Manuel Giuliani

Week 9

Human-Robot Interaction

Human-aware Motion Planning

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Lectures overview

W.	Lecture
1	Introduction to HRI
2	Human factors and context
3	Design for HRI systems
4	User studies
5	Social signal processing
6	Natural language processing
7	Dialogue & Speech synthesis
8	Human-aware motion planning
9	Symbolic reasoning for HRI
10	Architecture for HRI
11	Statistics for HRI user studies
12	Exam revision

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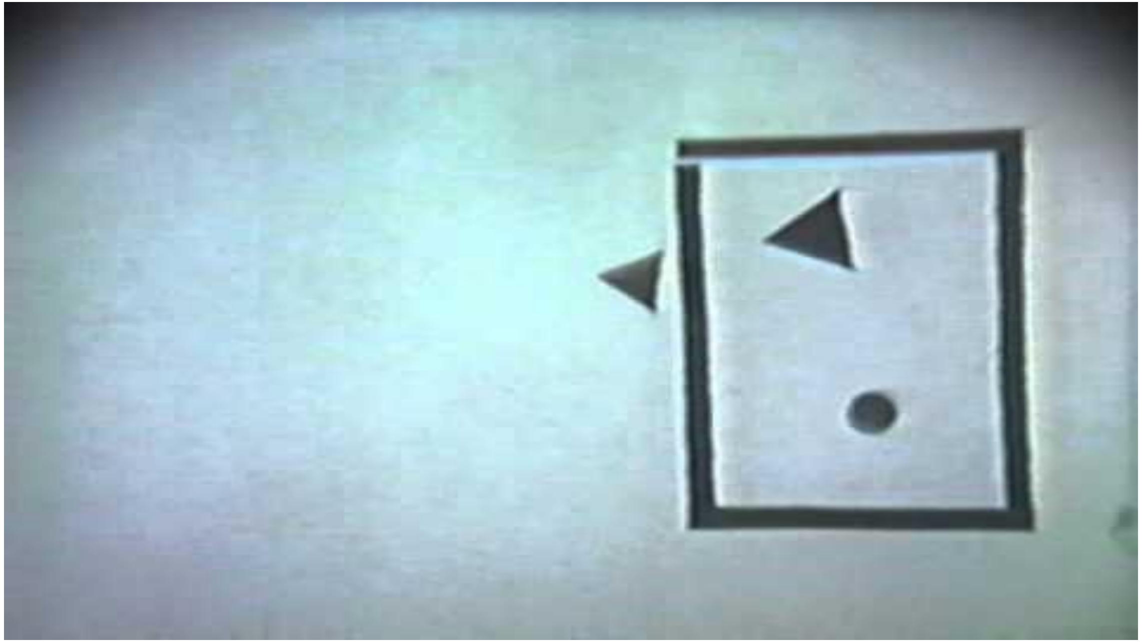
Learning outcomes

Get to know different approaches for human-aware motion planning

Why study human-aware motion planning?



Heider, F., & Simmel, M. (1944). An experimental study of apparent behavior. *The American journal of psychology*, *57*(2), 243-259.

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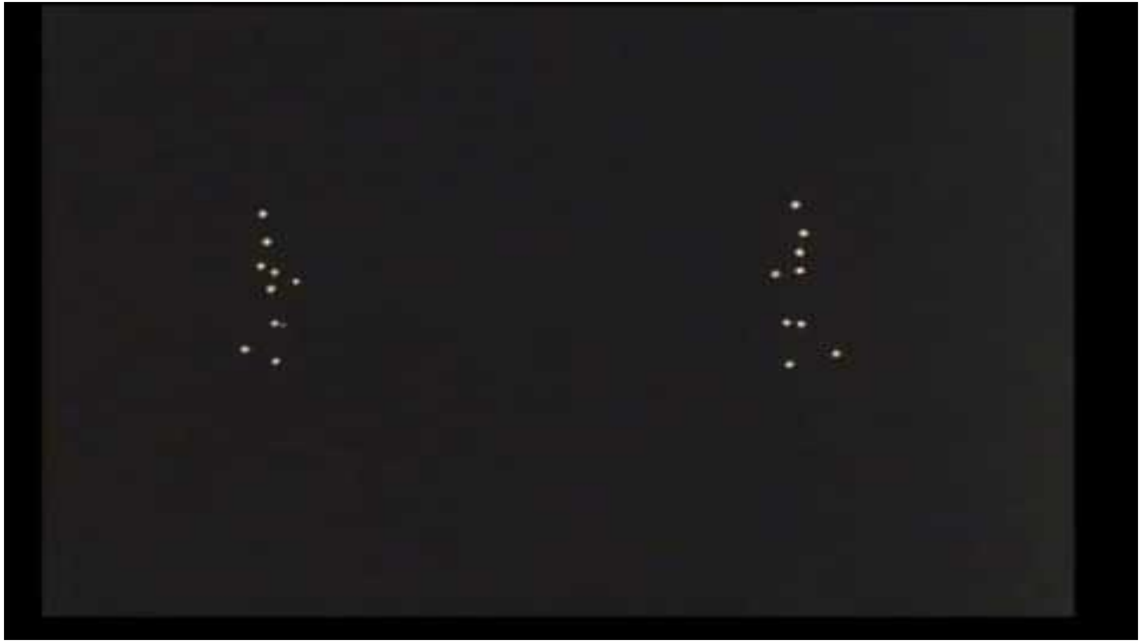
https://www.youtube.com/watch?v=8FIEZXMUM2I

