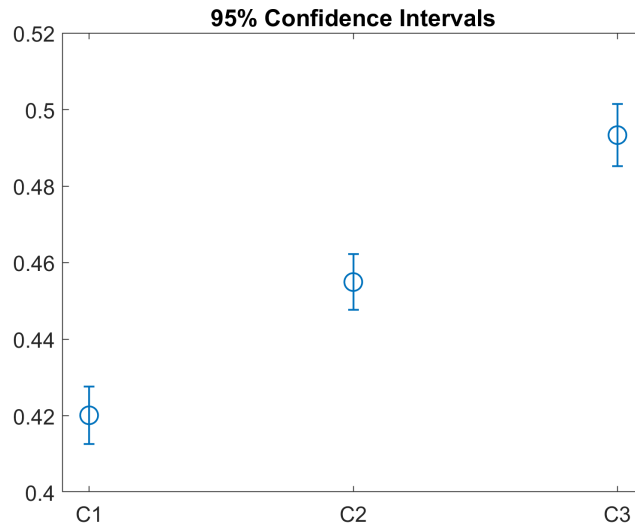


Figure 4.4: 95% Confidence Intervals for the mean guess scores for different object configurations. C1: side-by-side, C2: diagonal, C3: one in the front

(Fig. 3.2a) and worst in the configuration where one of the bottles was in front of the other (Fig. 3.2c). This suggests that the intent expression is not only dependent on the motion but also on the environment.

4.9 Summary

The outcome of the HHE prompted us to ask the following question: Would the identified communicative cues be used to improve intent expression of robots?

As a first step, we performed a gamified simulated robot experiment to systematically sweep the cues and their conditions. We have tested all the cues and all of their

possible combinations. Individually, we have seen that all the cues but the hand-aperture timing significantly changed the intent expressiveness of the robot motion (Tbl. 4.1). This led us to the aforementioned hypothesis of it being important for action communication rather than object communication. Another interesting find was that exaggeration affected intent expression negatively, unless it was coupled with grasp modality (Tbl. 4.1 and Fig. 4.3). We further see that two other combinations involving grasp modality has unique interaction effects for the better. This suggests that grasp modality is a synergistic communicative cue. Remaining combinations affected the expressiveness positively, with all the cues resulting in the best outcome (Tbl. 4.2 and Fig. 4.3).

Furthermore, we have evaluated object configuration's effect on intent expressiveness and found out that the participants have achieved the best guess scores in side-by-side configuration, worse guess scores in the diagonal configuration and the worst scores in the one-in-front configuration. As revealed through statistical analyses, the intent expression is also affected by the objects' configuration.

Chapter 5

INTENT EXPRESSIVE MOTION GENERATION

Following the results of the simulated robot experiment (Sect. 4.8), we have seen that an all cue combination enhances intent expressiveness of robotic reach-to-grasp motions. To investigate the effect of the cues in a real life human-robot interaction scenario, we needed trajectories that only change with respect to the given communicative cue inputs. Hence, a novel, communicative cue based intent expressive motion generation framework is developed.

The communicative cues identified in the first experiment (Ch. 3) were specific to human arm motion. In the second experiment, the simulated UR5 was not subject to joint rate limits and the simulated gripper enabled us to generate more human-like grasps.

In a realistic scenario, manipulator joints are subject to rate limits and the gripper we use on our robot is a 2-finger parallel gripper. The rate limits cause a slower motion which affects the *OT*. The gripper causes *MA* to be less effective in real life human-robot interaction scenarios. Furthermore, *MA* does not have a significant effect on intent expression as shown by t-tests and ANOVA of the second experiment. As a result, we decided to replace *MA* with the palm normal pointing at the target object (*PN*). An observation we made when looking back at the first experiment videos after the simulated robot experiment was that, the human palm normal was pointing towards the target object as soon as the maximum hand aperture was reached. Hence, we decided to use the palm normal as a communicative cue and remove *MA* from this experiment.

We have decided to generate motions using a minimum-jerk trajectory (i.e. using a quintic spline instead of a cubic one) since it has been shown to be a good model of

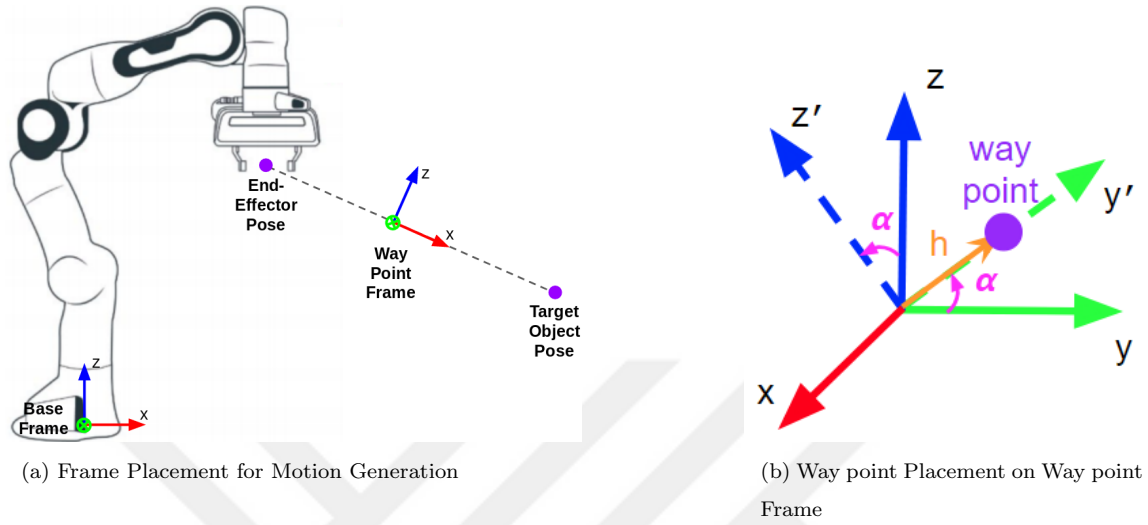


Figure 5.1: Middle way point placement. The h is the exaggeration amount and the y' and the z' axes are after the rotation for the grasp modality.

human motion by [Flash and Hogan, 1985]. To embed the cues in the robot motion, we place an intermediate way point and use the approach described by [Todorov and Jordan, 1998] to generate the robot end-effector trajectories.

Our method is similar to [Busch et al., 2017]’s via-point policy representation that would enable us to embed all of the cues both individually and all together: First, We place a new *way point* coordinate frame at the middle point between the end effector pose and the target object pose. This way point frame is oriented such that its x-axis points towards the target object, its y-axis is calculated based on the cross-product of the robot base frame’s z-axis and the x-axis of the way point frame, and finally, its z-axis is calculated with the cross product between the way point frame’s x and y axes (Fig. 5.1a). Then, to embed intent expressive cues in the robot’s motion, we define a way point, placed on the aforementioned *way point frame* according to the parameters described below (Fig. 5.1b). After transforming the defined way point to the robot’s base frame, we utilize a quintic spline trajectory that passes through the end-effector’s initial pose, the way point and the target object pose. The polynomial parameters of the spline are calculated to achieve minimum jerk motion.

5.1 Cue Parameters

The cues are embedded into the motion as follows:

1. **OT**: Overall motion duration is increased by the value of parameter t from the baseline duration.
2. **PN**: Palm normal cue is a percentage defined by a parameter r . Initially, the end effector (palm normal) points at the middle of two objects, than it incrementally rotates towards the target object as it reaches the r percentage of the trajectory (e.g. if r is defined to be 0.65, then the palm normal starts pointing exactly at the target object when 65% of the motion is conducted).
3. **Exg**: Exaggeration amount is defined by the way point's distance from the way point frame, in the direction of its y-axis in meters by the value of parameter h . As the robot's reaching range is limited, this parameter is limited at a maximum of 0.35 meters.
4. **GM**: Since the grasp modality is related to the angle the trajectory plane makes with the horizontal plane, we decided to explicitly define it as such. We depict it by α (radians), as the amount of rotation the way point frame is rotated about its x-axis (see Fig. 5.1b). Note that this is not the final angle between the gripper and the object, this definition only rotates the trajectory plane by the amount of α .

There is an interaction between the *Exg* and *GM* due to their definitions via h and α . The α parameter is insufficient by itself to generate different grasp modalities. Without h , the generated motion will always pass through the origin of the *way point frame* (the middle point between the initial end effector position and the target object position), which will result in the same grasp modality regardless of α . To generate different grasp modalities, a non-zero h is needed. Since choosing a small enough value that is imperceptible to the humans is sufficient, we do not treat the resulting robot trajectory as an *Exg+GM* combination (see Sect. 6.3).

5.2 Motion Generation Methodology

Motion generation methodology depends on the cue parameters ($\mathbf{t}$, $\mathbf{r}$, $\mathbf{h}$ and α) defined above.

The way point frame's position, $\mathbf{p}_{\text{wp}}$, is determined as the middle point between the initial end-effector position, $\mathbf{p}_{\text{ee}}$, and the target object position, $\mathbf{p}_{\text{obj}}$.

$$\mathbf{p}_{\text{wp}} = \frac{\mathbf{p}_{\text{obj}} + \mathbf{p}_{\text{ee}}}{2} \quad (5.1)$$

The way point frame's x-axis is determined to point towards the target object via the following:

$$\mathbf{u}_{\text{x}}^{\text{wp}} = \frac{\mathbf{p}_{\text{obj}} - \mathbf{p}_{\text{ee}}}{\|\mathbf{p}_{\text{obj}} - \mathbf{p}_{\text{ee}}\|} \quad (5.2)$$

where the unit vector $\mathbf{u}_{\text{x}}^{\text{wp}}$ is taken as the way point frame's x-axis. This is followed by determining the y-axis of the way point frame via a cross product between the unit vector of the newly determined way point frame's x-axis and the unit vector representing the base frame's z-axis.

$$\mathbf{u}_{\text{y}}^{\text{wp}} = \mathbf{u}_{\text{x}}^{\text{wp}} \times \mathbf{u}_{\text{z}}^{\text{base}}, \quad (5.3)$$

where $\mathbf{u}_{\text{y}}^{\text{wp}}$ represents the y-axis of the way point frame and $\mathbf{u}_{\text{z}}^{\text{base}}$ represents the robot base frame's z-axis.