Biological Motion



Johansson, G. (1973). Visual perception of biological motion and a model for its analysis. *Perception & psychophysics*, *14*(2), 201-211.

https://www.youtube.com/watch?v=1F5ICP9SYLU

Human-Aware Motion Planning

Goals

- Safe motion → no harm to human
- Reliable and effective motion → achieve task adequately
- Socially acceptable motion → take human into account

Challenges

- Calculating safe motions in a general way
- Tracking humans and updating motions on the fly

A Human Aware Mobile Robot Motion Planner

Emrah Akin Sisbot, Luis F. Marin-Urias, Rachid Alami, and Thierry Siméon, *Member, IEEE*

***Abstract*—Robot navigation in the presence of humans raises new issues for motion planning and control when the humans must be taken explicitly into account. We claim that a human aware motion planner (HAMP) must not only provide safe robot paths, but also synthesize good, socially acceptable and legible paths. This paper focuses on a motion planner that takes explicitly into account its human partners by reasoning about their accessibility, their vision field and their preferences in terms of relative human–robot placement and motions in realistic environments. This planner is part of a human-aware motion and manipulation planning and control system that we aim to develop in order to achieve motion and manipulation tasks in the presence or in synergy with humans.**

***Index Terms*—Human–robot interaction (HRI), motion planning, social interaction.**

I. Introduction

THE introduction of robots in our daily life raises a key issue that is "added" to the "standard challenge" of autonomous robots; the presence of humans in the robot environment and the necessity to interact with them. In the factory, the robot is systematically and physically separated from the human workers. This will not be the case for future applications where the robot will be in a situation where it will have to assist humans.

To allow the robots "coexist" with humans, human–robot interaction needs to be taken into account in all steps of the robot design. This paper addresses issues related to the close interaction between humans and robots from the standpoint of the motion decisions that must be taken by the robot in order to ensure:

- safe motion, i.e., that does not harm the human;
- reliable and effective motion, i.e, that achieves the task adequately considering the motion capacities of the robot;
- socially acceptable motion, i.e, that takes into account a motion model of the human as well as his preferences and needs.

Let us consider a simple "fetch and carry task" as illustrated in Fig. 1 for a socially interactive robot [1]. The robot has to perform motion and manipulation actions and should be able to determine where a given task should be achieved, how to place itself relatively to a human, how to approach him, how to hand the object and how to move in a relatively constrained environment in the presence of humans (an apartment for instance). Our goal is to develop a robot that is able to take into account "social constraints" and to synthesize plans compatible with human

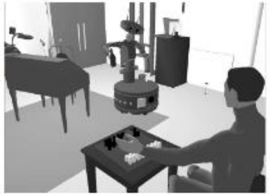


Fig. 1. "Fetch-and-carry" scenario in a domestic environment in presence of a person.

preferences, acceptable by humans, and easily recognizable in terms of intention.

This work is part of a broader effort to develop a decisional framework for human–robot interactive task achievement, embedded in a cognitive architecture, aimed to allow the robot not only to accomplish its tasks but also to produce behaviors that support its commitment vis-a-vis its human partner and also to interpret human behaviors and intentions [2].

We have introduced our approach and presented preliminary results in [3] and [4]. We have discussed in [5] how user studies have influenced the design of our planner. In this paper, we present in detail a human aware motion planner (HAMP) and its implementation with simulation and real world results.

In Section II, we briefly discuss related work. Section III provides the main characteristics and algorithms of our motion planner. We show simulation results in different scenarios in Section IV. Finally, we describe in Section V the implementation of the planner on a mobile robot and present real-world results.

II. Related Work

Although human–robot interaction is a very active research field, there is not extensive research on motion planning in the presence of humans.

In the factory, safety is assured by not allowing humans to approach robots at work. Although this method mostly prevents collision risks, it cannot be applied in applications where the robot has to assist, sometimes physically, a human. Obviously, safety issues become the primary concern when robots come into humans' everyday environment. The notion of safety becomes very critical and must be studied in detail with all of its aspects [6].

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Digital Object Identifier 10.1109/TRO.2007.904911

Sisbot, E. A., Marin-Urias, L. F., Alami, R., & Simeon, T. (2007).

A human aware mobile robot motion planner.

IEEE Transactions on Robotics, *23*(5), 874-883.

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Human-Aware Mobile Robots

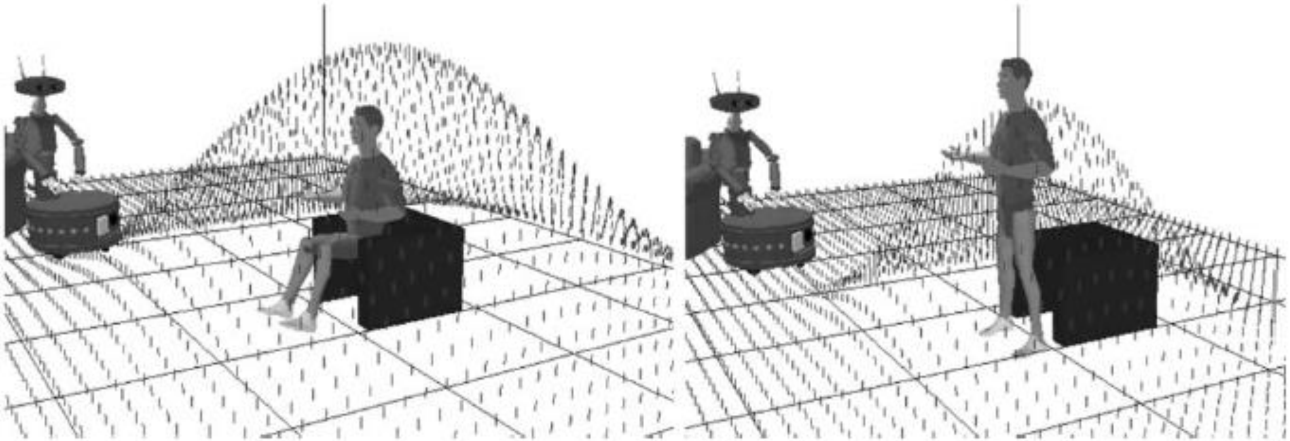

Fig. 2. Safety grid built around every human in the environment. This depends highly on the human's posture. As the person feels less "threatened" when standing, the value and the range of the costs are less important.

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Human-Aware Mobile Robots

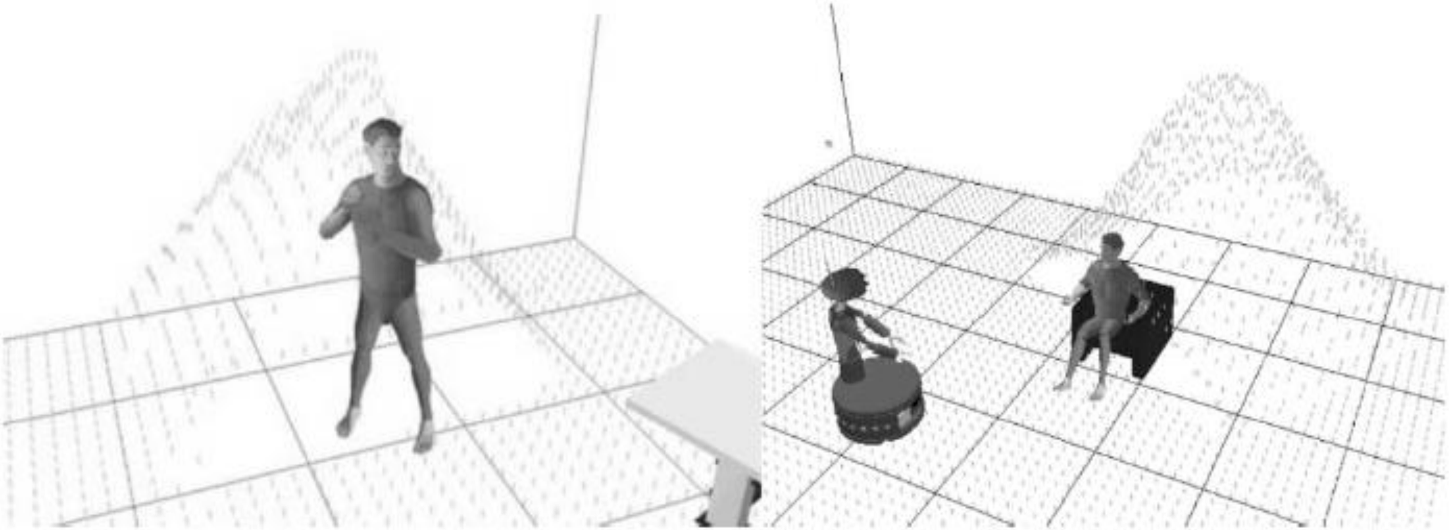

Fig. 3. Visibility grid computed by taking into account human's field of view. Places that are difficult for the human to see have higher costs.