Then the z-axis of the way point frame is determined via a cross product between the two:

$$\mathbf{u}_{\text{z}}^{\text{wp}} = \mathbf{u}_{\text{y}}^{\text{wp}} \times \mathbf{u}_{\text{x}}^{\text{wp}}, \quad (5.4)$$

where $\mathbf{u}_{\text{z}}^{\text{wp}}$ represents the z-axis of the way point frame.

After determining the way point frame, the way point position is calculated with the cue parameters $\mathbf{h}$ and α .

The whole way point frame is rotated around its x-axis by α to orient the trajectory plane to define a change in grasp modality. Then the way point is placed on the rotated way point frame at $(0, \mathbf{h}, 0)$. This deviates the motion trajectory by $\mathbf{h}$ on

the trajectory plane. Finally the way point is transformed to the robot base frame to calculate a spline between the end effector position, the calculated way point position and the target object position.

[Todorov and Jordan, 1998]’s minimum jerk trajectory generation methodology is utilized to generate two splines between (1) the end effector position and the way point, and (2) the way point and the target object position. Positions x_{ee} , x_{obj} , x_{wp} , velocities $\dot{x}_{ee} = 0$, $\dot{x}_{obj} = 0$, and accelerations $\ddot{x}_{ee} = 0$ and $\ddot{x}_{obj} = 0$ are known. [Todorov and Jordan, 1998]’s methodology optimizes the quintic polynomial parameters and the passage time through the way point for acquiring minimum jerk trajectory to generate the minimum-jerk motion passing through all three points, stitching the two generated splines together.

The baseline motion duration, t_{trj} , is selected based on the Cartesian speed and acceleration limits of the robot. After calculating the splines, we make sure that the resulting trajectory is within these limits. We generate another trajectory with $t_{trj} + t$ to embed the motion duration cue, OT . After this step, we have the Cartesian position trajectory of the end-effector but not the orientation trajectory.

The orientations of the end-effector trajectory are determined by, $\mathbf{r}$ and the object positions. The end effector is initially oriented towards the middle point between the two objects, $\mathbf{p}_{mid}$ before the execution. Then, the end effector is oriented incrementally towards the target object position, $\mathbf{p}_{obj}$, to finally point towards the target object when $\mathbf{r}$ amount of the trajectory is executed.

To achieve this, we first generate the position trajectory with pre-determined time-steps which gives us a discretized representation consisting of l_{trj} points. We then calculate a ratio between the trajectory point’s relative time we would like to calculate the orientation for, i , and the full length of the list of trajectory points l_{trj} . This gives us a executed trajectory ratio up to the i^{th} , r_{rt}^i .

$$r_{rt}^i = \frac{i}{l_{trj}} \quad (5.5)$$

We then calculate a second ratio for each point, r_{rel}^i , between r_{rt}^i and $\mathbf{r}$, to represent how close the end-effector’s orientation is towards the target object. If the robot has

executed r amount of the trajectory, then r_{rel}^i is always 1.0, i.e., pointing towards the object.

$$r_{rel}^i = \begin{cases} \frac{r_{rt}^i}{r}, & \text{if } r_{rt}^i \leq r \\ 1.0, & \text{otherwise} \end{cases} \quad (5.6)$$

After we have r_{rel}^i , we calculate the position that the end-effector should point to at the i^{th} point as follows

$$\mathbf{p}^i = (1.0 - r_{rel}^i) \cdot \mathbf{p}_{mid} + r_{rel}^i \cdot \mathbf{p}_{obj} \quad (5.7)$$

This results in the end-effector gradually pointing towards the target object from the middle of the objects. Finally end-effector frame's unit vectors at the i^{th} point is calculated similar to the previous approach we have conducted for the way point frame:

$$\mathbf{u}_z^i = \frac{\mathbf{p}^i - \mathbf{p}_{ee}}{\|\mathbf{p}^i - \mathbf{p}_{ee}\|} \quad (5.8)$$

$$\mathbf{u}_y^i = \mathbf{u}_z^i \times u_z^{base} \quad (5.9)$$

$$\mathbf{u}_x^i = \mathbf{u}_y^i \times u_z^i \quad (5.10)$$

We use these unit vectors to calculate unit quaternions of the end-effector at each point. We combine these together with the Cartesian position coordinates of point i , to achieve a 7-dimensional pose. We then utilize [Beeson and Ames, 2015]'s Trac-IK solver to solve for joint positions at each trajectory point and finally, execute the trajectory on the robot.

5.3 Summary

To investigate the cues' effect on intent expressiveness of motion, we need trajectories that only vary with respect to the communicative cues. Hence we develop a novel, intent expressive motion generation framework that handles the cues via four parameters: (1) t helps increase the overall motion duration and embeds OT in motion, (2) r

calibrates the relative time of palm normal pointing towards the target object (PN), (3) $\mathbf{h}$ aids in generating exaggeration (Exg) via pushing the end-effector further from the straight trajectory, and (4) α rotates the trajectory plane around the horizontal plane, achieving different grasp modalities (GM).

The aforementioned four parameters help with changing both the spatial and temporal aspects of the motion trajectory: $\mathbf{t}$ and $\mathbf{r}$ changes the temporal aspects of motion, while $\mathbf{h}$ and α places a way point through a coordinate frame placed on the middle point of the straight trajectory. We utilize this way point to create human-like trajectories through two fifth order splines from the starting point to the way point, and from the way point to the end point. Finally, [Todorov and Jordan, 1998]’s minimum jerk optimization methodology is utilized to stitch the two splines together.

Chapter 6

HUMAN-ROBOT INTERACTION EXPERIMENT

The human-human experiment (Ch. 3) confirmed that intent expressive subtle cues exist in human motion and helped us identify a subset of these cues. The following simulated robot experiment (Ch. 4) showed that these cues might allow robots to generate intent expressive motions as well. Motivated by these results, we designed a human-robot interaction experiment to verify that real-robots can use the identified cues for intent expression. To generate intent expressive motion, we utilize the motion generation methodology explained in Ch. 5.

This third experiment is similar to the second experiment. The participants watch the robot execute various trajectories and they try to guess which object the robot is reaching towards. The robot stops and moves back when they make their decision. This experiment is also gamified; we calculate a score for each participant and there is a prize for the highest scorer. There are also differences. Some of these differences are done intentionally, based on the lessons learned from the previous experiments. Some of them are due to using a different robot-gripper combination and working in a real-world setting.

This experiment was approved by the Internal Review Board (IRB).

6.1 Participants

20 male and 14 female participants from a campus community with a median age of 26 attended the experiment. 4 of them stated that they have not seen a robot in their lives, 18 of them stated that they have only seen a robot in videos, 9 of them stated that they have been interested in robotics but did not have any hands-on experience, 2 of them had minor interactions with robots but not in a research related way and

1 participant stated that they are conducting/have conducted research in robotics. To motivate the participants, a gift card of 100 TRY (~ 16 USD) for a nationwide hobby shop is promised to the top performer, based on the accuracy and speed of their intent understanding, as estimated by Eq. 6.1



Figure 6.1: The experimental setup as explained in Sect. 6.2.

6.2 Experimental Setup

In the HRI experiment, we have constructed a setup that is similar to the one in the simulated robot experiment. We used a 7-DOF Franka Emika Panda manipulator with the gripper provided by the manufacturer. A small table ($100 \times 80 \times 70$ cm) was placed in front of the robot with one red and one blue bottle residing on top of it as shown in Fig. 6.1.

In the simulated robot experiment, we have observed that *Exg* affects intent expression negatively. We think that this cue requires a more detailed formulation, by

taking the observer viewpoint and relative object configurations into account. Hence, in this HRI experiment, the participant viewpoint is also varied in addition to the bottle configuration.

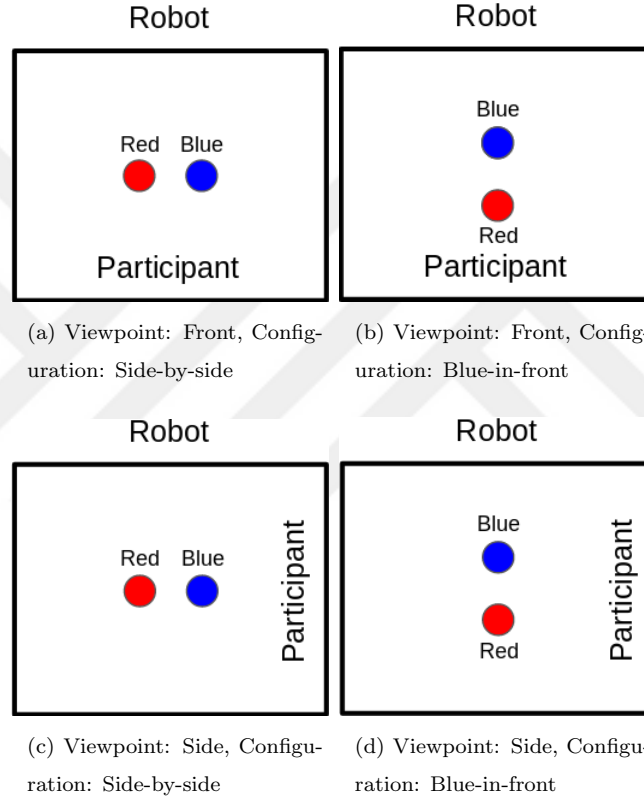


Figure 6.2: Top-view for the configurations of the objects for different viewpoints of the participants.

The participants were asked to sit in two different locations to view the robot from two different perspectives: (1) Opposite side of the robot and (2) beside the table. Two bottle configurations from the original experiment were used in each of the viewpoints: (1) where the bottles are placed side-by-side and (2) where the blue bottle was placed in front of the red bottle, closer to the robot (Fig. 6.2). We removed the diagonal configuration in this experiment, as it neither blocks the vision of the participant nor the robot's motion trajectory.

Instead of a graphical user interface, a transparent three-button box was provided to the participants with green, red and blue buttons (Fig. 6.3).



Figure 6.3: Transparent three-button box used by the participants to start the robot motion (green) and make an object guess (red and blue).

6.3 Experimental Protocol

Before the experiment, the participants are given the informed consent form and enough time to go over it. The experiment begins after they sign the form.