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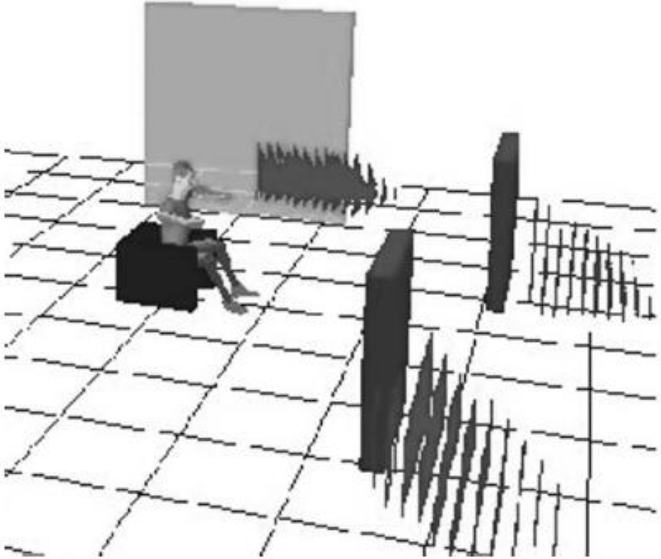

Fig. 4. Decreasing costs attributed to the zones hidden by obstacles. The supplementary costs discourage the robot getting too close to the obstacles and thus, prevents the robot from appearing suddenly behind hidden places.

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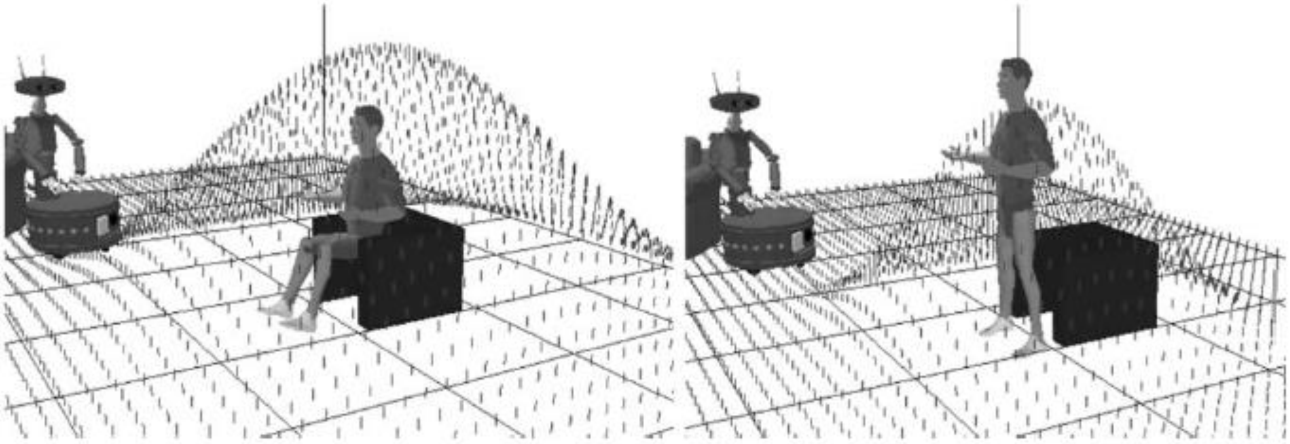

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2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
September 24–28, 2017, Vancouver, BC, Canada

Socially Aware Motion Planning with Deep Reinforcement Learning

Yu Fan Chen, Michael Everett, Miao Liu[†], and Jonathan P. How

Abstract— For robotic vehicles to navigate safely and efficiently in pedestrian-rich environments, it is important to model subtle human behaviors and navigation rules (e.g., passing on the right). However, while instinctive to humans, socially compliant navigation is still difficult to quantify due to the stochasticity in people's behaviors. Existing works are mostly focused on using feature-matching techniques to describe and imitate human paths, but often do not generalize well since the feature values can vary from person to person, and even run to run. This work notes that while it is challenging to directly specify the details of what *to* do (precise mechanisms of human navigation), it is straightforward to specify what *not to* do (violations of social norms). Specifically, using deep reinforcement learning, this work develops a time-efficient navigation policy that respects common social norms. The proposed method is shown to enable fully autonomous navigation of a robotic vehicle moving at human walking speed in an environment with many pedestrians.

Fig. 1: A robotic vehicle navigating autonomously in a pedestrian rich environment. Accounting for social interactions is important for operating such vehicles safely and smoothly.

I. Introduction

Recent advances in sensing and computing technologies have spurred greater interest in various applications of autonomous ground vehicles. In particular, researchers have explored using robots to provide personal mobility services and luggage carrying support in complex, pedestrian-rich environments (e.g., airports and shopping malls) [1]. These tasks often require the robots to be capable of navigating efficiently and safely in close proximity of people, which is challenging because pedestrians tend to follow subtle social norms that are difficult to quantify, and pedestrians' intents (i.e., goals) are usually not known [2].

A common approach treats pedestrians as dynamic obstacles with simple kinematics, and employs specific reactive rules for avoiding collision [3]–[6]. Since these methods do not capture human behaviors, they sometimes generate unsafe/unnatural movements, particularly when the robot operates near human walking speed [2]. To address this issue, more sophisticated motion models have been proposed, which would reason about the nearby pedestrians' hidden intents to generate a set of predicted paths [7], [8]. Subsequently, classical path planning algorithms would be employed to generate a collision-free path for the robot. Yet, separating the navigation problem into disjoint prediction and planning steps can lead to the *freezing robot problem*, in which the robot fails to find any feasible action because the predicted paths could mark a large portion of the space untraversable [9]. A key to resolving this problem is to account for cooperation, that is, to model/anticipate the impact of the robot's motion on the nearby pedestrians.

Existing work on cooperative, socially compliant navigation can be broadly classified into two categories, namely *model-based* and *learning-based*. Model-based approaches are typically extensions of multiagent collision avoidance algorithms, with additional parameters introduced to account for social interactions [7], [10]–[13]. For instance, to distinguish between human–human and human–robot interactions, the extended social forces model [11], [12] augments the potential field algorithm with additional terms that specify the repulsive forces (e.g., strength and range) governing each type of interaction. Model-based methods are designed to be computationally efficient as they often correspond to intuitive geometric relations; yet, it is unclear whether humans do follow such precise geometric rules. In particular, the force parameters often need to be tuned individually, and can vary significantly for different pedestrians [12]. Also, it has been observed that model-based methods can lead to oscillatory paths [2], [14].

In comparison, learning-based approaches aim to develop a policy that emulates human behaviors by matching feature statistics, such as the minimum separation distance to pedestrians. In particular, Inverse Reinforcement Learning (IRL) [15] has been applied to learn a cost function from human demonstration (teleoperation) [16], and a probability distribution over the set of joint trajectories with nearby pedestrians [2], [17]. Compared with model-based approaches, learning-based methods have been shown to produce paths that more closely resemble human behaviors, but often at a much higher computational cost. This is because computing/matching trajectory features often requires anticipating the joint paths of all nearby pedestrians [2], and might depend

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Chen, Y. F., Everett, M., Liu, M., & How, J. P. (2017, September).

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Human-Aware Mobile Robots

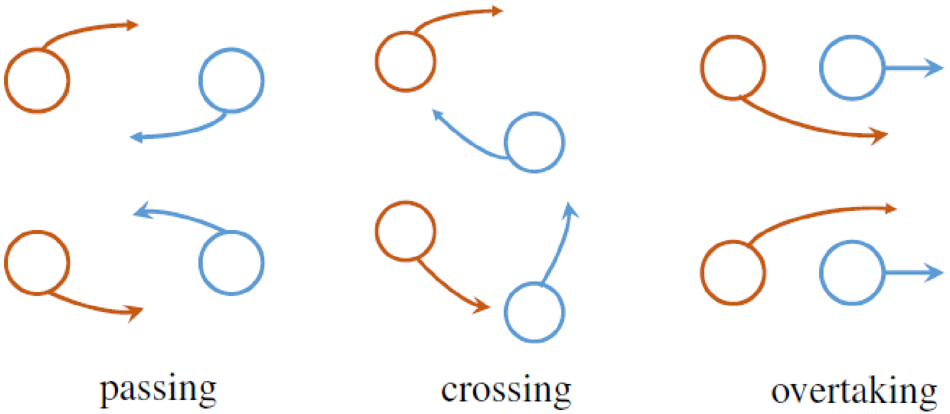

Fig. 2: Symmetries in multiagent collision avoidance. Left to right show two equally time-efficient ways for the red agent to pass, cross and overtake the blue agent. The top row is often called the left-handed rules, and bottom row the right-handed rules.