The experiment starts by telling the participants about the experiment and what they were asked to do. We asked the participants to try to understand robot's target intent as soon and as accurate as possible, and we specifically informed them about the robot not being deceitful or misleading in expressing its target intent.

The experiment was divided into two phases: (1) a tutorial phase and (2) the experiment phase. At the tutorial phase, the participants were shown six predefined robot motions to get them used to the robot's movements. At the experiment phase, the participants were shown six motions including different cue combinations for each of the objects and each of the four configurations (i.e. $6 \text{ motions} \times 2 \text{ objects} \times 4 \text{ configurations} = 48 \text{ motions}$). We defined four sets of motions for the experiment phase, depending on the bottle configurations or the participant viewpoint (see Fig. 6.2). The motions change between sets that has different bottle configurations, however, they are the same for the different viewpoints when the bottle configuration does not change (e.g., same motion set is used for Fig. 6.2a and 6.2c, while the motion set changes between Fig. 6.2a and 6.2b). See the videos in the Extensions 4, 5, 6 and 7 for more detail on the motion sets. This allows us to investigate viewpoint's effect on intent expression. The specified list of cue combinations for the aforementioned six motions is as follows:

1. No cues (*Non*)
2. Increased Overall Motion Duration (*OT*)
3. Earlier palm normal pointing (*PN*)
4. Exaggerated motion (*Exg*)
5. Change in Grasp Modality (*GM*)
6. All four cues combined (*OT+PN+Exg+GM* or *All*)

The tutorial phase was conducted with the first configuration for all participants (Fig. 6.2a). However, the two participant viewpoints were counterbalanced between the participants during the experiment phase. The participants were asked to pause when their one set of experiment phase has ended, then the experimenter arranged the participant viewpoint and the bottle configuration before the next set of motions started.

To motivate the participants, the experiment was gamified through a similar methodology with the simulated robot experiment. The participants were asked to press the green button to start the next motion. After the green button is pressed, the robot has a ~ 1 second (± 0.3 seconds) trajectory calculation delay before it starts executing its motion. After the motion starts, the participants were asked to press the red or the blue button depending on their object guess' color. This gave the participants total control of the experiment except the configuration changes between motion sets. Participant interaction with the robot can be seen in Extension 8 (App. A).

During the tutorial phase, the participant's guess did not affect the robot motion and the robot has conducted its full motion trajectory for the participant to get accustomed to the robot's movement. However, during the experiment phase, the robot immediately moved back to its initial stance for the next motion to start, i.e., the participants could not see if their guess was correct or not. This implementation is different from the simulated robot experiment. In the simulated robot experiment, when the participants had a guess, they could stop the robot motion and had time to think before they made a guess between the red or blue objects on a black screen,

without seeing the robot's final stance (see Fig. 4.2a). However, in this third experiment, they had to make a guess *during* the robot motion. This implementation is more realistic, as humans' response would be immediate in real life scenarios.

6.4 Cue Parameter Selection

Table 6.1: Cue parameter values for communicative motion generation

Configuration	Bottle	Case	t	r	h	α
Side-by-side	Blue	Non	0	0.65	0	0
		OT	0.7	0.65	0	0
		PN	0	0.35	0	0
		Exg	0	0.65	0.2	0
		GM	0	0.65	-0.02	1.5
		All	0.7	0.35	0.2	-0.3
	Red	Non	0	0.65	0	0
		OT	0.7	0.65	0	0
		PN	0	0.35	0	0
		Exg	0	0.65	-0.2	0
		GM	0	0.65	-0.02	1.5
		All	0.7	0.35	-0.2	0.35
Blue-in-front	Blue	Non	0	0.65	0	0
		OT	0.7	0.65	0	0
		PN	0	0.35	0	0
		Exg	0	0.65	0.2	0
		GM	0	0.65	-0.02	1.5
		All	0.7	0.35	0.2	-0.3
	Red	Non	0	0.65	0.05	1.5
		OT	0.7	0.65	0.05	1.5
		PN	0	0.35	0.05	1.5
		Exg	0	0.65	-0.3	0
		GM	0	0.65	0.1	1.5
		All	0.7	0.35	0.25	0.65

The parameters for the communicative cues can be seen in Tbl. 6.1. The parameters were selected via trial-and-error by observing the similarity of robot's motion to the human-human interaction cases. The justification for the parameter values are as follows:

1. t : Due to rate limits, the robot motion is not as fast as a human's. The minimum

- duration for the minimum effort trajectory is ~ 2 seconds in our scenario. This is ~ 1.2 seconds slower than the human motion. Overall motion duration increased by ~ 0.1 seconds for a human as calculated by the t-tests in the human-human experiment we have conducted. For the overall motion duration increase to be observable by the participants, we decided to increase the motion duration by 0.7 seconds in the motions that have *OT* as a communicative cue.
2. ***r***: As no rotation ($r = 1$) or direct rotation ($r = 0$) would not be human-like, ***r*** is chosen to be 0.65 at the no *PN* case. Due to pre-35% of motion being too early in robot's approach towards the objects as observed through the human-human experiment videos, $r = 0.35$ is selected to inject the *PN* cues in the motion trajectory.
 3. ***h***: For the exaggeration to be observable and intent expressive, a deviation of 20 centimeters from the minimum effort trajectory was selected. This is inline with the qualitatively noticeable deviations we could observe in the human-human interaction experiment which were $\sim 15cm$ (see Sect. 3.4).
 4. **α** : To inject *GM* in robot motion, several different α and ***h*** combinations were utilized: (1) $h = -0.02$ and $\alpha = 1.5$ achieves a frontal grasp as y-axis of the *way point frame* is rotated by $\sim 90^\circ$ and a small negative ***h*** pushes the end effector closer to table for a frontal grasping of the object, (2) $h = 0.1$ and $\alpha = 1.5$ achieves a top grasp as y-axis of the *way point frame* is rotated by $\sim 90^\circ$ and a small positive ***h*** pushes the end effector further from table for a grasping of the object through the top.

We have applied different α values in the *All* cases to push the way point closer to the table, providing a better grasp modality change when a large ***h*** is applied. To generate an intent expressive *Exg+GM* combination, a larger ***h*** would be required.

Some other changes we have made in the cue values were for the red object in the blue-in-front configuration. Since *Exg*, by itself, is applied towards the sides, there should be different amounts of *Exg* when reaching to different bottles in the blue-in-front configuration. Therefore, we apply an additional 10 centimeters of deviation to

signal the participant that the robot is reaching towards the object residing behind the other. Also, in the *All* case, we pushed the trajectory further from the table with an α value of 0.65, again to signal the participants that we are reaching towards the object residing behind.

Robot motion generated with different cue parameters can be seen in Extensions 4, 5, 6 and 7 from the perspective of the participants.

6.5 Data Collection

We used the same data collection methodology with the simulated robot experiment (Sect. 4.5) with a small change in the participant score (Eq. 4.4).

$$S = \sum_{i=1}^n (G_i(t_{i,dur} - t_{i,guess})) \quad (6.1)$$

where,

$$G_i = \begin{cases} 1, & \text{if } C = 1 \\ 0, & \text{if no guess} \\ -1, & \text{otherwise} \end{cases} \quad (6.2)$$

We have used -1 instead of 0 for the wrong guesses, as wrong guesses should be penalized further than not making a guess for the whole motion duration.

We have also observed ambition while hitting the buttons and rivalry towards the robot in some of the participants during the experiment. This did not happen during the simulated robot experiment. Thus, we have conducted a survey on the last 10 participants asking the following 7 degree Likert scale questions:

1. Did you get ambitious during the experiment?
2. Did you think (at any point) the robot was trying to deceive you?
3. Would you take the experiment more seriously or less seriously if there was not a prize at the end?

6.6 Hypotheses

Based on our results of the simulated robot experiment, we define our hypotheses as:

1. The individual communicative cues (*OT*, *PN*, *Exg*, *GM*) or their combinations affect the expressiveness of the robot motion compared to the no cue (*Non*) case.
2. Human viewpoint, affects the intent expressiveness of the robot motion.
3. Object configuration, affects the intent expressiveness of the robot motion.

6.7 Statistical Analyses

The hypothesis 1 (**H1**) is evaluated using a one-way ANOVA with the conditions defined in Sect. 6.3 as the independent variable and the guess score (Eq. 4.5) as the dependent variable (Tbl. 6.2). We do not perform an analysis similar to the one in the simulation experiment (Sect. 4.7) due to the lack of conditions to get the interaction effects. We further present the follow up t-tests between the *Non* case and all other cue cases (Tbl. 6.3) and the corresponding confidence intervals (Fig. 6.4).

The hypothesis 2 (**H2**) is evaluated using a paired t-test (Tbl. 6.4) between the two view-point configurations and corresponding confidence interval calculations (Fig. 6.5). We further present confidence intervals (Fig. 6.6) of the guess score differences between the individual cue conditions for each of the view-points. Specifically subtract the front viewpoint scores from the side viewpoint scores. The hypothesis 3 (**H3**) is evaluated the same way as the **H2** but with object configurations, subtracting the side-by-side configuration from the blue-in-front configuration.. The cue differences are presented in Fig. 6.7. Note that these latter confidence intervals are not calculated between the *Non* case and all the other cases, but between individual cases of the configurations.

Table 6.2: One-way ANOVA Results for the HRE

Source	SS	df	MS	F	p-value
Conditions	2.38	5	0.48	10.90	$< 1e - 9$
Error	71.21	1626	0.044		
Total	73.60	1631			

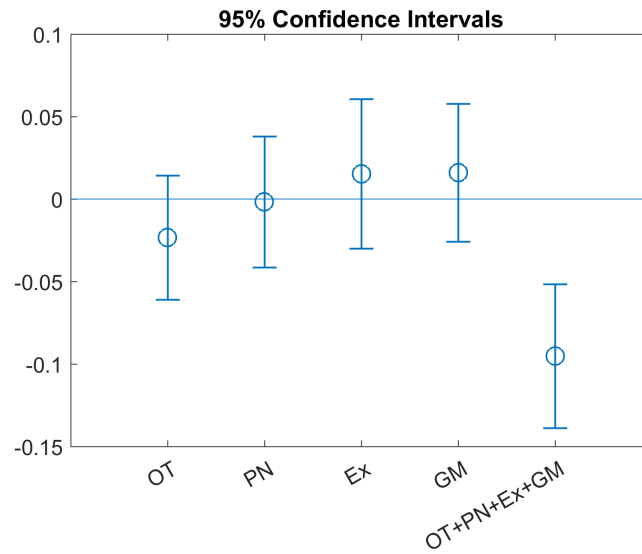


Figure 6.4: 95% Confidence Intervals of the differences between the cue cases and the no cue case (All samples).

Table 6.3: Mean guess scores along with significance results for the paired tests for all samples. Degrees of freedom is 542 for all.

Cue Combinations	Mean	t	p-values
No Intention	0.6426	N/A	N/A
OT	0.6192	1.3561	> 0.05
PN	0.6408	0.0990	> 0.05
Exg	0.6578	-0.7698	> 0.05
GM	0.6586	-0.9050	> 0.05
MA + OT + Exg + GM	0.5474	5.5354	$< 1e - 7$

6.8 Hypotheses Evaluation

H1: The Tbl. 6.2 shows that there is at least one condition that significantly affects the intent expressiveness of the robot motion. The follow-up multiple t-tests (Tbl. 6.3) reveal that only the combination of all the cues has a significant effect and the confidence intervals show that this is towards a better guess score. We conclude that this hypothesis is partially and weakly satisfied. The important point is that the cues can be combined to generate intent expressive motion.

It is interesting to see that the results of the simulation experiment can be considered to be better than the real-robot experiments. There could be multiple reasons for this and we discuss them in detail at Sect. 6.11.

Table 6.4: Difference in the mean guess scores along with significance results for the different view-points (V0: front, V1: side) and object configurations (C0: side-by-side, C1: blue in front). Degrees of freedom is 1630 for both.

Difference	Mean	t	p-values
View-point: V1-V0	0.032	3.027	$< 1e - 2$
Object Config: C1-C0	0.17	17.78	$< 1e - 15$

H2: The change in the viewpoint affects the intent expressiveness of the robot motion significantly as shown by the first results row of the Tbl. 6.4. The front view-point results in slightly better guess scores (Fig. 6.5). Even though the difference is statistically significant, its magnitude is small enough to be deemed negligible. The Fig. 6.6 shows that the *OT* cue affects the guess score significantly differently between the view-points. Thus, *OT* may be a better cue when the human is facing the robot. All cue combination case, noting that it significantly improves intent expression, may be robust against the view-point changes considering the near zero difference of the means.

H3: The change in the object configuration affects the intent expressiveness of the robot motion significantly as shown by the second results row of the Tbl. 6.4. The

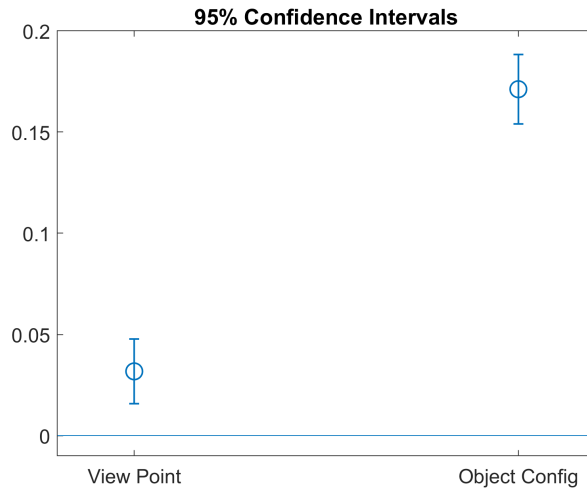


Figure 6.5: 95% Confidence Intervals of the differences in the viewpoints (Side - Front) and object configurations (Blue in front - side-by-side).

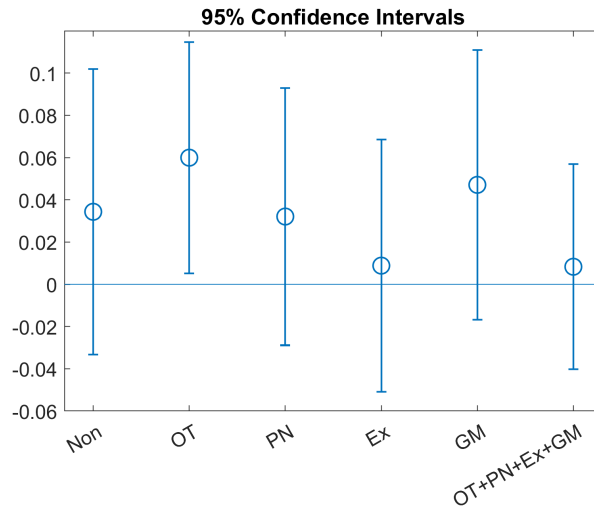


Figure 6.6: 95% Confidence Intervals of the differences between the mean guess scores of the cue cases for different viewpoints (Side - Front).

side-by-side object configuration results in better guess scores (Fig. 6.5) by a large margin. This mirrors our results from the simulated robot experiment (see Fig. 4.4 and Sect. 4.8).

The Fig. 6.7 shows that all the conditions result in statistically worse guess scores

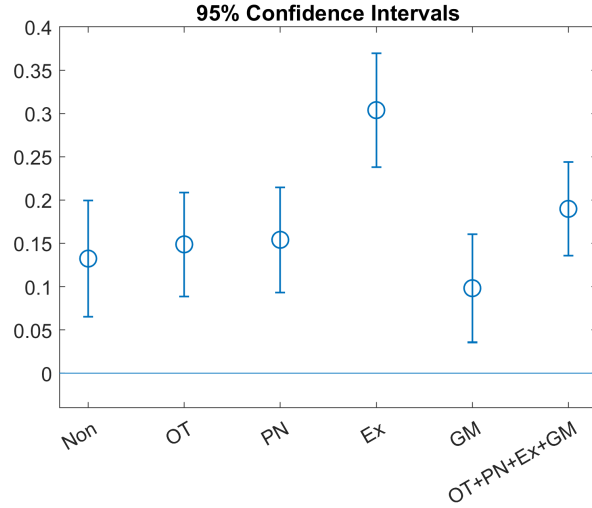


Figure 6.7: 95% Confidence Intervals of the differences between the mean guess scores of the cue cases for different object configurations (Blue in front - side-by-side).

for the blue in front configuration, including the no cue case. One interpretation of Fig. 6.7 is that the cues are not robust to differences in object configurations. Together with the results from the SRE, we argue that either this configuration is inherently difficult to express intent for or that a better cue and/or parameter selection is needed.

Exaggeration: Even though we did not have a specific hypothesis for exaggeration, we have observed an interesting result during our analysis which is inline with one of our previous arguments; exaggeration may be object configuration dependent. The Fig. 6.8, shows that exaggeration helps with intent expression when the objects are side-by-side (the common testing condition found in the existing literature) and hinders it when the objects are in front of each other.

Gender's Effect: We did not have a specific hypothesis for gender's effect on intent understanding, however, we evaluated it through an independent two-tailed t-test. We observed no effect of gender on intent understanding with $p > 0.5$ and did not evaluate it further.

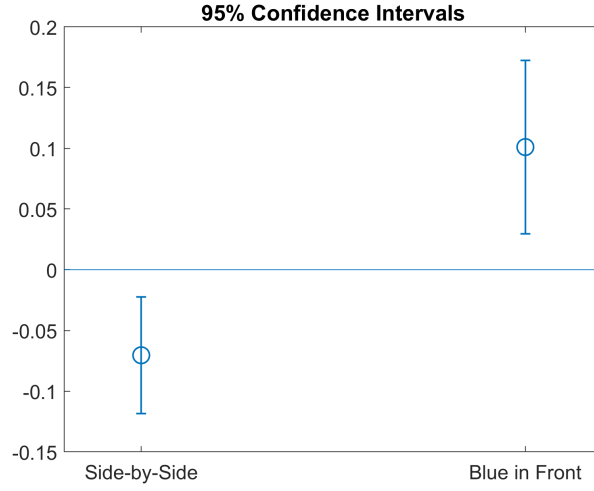


Figure 6.8: 95% Confidence Intervals of the differences between the Non cases and Exg cases for different object configurations.

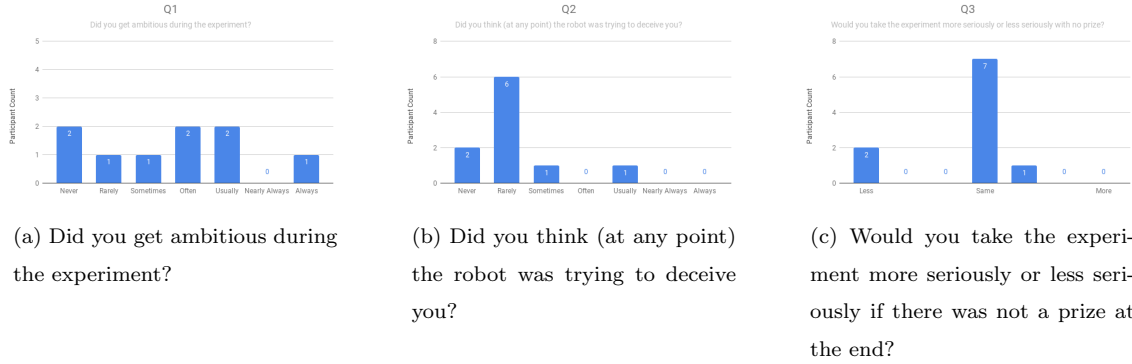


Figure 6.9: Participant answers to survey questions.

6.9 Answers to Survey Questions

As explained in Sect. 6.1, our observations during experiments led us towards conducting a participant survey on the last 10 participants since we have observed rivalry and ambition. The participant answers to survey questions can be seen in Fig. 6.9.

Q1: Fig. 6.9a demonstrates that the participants reported different levels of ambition towards the experiment. It is difficult to conclude anything from the uniformly distributed answers but the fact that this is uniform is interesting and hint to a diverse

participant pool.

Q2: Although the participants were specifically informed that the robot was not trying to deceive or mislead them, 6 of the participants thought that there was some level of deception while 1 of them usually thought of the robot being deceitful (Fig. 6.9b). This seems to show that our results might have been affected by participants seeing the robot as a rival and not a collaborator which may have skewed our results. Our anecdotal experience suggest that some participants changed their guesses thinking that the robot was trying to trick them.