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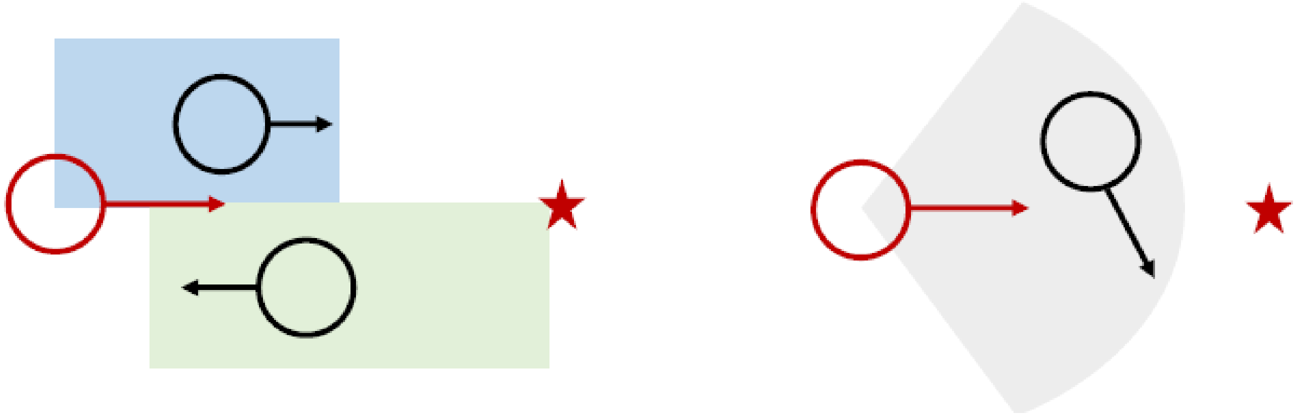

Fig. 4: Norm inducing reward function (depiction of (10)-(12)). The red agent is penalized if there is another agent in the blue, green or gray shaded regions, corresponding to overtaking, passing and crossing, respectively. This induces the right-handed rules as shown in Fig. 2.

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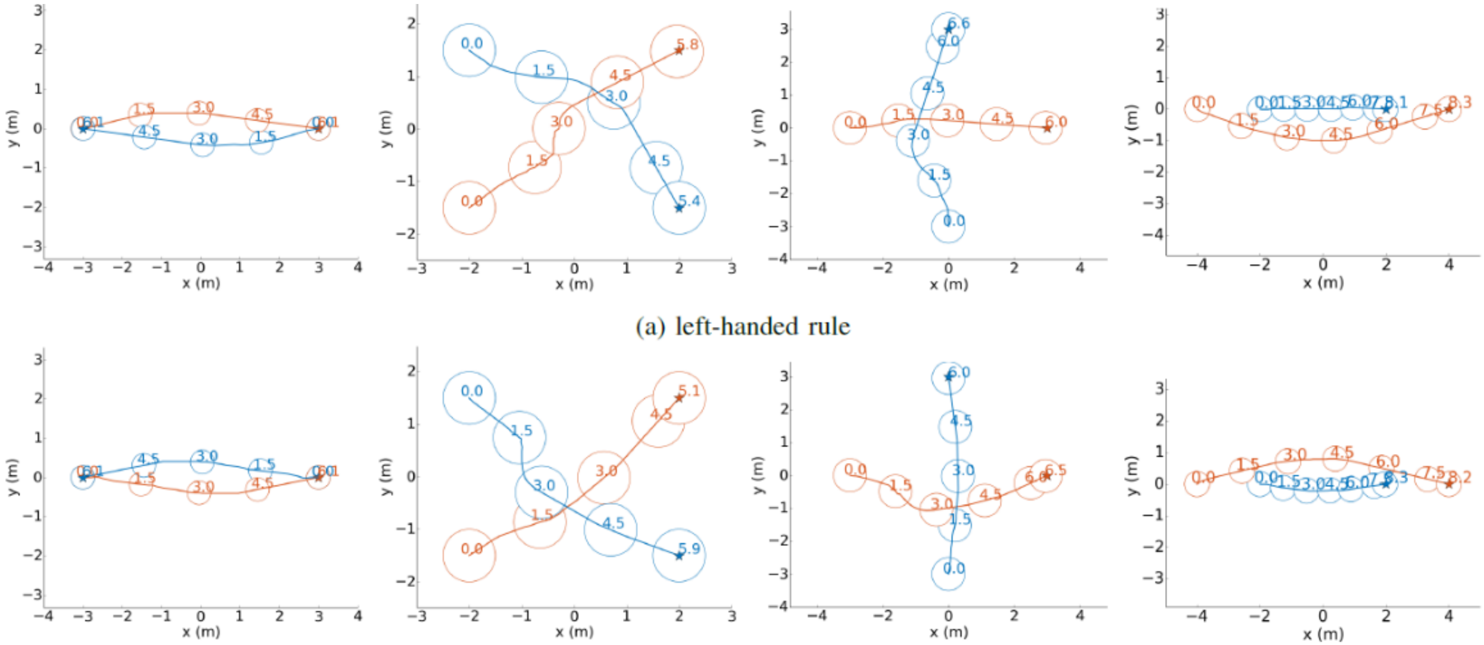

(a) left-handed rule

(b) right-handed rule

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The 2009 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 11-15, 2009 St. Louis, USA

Influences on Proxemic Behaviors in Human-Robot Interaction

Leila Takayama and Caroline Pantofaru

Abstract— As robots enter the everyday physical world of people, it is important that they abide by society's unspoken social rules such as respecting people's personal spaces. In this paper, we explore issues related to human personal space around robots, beginning with a review of the existing literature in human-robot interaction regarding the dimensions of people, robots, and contexts that influence human-robot interactions. We then present several research hypotheses which we tested in a controlled experiment (N=30). Using a 2 (robotics experience vs. none: between-participants) x 2 (robot head oriented toward a participant's face vs. legs: within-participants) mixed design experiment, we explored the factors that influence proxemic behavior around robots in several situations: (1) people approaching a robot, (2) people being approached by an autonomously moving robot, and (3) people being approached by a teleoperated robot. We found that personal experience with pets and robots decreases a person's personal space around robots. In addition, when the robot's head is oriented toward the person's face, it increases the minimum comfortable distance for women, but decreases the minimum comfortable distance for men. We also found that the personality trait of agreeableness decreases personal spaces when people approach robots, while the personality trait of neuroticism and having negative attitudes toward robots increase personal spaces when robots approach people. These results have implications for both human-robot interaction theory and design.

I. INTRODUCTION

Simple robots such as robotic vacuum cleaners are becoming increasingly prevalent in everyday human environments, and it is only a matter of time until larger and more complex robots join them. As in human-to-human interactions, a contributing factor to human acceptance of such machines may be how well the robots obey comfortable human-robot spatial relationships. There is a wealth of information from both natural field observations and controlled laboratory experiments regarding the personal spaces of interacting people (e.g., [2][8]), but it is unclear exactly how this will inform human-robot personal spaces.

The media equation theory states that people interact with computers as they interact with people [14][16]. This may become increasingly true for human-robot interaction, where the computers that take action in the physical human environment. However, people do not always orient toward robots as they orient toward people. At times, people engage with robots in the way that they engage with tools [20], particularly when they are roboticists whose job it is to build and maintain the robot. Thus, it is necessary to gain a better understanding of which robot design decisions influence human proxemic behaviors around robots, and how human factors such as experience with robots can affect them.

By gaining a deeper understanding of the factors that most influence human-robot proxemic zones, one may gain a better sense of how to design better models of human-robot interaction, optimizing algorithms for how close robots should approach people. Indeed, using proxemic distances to alter interactive system behavior has already been effective in human-computer interactions with systems such as digital white boards [12]. Similar research is currently being done on how end-users might teach robots to engage in acceptable proxemic behaviors [13].

The goals of this study are to more thoroughly explore the human and robot factors that influence optimal proxemic behaviors in human-robot interaction and to turn those findings into implications for human-robot interaction design. As such, we first present a review of existing literature on issues of human proxemics, human dimensions of HRI proxemics, robot dimensions of HRI proxemics, and pose hypotheses to be tested by this study.

Our theoretical stance is that people will engage in proxemic behavior with robots in much the same way that they interact with other people, thereby extending the Computers as Social Actors theory [14][16] to human-robot interaction. Based on the existing empirical literature in human proxemics and HRI, we present more specific research hypotheses and test them with a controlled experiment, focusing on personal experience with pets and robots, personality characteristics, and the robot's head direction (facing the person's face vs. facing the person's legs), as they influence the personal spaces between people and robots.

II. RELATED LITERATURE

A. Human Proxemics

Fifty years ago, Edward T. Hall [8] introduced the concept of proxemics, which refers to the personal space that people maintain around themselves. Much of the research on this topic is summarized by Michael Argyle [2], who introduced an intimacy equilibrium model [1], which reasons about the interactions between mutual gaze and proxemic behavior. If a person feels that someone else is standing too close for comfort, that person will share less mutual gaze and/or lean away from the other person. As noted by Argyle [2], there are many factors that influence proxemic behaviors, including individual personalities, familiarity between people, to what degree people are interacting, the social norms of their culture, etc.

The unspoken rules of personal space tend to hold true with nonhuman agents. In virtual reality settings, people

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Influences on proxemic behaviors in human-robot interaction.