Q3: Even though we have tried to motivate the participants with a prize, 7 of the surveyed participants reported that this was not important for them (Fig. 6.9c). Still, two participants declared that they would take the experiment less seriously if there was not a prize at the end. We still think that such a prize is a good motivator but the answers may suggest that it was not the source of the rivalry against the robot.

6.10 Discussion and Observations

The results of the HRI experiment was not as clear-cut as the simulated robot experiment. We only have significant results when all the cues are combined. We think that there are multiple reasons for this:

- Lower statistical power due to amount of data (30 participants $\times$ 96 trajectories vs 34 participants $\times$ 48 trajectories) and less sophisticated experimental design
- Immediate decision making in the HRE vs delayed decision making in SRE
- Perceived rivalry in the HRE
- Less anthropomorphic gripper in the HRE
- Addition of different view-points
- Cues by themselves are not as useful and their combination may be necessary, as seen by the boost in intent expressiveness (Fig. 6.4)

We also argue that more time that a user spends with the robot, the better their understanding will become. For example based on our own experience, the palm-

normal cue is very salient if it has been noticed. An interesting follow-up experiment would be to perform a longitudinal study.

We think that exaggeration needs a more detailed formulation, taking the observer view-point and object configuration into account. We show that the effects of exaggeration differ significantly and by a large margin between object configurations for both the simulated robot experiment (Fig. 4.4) and the real-robot experiment (Fig. 6.5). We saw that exaggeration helps intent expression when the objects are side-by-side and hinders it when they are in-front of each other (Fig. 6.8). The effect of object configuration on exaggeration's ability to communicate intent may explain some of the inconsistent results within the literature.

We have selected the cue parameters manually for the HRE. However, there is a benefit of our communicative cue formulation: It captures the nature of intent expressive motion in a small parameter space. Machine learning or optimization based on human data and user feedback is a very promising avenue of research that can generalize intent expressive motion among different user types and it can lead us towards universal intent expressive motion as we present in the following chapters.

6.11 Summary

We followed the simulated robot experiment (Ch. 4) with a gamified human-robot experiment, utilizing the lessons learned. We have removed the hand-aperture timing and instead used palm-normal direction as a communicative cue (Ch. 5). We further utilized multiple observer view-points in addition to object configurations (Fig. 6.2).

The view-points did not affect the intent expressiveness of the cues by a large margin, even though there was a small but statistically significant difference (Fig. 6.5). On the other hand, the object configurations affected the expressiveness greatly (Fig. 6.5). Even when no-cues are present, the participants were much better at guessing the target object when the objects were side-by-side (Fig. 6.7).

On par with our observations, we argue that *PN* might help with intent understanding further for the careful users, and *Exg* requires a more detailed formulation

taking the user viewpoint and object configuration into account.

The main take away from the last two robot experiments is that the robot motion generated by combining all the communicative cues is highly intent expressive and robust to viewpoint and object configuration differences. Furthermore, our communicative cue formulation captures the nature of intent expressive motion in a small parameter space, enabling generalization of intent expressive motion through machine learning approaches.



Chapter 7

LEARNING INTENT EXPRESSION

The observed results from the HRE (Sect. 6.8), motivated us to look for optimal parameters through active reinforcement learning ([Sutton and Barto, 1998]) with *Policy learning by Weighting Exploration with the Returns* (PoWER) ([Kober and Peters, 2009]). In this episodic expectation-maximization (EM) based algorithm, we used cue parameters (Sect. 5.1) as the policy parameters to be optimized and a modified version of the guess score (Eq. 4.5) as the reward.

The motion generation methodology is explained in Ch. 5. From a reinforcement learning (RL) perspective, the motion generation can be thought of as a policy that maps the cue parameters to the trajectories, depending on a state, resulting in an end reward based on the participant’s guess timing. Following this approach, we construct our reinforcement learning formulation depending on a state S , a policy π and a reward r .

7.1 State

$$S = (b, c, v) \tag{7.1}$$

where state S is defined by the target object b , object configuration c , and participant viewpoint v .

The results of the human-robot interaction experiment show that there is very little statistically significant difference between viewpoints based on the cues and cue combinations as shown in Fig. 6.6. Furthermore, side-by-side object configuration seems to provide a better statistically significant improvement of intent expression compared to the blue-in-front case (Fig. 6.7). Following these observations, we have

decided to constrain our state S to be $(b, 0, 0)$ during the experiment, as the experiment's aim is to solely validate the learning methodology and the help of learned cue parameters on intent expression. This corresponds to the configuration shown in Fig. 6.2a and the parameters only depend on whether the target object is on the right side or the left side of the robot base frame's x-z plane (see Fig. 5.1a).

7.2 Policy

The policy π can be thought of as a function that maps the state S and the policy parameters w to a trajectory τ . As such:

$$\pi_w(S) = \tau \quad (7.2)$$

where $w = (t, r, h, \alpha)$. Since the policy generates the motion trajectory depending on the state and the cue parameters, it actually corresponds to the motion generation methodology explained in Ch. 5. Furthermore, we only conduct learning for the blue bottle and change h and α parameters to be symmetric with respect to zero for the red bottle. This corresponds to symmetric trajectories with respect to the robot base frame's x-z plane and it is appropriate as the bottles are residing side-by-side.

7.3 Reward

As we have evaluated the intent expressiveness of the motion through guess score (Eq. 4.5) in the earlier experiments, the guess score is utilized as the reward in policy optimization with small modifications: (1) As a smaller guess score corresponds to a better intent expression, the negative of the guess score is used, (2) as several problematic trajectories can be generated due to exploration (i.e. trajectories with a velocity/acceleration above the limits, trajectories with no inverse kinematics (IK) solution due to the found waypoint, trajectories that cause self-collision or collision with the table/objects), a larger negative reward is required.

Hence, we first define a new variable t_g as follows:

$$t_g = \begin{cases} t_{limit}, & \text{if there is a collision, limit or IK error} \\ t_{total}, & \text{if } C = 0 \\ t_{guess}, & \text{otherwise} \end{cases} \quad (7.3)$$

where t_{limit} corresponds to the maximum time a trajectory can last (i.e. with maximum allowable t and h parameters). Note that this is different than t_{total} , as t_{total} corresponds to the time the current trajectory will take to be finished while t_{limit} is a scalar that does not depend on the current cue parameters and only depends on the maximum possible t and h .

Then, the reward is defined as:

$$r(\tau) = -\frac{t_g}{t_{total}} \quad (7.4)$$

This reward is highly dependant on human response time and hence, a high variance in the rewards is expected.

7.4 PoWER Implementation:

PoWER ([Kober and Peters, 2009]) has been shown to be a very useful tool for policy optimization through episodic Expectation-Maximization (EM). Its value in robot motor skill learning is shown in several studies: It was utilized for a pancake flipping task in [Kormushev et al., 2010] as well as a ball-in-a-cup and ball-paddling tasks in [Kober and Peters, 2009]. Its advantages over policy gradient approaches are two-fold as explained in [Kormushev et al., 2010]: (1) it does not require a learning rate which is very difficult to tune in control based scenarios, and (2) it can be combined with importance sampling for a better utilization of past experience for parameter estimation/optimization. In return, PoWER helps reduce the number of episodes required for convergence.

We utilize the PoWER update as follows:

$$w_{i+1} = w_i + \frac{\sum_{k=1}^K [(W_i^k - w_i)(R_i^k)]}{\sum_{k=1}^K (R_i^k)} \quad (7.5)$$

where i denotes the current episode; w is the cue parameters vector; R_i is the set of rewards, r , gathered until the current episode, i , sorted from highest to lowest; W_i is the collection of cue parameters until the current episode, i , sorted with the same indices as R_i . Finally, K handles the importance sampling: Best K number of parameters and rewards are used to update w_i . We have used 6 most important samples to update w_i in our implementation (i.e. $K = 6$).

7.5 Exploration:

Since we want the motions to be human-like and due to the limitations of the robot as explained in Ch. 5, we need to limit the parameters as follows:

$$\begin{aligned} 0 &\leq t \leq 1.5 \\ 0.2 &\leq r \leq 0.8 \\ -0.275 &\leq h \leq 0.275 \\ -\pi &\leq \alpha \leq \pi \end{aligned} \tag{7.6}$$

For the whole parameter space to be explored by an equal amount, we normalize the parameters between $[0, 1]$ and then perturb them as follows:

$$\begin{aligned} \epsilon &\sim N(0, I) \\ w_e &= w_i + \gamma\epsilon \end{aligned} \tag{7.7}$$

where ϵ is a zero mean unit variance Gaussian noise, w_e is the exploration parameters, w_i is the current parameters, and γ is the exploration step size. Then, we denormalize the parameters and use them to generate trajectories.

To cover the whole parameter space, γ is initialized as $\gamma_0 = 0.33$ and kept as such until the episode in which the decay starts, n_d . Then, we decay the γ according to the following rule:

$$\gamma = \gamma_0 \left(1 - \frac{i - n_d}{n_e - n_d}\right) \tag{7.8}$$

where n_e is the total number of episodes. As the aim of our learning experiment is to test whether helpful intent expressive parameters can be learned quickly, we

constrain the number of episodes to be 50 and we start decaying γ after 25 episodes. We chose $n_d = 25$ since the no cue case generates "straight" motion and as there might be a large need to explore based on the fact that no cue case may be a local optima as shown in [Zhao et al., 2016]. Due to the large amount of exploration during the training phase, a high variance in the rewards is expected.

7.6 Parameter Initialization:

The parameters are initialized on par with the no cue case as $w_0 = (0, 0.5, 0, 0)$

Algorithm 1 PoWER Update

Initialize:

$W_i \leftarrow \text{empty}, R_i \leftarrow \text{empty}, \gamma_0 = 0.33, w_i = (0, 0.5, 0, 0)$

while $i \leq n_e$ **do**

$\epsilon \sim N(0, I)$

if $i < n_d$ **then**

$\gamma \leftarrow \gamma_0$

else

$\gamma \leftarrow \gamma_0(1 - \frac{i - n_d}{n_e - n_d})$

end if

$w_e \leftarrow \text{normalize}(w_i) + \gamma\epsilon$

$w_e \leftarrow \text{denormalize}(w_e)$

$W_i.\text{insert}(w_e)$

$\tau_i \leftarrow \pi_{w_e}(S)$

$R_i.\text{insert}(r(\tau_i))$

$w_i \leftarrow w_i + \sum_{k=1}^K [(W_i^k - w_i)(R_i^k)] / \sum_{k=1}^K (R_i^k)$

$i \leftarrow i + 1$

end while

7.7 Summary

As the cue parameters were calibrated manually in the HRE to be consistent with the human motion, the generated trajectories might be sub-optimal. To optimize the parameters, we develop an active reinforcement learning based approach utilizing exploration in the parameter space and the *PoWER* update rule with importance sampling.

To achieve this, we first explore the parameter space through perturbation with a zero mean unit variance Gaussian noise at every episode. We start with the no cue (“*straight*”) trajectory and utilize large exploration steps to avoid a possible local optima (Sect. 7.5). We decay the amount of exploration through Eq. 7.8 after we pass a predetermined number of episodes. We generate the robot motion through the motion generation framework (Ch. 5) with the explored parameters (Sect. 7.2) according to the current state (Sect. 7.1) to receive feedback from the user and receive the episode reward (Sect. 7.3). We finally proceed with the *PoWER* update rule, based on the rewards and the parameters explored so far, following Eq. 7.5.

Chapter 8

LEARNING EXPERIMENT

The results of the human-robot interaction experiment point towards an interesting find: The existence of all cues embedded in a motion trajectory, enables intent expression in a real world human-robot interaction scenario as shown by statistically significant results through a one-way ANOVA (Tbl. 6.2), paired t-tests (Tbl. 6.3) and 95% confidence intervals (Fig. 6.4). However, as the parameters used in the human-robot interaction experiment (Sect. 6.4) were chosen by trial-and-error on par with the similarity to the human-human interaction cases in Ch. 3, they bear the presumption of sub-optimality.

Hence, we modified the human-robot interaction experiment to include a learning phase through feedback from the participant, utilizing the methodology explained in Ch. 7. After the learning phase, we have shown the motion trajectory embedded with the learned parameters and the no cue trajectories to the participant to evaluate the intent expressiveness of the learned motion compared to the no cue case. This experiment is also gamified; we calculate a score for each participant and there is a prize for the highest scorer.

Our aim in this experiment was to validate that the cue parameters learned through feedback from even naïve users (users with below-average robotic expertise) over a short, 50 episode period improves intent expressiveness of motion, where one episode corresponds to one trajectory demonstration to the participant.

Furthermore, we looked at the learned, participant-specific cue parameters' means and utilized them to investigate whether there might be universal cue parameters that improve intent expressiveness for any user, through a follow up experiment.

Both experiments were approved by the Internal Review Board (IRB).

8.1 Participants

21 male and 9 female participants from a campus community with a median age of 22 attended the experiment. 1 of them stated that she has not seen a robot in her life, 25 of them stated that they have only seen robots through videos, 3 of them had minor interactions with robots but not in a research related way and 1 of them stated that they are conducting/have conducted research in robotics. To motivate the participants, a gift card of 100 TRY (~ 19 USD) for a nationwide hobby shop is promised to the top performer, based on the accuracy and speed of their intent understanding as estimated by Eq. 8.1.

8.2 Experimental Setup

The same experimental setup as the human-robot interaction experiment (Sect. 6.2 and Fig. 6.1) is used for the learning experiment. However, we have only utilized the frontal viewpoint with the side-by-side object configuration as shown in Fig. 6.2a.



Figure 8.1: Different screenshots of the GUI.

One addition to the experimental setup is a GUI that signals the different phases of the robot and the experiment to the participant. The GUI is developed using the

TkInter Python package and it has four different sets of background colors and texts to show to the participant:

1. "You can press green now!" text on a white background to let the participant know that the robot is ready to proceed to the next motion (Fig. 8.1a).
2. "Calculating..." text on a blue background to let the participant know that the robot is conducting internal calculations (i.e. regarding the inverse kinematics, collision checks and velocity/acceleration limit checks) (Fig. 8.1b).
3. "Starting!" text on a green background to let the participant know that they can make their guesses through the button interface in front of them (Fig. 8.1c).
4. "Thanks for your participation!" text on a black background to let the participant know the experiment has ended (Fig. 8.1d).

8.3 Experimental Protocol

Before the experiment, the participants are given the informed consent form and enough time to go over it. The experiment begins after they sign the form.

The experiment begins by telling the participants about the experiment and what they were asked to do. We asked the participants to try to guess the robot's target intent as soon and as accurate as possible, and we specifically informed them about the robot not being deceitful or misleading in expressing its target intent.

The experiment was divided into three phases: (1) the tutorial phase, (2) the training phase and (3) the test phase. At the tutorial phase, the participants were shown four predefined robot motions to get them used to the robot's movements, the button interface and the GUI. At the training phase, the participants were shown fifty learning episodes of motions in which they improve the robot's intent expressiveness. At the test phase, twenty motions are shown to the participant (10 no cue motions and 10 motions with the learned parameters). The current phase the experiment is in, and how many motions are left in that phase can be followed through a progress bar in the GUI. Also, the GUI presents the participant with their score (Eq. 8.1)

and the current high score during the test phase. Current high score is shown in the GUI for the participants to direct their rivalry towards other participants and not to the robot. Furthermore, no information regarding how to train the robot better was provided to the participants. However, we explained them that their training performance will affect their score in the test phase.

To motivate the participants, the experiment was gamified through a similar methodology with the simulated robot experiment. The participants were asked to press the green button to start the next motion when they see that the robot is ready through the GUI. After the green button is pressed, the robot has a trajectory calculation delay before it starts executing its motion. During this calculation delay, GUI turns blue as shown in Fig. 8.1b and the robot checks if the found parameters would cause an error and it receives a large negative reward as explained in Sect. 7.3 if they do. After the motion starts, the GUI turns green (Fig. 8.1c) and the participants are asked to press the red or the blue button depending on their object guess' color. This gave the participants total control over the experiment.

8.4 Data Collection

We used the same data collection methodology with the human-robot interaction experiment (Sect. 6.5) but we changed the participant score (Eq. 6.1) to create a better game experience for the participants.

$$S_N = \sum_{n=1}^N G_n \left(1 - \frac{t_{n,g}}{t_{n,total}}\right) \quad (8.1)$$

where N is the number of motions seen by the participant and,

$$G_n = \begin{cases} 100, & \text{if } C = 1 \\ 0, & \text{otherwise} \end{cases} \quad (8.2)$$

8.5 Learning Analysis

An active reinforcement learning approach with PoWER updates, over the whole parameter space was used for intent expressive motion learning, as explained in Sect. 7.5.

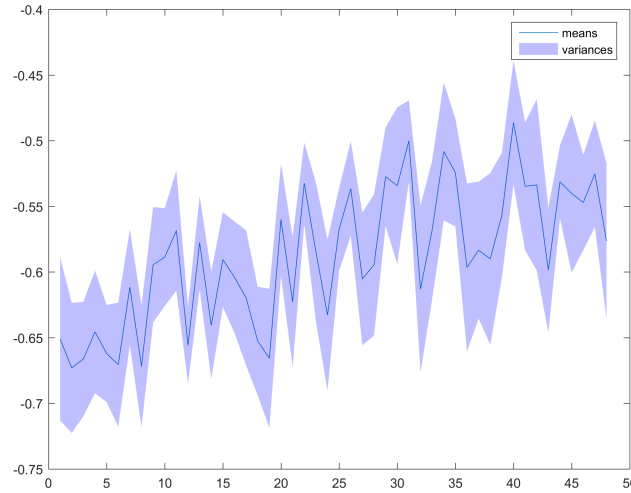


Figure 8.2: Training phase rewards with the mean and variance calculated over the participants.

Each participant has trained the robot for 50 episodes. As the training is highly dependant on participant responses, we do not guarantee convergence at 50 episodes. However, we strongly expect improvement regarding intent expression as evaluated by the guess score.

We present the training rewards in Fig. 8.2. The high variance in the rewards is due to the reward being dependant on the participant response time as discussed in Sect. 7.3 and the exploration among the whole parameter space as discussed in Sect. 7.5.

The increase in training rewards shows that the reinforcement learning approach allows training with even naïve users. As we have aimed for a fast training by even the users with below-average robotic expertise, we can conclude that the utilized approach is successful.

Fig. 8.3 presents a box plot for the learned parameters over all participants, showing that the participant-specific cue parameters vary throughout the whole parameter space within their individual limits (see Eq. 7.6). Note that α is normalized between -1 and 1 for Fig. 8.3. This might present two new interesting issues to investigate: (1) whether the parameters that express intent is highly user dependant, and (2) whether

there are universal parameters that improve intent understanding of all users. These issues are further discussed in Sect. 8.12.

Table 8.1: Means of the participant-specific cue parameters

Configuration	Bottle	t	r	h	α
Side-by-side	Blue	0.7	0.43	-0.0015	-0.1
	Red	0.7	0.43	0.0015	0.1

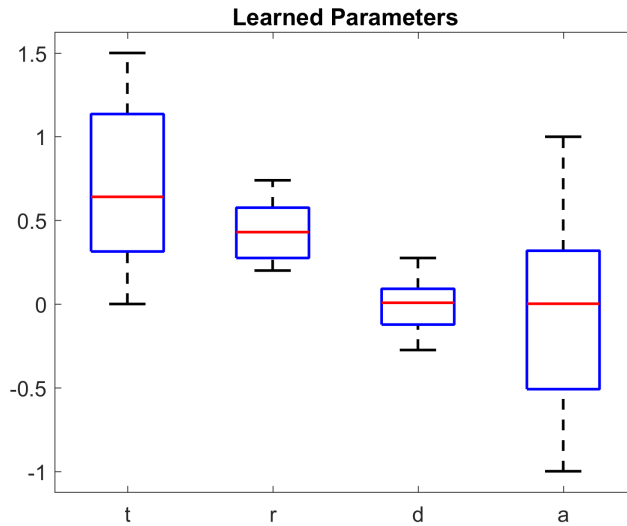


Figure 8.3: Box plots of the learned parameters.

Means for the participant-specific cue parameters are provided in Tbl. 8.1. h and α are symmetric with respect to zero for the blue and red bottles as explained in Sect. 7.2. Note that t (overall duration, *OT*) is increased, r (relative time of palm normal rotating towards the target object, *PN*) is decreased while h (exaggeration, *Exg*) and α (change in grasp modality, *GM*) are very close to 0. This reveals that the temporal cues might be more important than the spatial cues for an improvement in intent expressiveness. Also, it seems that a very subtle change in grasp modality and exaggeration seems to be enough to improve intent expression.

8.6 Investigation for Universal Parameters

We have presented the results of the human-robot interaction experiment in Sect. 6.8 and a learning analysis for LE in Sect. 8.5. One question that comes to mind is whether there are universal parameters that would work for everybody and Sect. 8.5 provides a good starting point for an investigation. Hence, we conducted a fifth, follow-up experiment that investigates the effects of mean learned cue parameters.

We modified the learning experiment to omit the training phase and we only ran the test phase with the mean of the learned cue parameters (Tbl. 8.1) for the participants to compare the generated trajectories with the no cue case. This experiment is also gamified: we calculate a score (Eq. 8.1) for each participant and there is a prize for the highest scorer.

This experiment was approved by the Internal Review Board (IRB).

8.6.1 Participants

11 male participants from a campus community with a median age of 21 attended the experiment. 1 of them stated that they have not seen a robot in their life, 8 of them stated that they have only seen robots through videos, and 2 of them had minor interactions with robots but not in a research related way. To motivate the participants, a gift card of 50 TRY (~ 9.5 USD) for a nationwide hobby shop is promised to the top performer, based on the accuracy and speed of their intent understanding as estimated by Eq. 8.1.

8.6.2 Experimental Setup, Experimental Protocol and Data Collection

The same experimental setup (Sect. 8.2, Fig. 6.1 and Fig. 8.1) and protocol (Sect. 8.3) as the learning experiment is utilized in the investigation for universal parameters, except that the training phase is omitted and the the mean of the learned cue parameters (Tbl. 8.1) were used instead of the participant-specific cue parameters. The data collection strategy is also the same with the learning experiment (Sect. 8.4).

8.7 Hypotheses

Based on our results of the human-robot interaction experiment, we define our hypotheses as:

1. The learned participant-specific cue parameters positively affect the expressiveness of the robot motion compared to the no cue (*Non*) case.
2. The mean learned cue parameters positively affect the expressiveness of the robot motion compared to the no cue (*Non*) case.

8.8 Statistical Analyses

Both hypotheses (**H1** and **H2**) are evaluated through paired right-tailed t-tests between the no cue (*Non*) case and the cue cases that contain the learned parameters. We also evaluate **H1** and **H2** through corresponding confidence intervals (Fig. 8.4).

8.9 Hypotheses Evaluation

The paired right-tailed t-tests between the no cue case and the cue cases with the learned parameters reveals that the cue cases has a positive statistically significant effect on intent expressiveness of robot motion compared to the no cue case ($p < 1e-5$, $t = 5.2492$ for the participant-specific cue parameters and $p < 5e-4$, $t = 3.7251$ for the mean learned cue parameters). Fig. 8.4 also shows that cue cases' effect on intent expressiveness of robot motion is statistically significant and positive.

Guess score means are 0.38 for the no cue case and 0.33 for the cue cases embedded with participant-specific cue parameters. Hence, there is a 5% overall and 15% relative improvement in intent expressiveness with the participant-specific cue parameters that can be reported by looking at the mean guess scores. For mean learned cue parameters, guess score means are 0.27 for the no cue case and 0.21 for the cue case. Hence, we report a 6% overall and 28.6% relative improvement in intent expression. While the overall improvement is similar to the case with the participant-specific cue

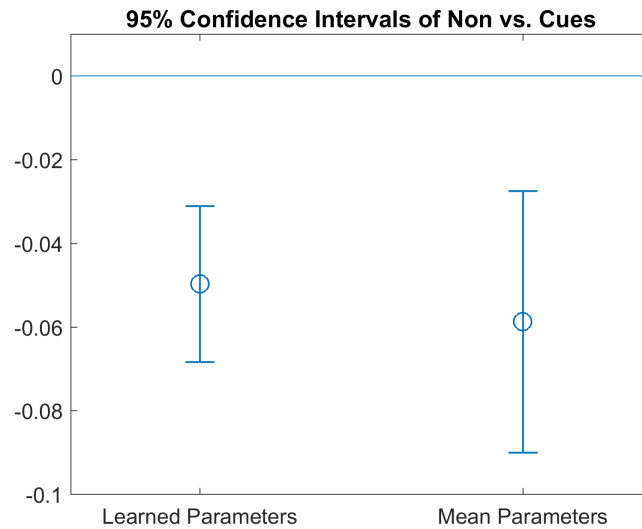


Figure 8.4: 95% Confidence Interval of the difference between the cue cases and the Non case for both the participant-specific cue parameters (left) and the mean learned cue parameters (right).

parameters, the mean learned cue parameters seems to have a better positive impact by looking at the relative improvement from the no cue case.

8.10 Parameter Evaluation

Fig. 8.4 presents a comparison between the cue cases in which the participant-specific cue parameters are utilized and the cue case in which the mean learned cue parameters are utilized. Note that there are more samples for the 'Learned Parameters' case compared to the 'Mean Parameters' case, hence the larger confidence interval. Even though the 'Mean Parameters' case provides a better relative improvement looking at the differences between the means of no cue cases and the cue cases, the 95% confidence intervals and the provided means are not enough to conclude that there are parameters that are intent expressive for any user.

8.11 Observations

During the training phase of LE, we observed some explored motions that mislead the participant through exaggeration: Robot motion was towards one side while it ultimately reached towards the object on the other side. This seemed to confuse the participants and they preferred to wait until they are sure which object the robot reaches towards when there is a sideways exaggeration present in robot motion. In turn, this led the robot to emphasize over other cues instead of *Exg*. This observation strengthens our claim that *Exg* might actually be confounding for naïve users that are not accustomed to robot motions. As there is also an interaction between *Exg* and *GM* due to their definitions via $\mathbf{h}$ and α as explained in Ch. 5, *GM* might also have lost its importance with *Exg*.

Furthermore, an earlier palm normal seems to cause the robot to cross out the probability of choosing the non-target object and place a higher emphasis on the target object, in turn helping the careful participants to make faster guesses. *PN* helps with intent expressiveness when there are only two objects, however its effect in a crowded cluster of objects should further be investigated.

Learning experiment presented us with another observation: There are some super-users that seem to feel more confident and trusting towards the robot. Even though these super-users still have below-average robotics expertise, they press the buttons immediately after the robot starts its motion and still make correct guesses. This points towards a new issue as to whether there are different types of users regarding intent expressive robot motion. Multiple user types might overthrow our universal cue parameters hypothesis, however this might lead us towards different sets of cue parameters that correspond to different user types.

8.12 Summary

Motivated by HRE results, in which we concluded that an all cue combination positively affects the intent expression, we decided to investigate the cue parameters

further. As we have utilized a manually calibrated set of cue parameters, the generated intent expressive motion bears the presumption of sub-optimality. Furthermore, the intent expressive effect of the cues, begs the questions of whether there are different sets of parameters for different users and whether there are universal parameters that help improve intent understanding of any user.

We developed an active reinforcement learning methodology that is based on PoWER updates and an exploration over the whole parameter space for the learning experiment (LE) (Ch. 7). The participants, first, trained the robot for 50 episodes and participant-specific cue parameters are evaluated at the end, again by themselves.

Through LE, we verified that the developed learning methodology allows training in considerably short time (50 episodes) by even naïve users (Fig. 8.2). Furthermore, the participant-specific cue parameters seem to improve the intent expressiveness of robot motion by overall 5% and relative 15% (Fig. 8.4 and Sect. 8.9).

We have also observed that exaggeration might actually be confounding for the users and the robot tries to avoid exaggeration in its learned trajectories. This also causes a loss of importance for *GM* due to the interaction between *Exg* and *GM* as explained in Sect. 5.1. This can also be seen by looking at the means of participant-specific cue parameters learned in the first phase of the learning experiment. This further implies that the spatial aspects of intent expressive trajectories might not be as important as the temporal aspects.

Another observation we have made is related to *PN*: An earlier pointing of the palm normal towards the target object seems to cross out the possibility of reaching towards the non-target object and it actually helps careful participants to make faster guesses. This positive effect of *PN* on intent expressiveness was also seen in the HRE (Sect. 6.10).

The box plot in Fig. 8.3 provides an overview for the participant-specific cue parameters and the parameters seem to vary throughout the whole parameter space within the allowed limits. This issue requires further investigation to understand whether the intent expressive cue parameters are highly user dependent or if there

are universal parameters that improve intent understanding of all users.

We conduct a fifth, follow up experiment that utilizes only the mean learned cue parameters (Tbl. 8.1) in the cue case, to investigate the issue of universal parameters. This investigation revealed that there might be universal cue parameters that improve intent expressiveness of robot motion by overall 6% and relative 28.6% (Sect. 8.9 and Fig. 8.4). Even though there are more samples for LE, a common set of mean learned cue parameters seem to help with intent expressiveness more than their participant-specific counterparts. However, comparing the %95 confidence intervals for two separate experiments with different sample sizes are not enough to conclude this and a further evaluation is required. Our observation of different user types might hinder our argument regarding the existence of universal cue parameters but there might still be more than one general set of cue parameters that help with intent understanding for different user types.

Chapter 9

CONCLUSION

The work presented in this thesis enables the utilization of human-inspired communicative cues in intent expressive robot motion. In a broad sense, we tackle the intent expression problem in human-robot interaction through spatial and temporal kinematic cues by taking inspiration from human motion and come up with a framework that enables embedding and learning these cues in robot motion trajectories.

We start by investigating human motions through a human-human interaction experiment and find out that there are at least four communicative cues that are used by humans in reach-to-grasp motions to express their intent. We proceed with systematical robot experiments: through a simulated robot experiment, we reveal that the communicative cues are also helpful in robot motion and we identify the interactions between them. As the communicative cues' positive effect is shown in the simulated robot experiment, an intent expressive motion generation framework is introduced and utilized in a follow up experiment with a real robot. This human-robot interaction experiment further revealed that a combination of all cues is robust to changes in both observer viewpoint and object configuration. However, the cues were embedded in robot motion trajectories manually, such that the trajectories resembled human motion. We improved our intent expressive motion generation framework with an active reinforcement learning methodology, as the manual calibration of the cues suffered from the presumption of sub-optimality. We utilized our active reinforcement learning approach in a learning experiment and in turn, our robot learned participant-specific cue parameters. Seeing the positive effect of the participant-specific cue parameters, we investigated further, revealing that there might be universal cue parameters that improve intent understanding of any user. At the end, we have shown the efficacy of

the human-inspired communicative cues and developed an intent expressive motion generation framework enhanced with active reinforcement learning, that can come up with intent expressive motion trajectories for all users. Overall, five experiments were conducted with nearly 120 participants to identify, verify and utilize the communicative cues in intent expressive robot motion, leading to the following contributions:

9.1 Summary of Contributions

9.1.1 Human-Inspired Communicative Cues for HRI

The human-human interaction experiment revealed that there are both spatial and temporal communicative cues hidden in motion kinematics as also suggested by [Becchio et al., 2012]. We looked at these communicative cues from an HRI perspective and showed that they can be embedded in robot motion to improve intent expressiveness through a simulated (Ch. 4) and a real (Ch. 6) robot experiment. Furthermore, the existing body of literature places more importance towards the spatial aspects of motion, being inspired by animation. We reveal that temporal aspects are at least as important as the spatial aspects of motion for intent expression and later show that they might be even more important than the spatial aspects as can be seen through the results of the learning experiment (Ch. 8).

9.1.2 Robustness of Cue-based Intent Expressive Motion

Body of literature generally consists of intent expressive robot arm motions that are viewed from the front with the objects residing in a side-by-side configuration. The robustness of the existing approaches are not proven in different configurations. A full combination of the human-inspired communicative cues have proven to be robust against these changes in both the simulated robot experiment (Ch. 4) and the real robot experiment (Ch. 6).

9.1.3 Automated Intent Expressive Motion Generation

The generation of motion trajectories, that vary depending on the desired communicative cues, is difficult to achieve with standard approaches. We present a novel approach that enables the generation of intent expressive motion trajectories with the parameterized cue inputs alone (Ch. 5). The efficacy of this approach is proven through the human-robot experiment (Ch. 6) and later in the learning experiment (Ch. 8).

9.1.4 Learning Intent Expressive Robot Motion

One of the advantages of our intent expressive motion generation framework and our communicative cue formulation is that the essence of intent expression can be captured in a small parameter space. Considering the cue parameters as the policy parameters, we enhanced our motion generation framework with a *POWER* based active reinforcement learning approach (Ch. 7). The added learning capability of automated intent expressive motion generation has proven to be helpful in generating participant-specific cue parameters that in turn provide an improved intent expression for any user.

9.1.5 User-Specific and Universal Cues

Through our active reinforcement learning methodology, the robot came up with participant-specific cue parameters. However, this unraveled another question for us: Whether there are universal cue parameters that can improve intent expression for any user. We utilized the means of the participant-specific cue parameters from the first phase of the learning experiment to investigate this issue and achieved an equivalent improvement with the participant-specific cue parameters. This suggests that there might actually be universal cue parameters that improve intent understanding of any user or at least general cue parameter sets that can improve intent expression for different user groups.

9.2 Secondary Observations

We have made certain observations that are not directly related to intent expressive motion but nevertheless interesting from robotics and human-robot interaction point of view.

Participant answers to the survey questions of the HHE (Sect. 3.8) are very informative (e.g. the responses about the body posture change). They show that some communicative cues are conscious. We argue that participant opinions should be taken in similar circumstances which may speed up communicative cue discovery and aid intent recognition.

We were surprised to see the ambition of the participants and their rivalry against the robot during HRE. Despite being told that the robot was not trying to deceive them, some participants assumed that the robot was being deceptive. This specifically manifested when they were pressing the buttons. This might be related to changes in the robot's "thinking" phase (the $\sim 1 \pm 0.3$ seconds trajectory calculation delay). The change in this "thinking" phase duration, amplified with the rivalry towards the robot, might have been interpreted by the participants as changes in the robot's confidence level (as in "the robot is winning/losing now") and might be fueling the ambition in button presses. The ambitious behavior (as we have not observed this in the simulated robot experiment) might also be caused by making two decisions in one button press: In the simulated robot experiment, the participants were making "I now have a guess" decision by pressing the space bar, and "my guess is this one" decision by clicking a button. In the real robot experiment, they had to make both of these decisions at the same time with a single button press. This might have caused stress and increased ambition. An interesting point is that, participants report different levels of ambition during the experiment but our answer pool is not large enough to draw any conclusions.

The reason for this perceived rivalry might be due to the gamified nature of the experiment along with the prize. The reason that this did not manifest itself during the simulated robot experiment is that participants were told they were watching

videos, thus they knew that the robot did not make any decisions. The real-robot computed its trajectories online, with pre-determined durations and communicative cue parameters, which resulted in a variable delay after the participants press the green button. Coupled with this "thinking" duration, the button presses might have given the interaction a turn-taking game flavor, furthering the rivalry. Finally, the physicality of the robot and all the above points might have increased the perceived agency of the robot and mind-attribution. We think that these reasons resulted in the robot being perceived as a competitor. In LE, we presented the participants with a high score at the test phase to signal them that they are not competing with the robot. This seemed to help redirect their rivalry towards other participants instead of the robot and they considered the robot more as a collaborator.

9.3 Future Work

We have utilized an active reinforcement learning approach to identify user-specific cue parameters and investigated whether there is a common set of universal cue parameters that can be utilized for all users. However, the user-specific cue parameters were utilized before the learning completely converged and hence, our common set of cue parameters are still far from being optimal. An immediate future step could be to investigate the issue of universal parameters through a more extensive study. Another observation we have made during the learning experiment was that there might be different user types as explained in Sect. 9.2. Different set of cue parameters for different user types might be a possible issue to investigate.

Furthermore, we have only investigated the effects of cue parameters and learned them in a single configuration. A better approach could be to modify our state definition to include the target object's location with respect to other objects in the vicinity. With this, modified state formulation, the learning methodology can be extended to a cluster of objects instead of just two of them and would handle both the target object and the different object configurations.

The scope of the presented work includes only reach-to-grasp motions towards

cylindrical objects. However, other human-human interaction scenarios involving other actions and other objects should also be investigated. Future extensions to this study might consider other actions such as grasping-to-pour or reaching-to-touch. Another future avenue could be to investigate communicative cues in intent expressive reaching-to-grasp motions towards other objects of different shapes and forms (e.g. a light and flat paper or a heavy and sturdy hammer). As we have discussed in Sect. 4.9, *MA* might be important for action communication rather than object communication and its effect in these different actions could also help with evaluating this hypothesis.

[Donnarumma et al., 2017] suggest that cues in sequential tasks, such as a reach-to-grasp action followed by a grasp-to-pour action, are automatically generated in human-human interactions. An investigation of communicative cues in sequential tasks could be another interesting future step to take. Several joint action studies (e.g. by [Sartori et al., 2009] and by [Donnarumma et al., 2018]) examine the effects of communicative cues in various human-human interaction scenarios. Our examination may have been inadequate to find all hidden cues in human reach-to-grasp motions. The joint action psychology literature should be analyzed in more detail to identify other communicative cues, and their effects on intent expression.

We have discussed in Sect. 6.10 and 9.2 that we have observed competitive reactions from some of the participants against the robot in the HRE. A less competitive and a more cooperative experimental design would circumvent this issue and may result in less noisy observations.

Intent expressive cues help improve efficiency and fluency in human-robot interactions; however their absence, negation or abuse could be used for generating deception in games and for other entertainment purposes. Towards this end, the same motion generation methodology from HRE could be used to generate deceptive motion and a gamified deception analysis could be conducted through the same approach we have utilized in HRE. Deception in HRI was also investigated by [Dragan et al., 2014].

The answers to HHE survey questions suggest that body posture could be utilized

for intent expression by robots that have a torso or it could also be utilized to recognize human intent. Furthermore, We only looked at hand motion and thus developed our spatial cues for end-effectors. However, there may be cues related to specific joints such as how the elbow is positioned during motion. For redundant manipulators, we may come up with additional cues, such as relating to the elbow twist. Similarly there are other informative cues in human-human interactions hidden in gaze and haptics as studied by several HRI researchers (see Sect. 2.1). Such insights and data from human-human studies can be used to create or learn models for both intent expressive motion generation or human intent recognition.

9.4 Final Remarks

To the best of our knowledge, this is the first robotics study that investigates human motion to identify communicative cues for an intent expressive robotic manipulator and tests the identified cues with a two layer systematic analysis. The study is highly interdisciplinary, nourished with joint action psychology studies to culminate its ideas in human-robot interaction. Furthermore, a novel intent expressive motion generation framework is formulated and utilized with active reinforcement learning to improve the understanding of target intent in human-robot interaction scenarios.

There are several interesting points that we discovered, such as the effects of relative agent positions and objects, whether there are other communicative cues to be identified in human motion kinematics for other joint tasks, and whether there are universal communicative cue parameters that improve intent expressiveness for any user. It was shown that changes in spatial aspects of motion might not be enough by themselves and temporal aspects of motion should also be considered as they can actually be more helpful as proven by the learning experiment.

The interesting avenues of extension include investigation of universal cue parameters, reinforcement learning with a more extensive state formulation, testing the cues in different scenarios, identification and evaluation of other cues for HRI, analyzing the effect of rivalry against the robot vs. cooperation and utilization of the cues for

deceptive motion generation.



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Appendix A

INDEX TO MULTIMEDIA EXTENSIONS

Table A.1: Table of Multimedia Extensions

Extension	Media Type	Description
1	Video	HHE: Cue Identification
2	Video	SRE: Motions in Config. 1 - Bottle 2
3	Video	SRE: Motions in Config. 3 - Bottle 2
4	Video	HRE: Motions V0-C0
5	Video	HRE: Motions V1-C0
6	Video	HRE: Motions V0-C1
7	Video	HRE: Motions V1-C1
8	Video	HRE: User Interaction
9	Video	LE: Participant's POV
10	Video	LE: Misleading Exaggeration
11	Video	LE: Different User Types