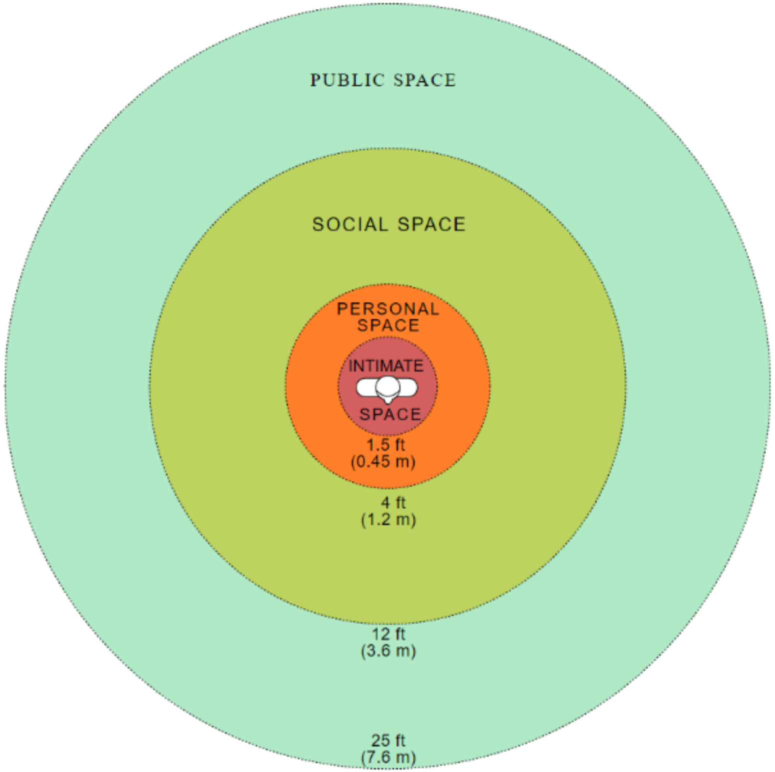
In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 5495-5502). IEEE.

Approaching Behaviour

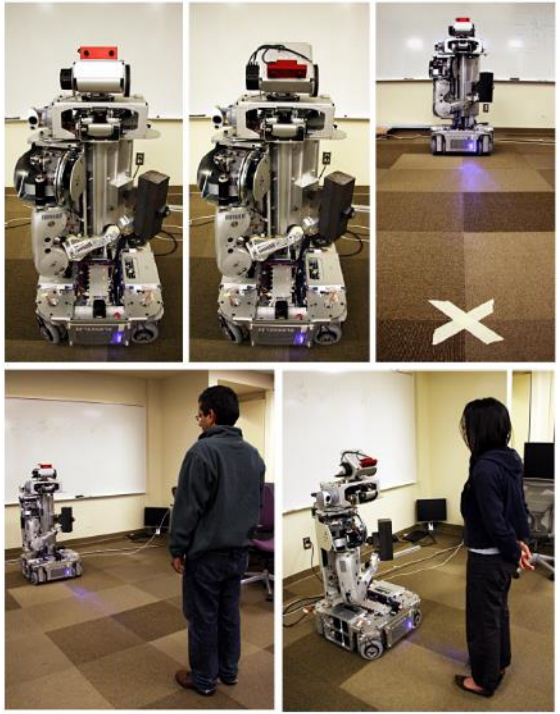
Proxemics

- Study of human use of space
- Effects of population density on behaviour, communication, and social interaction
- Term coined by Edward T. Hall, 1963

Hall, Edward T. (1966). The Hidden Dimension. Anchor Books. ISBN 978-0-385-08476-5.



Approaching Behaviour



Study design

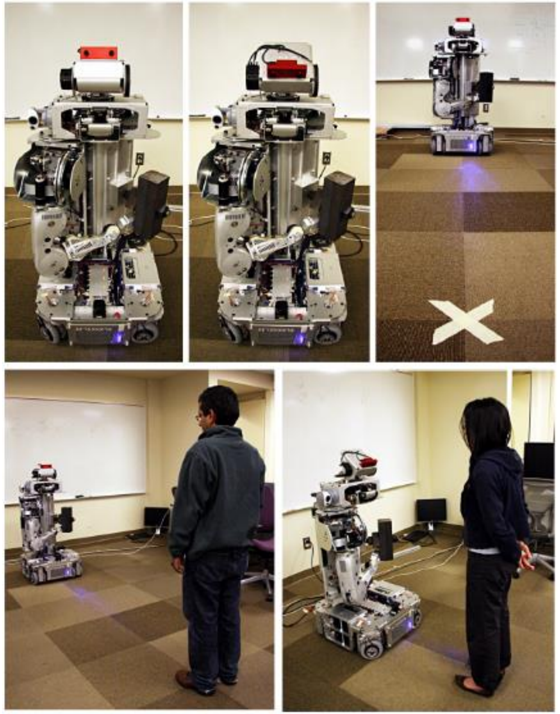
- Humans move towards robot and stop when they still feel comfortable
- Robot approaches human, human has to step aside once the robot feels too close for them

Conditions

- robotics experience vs. none
- robot head turned to participant's face vs. legs

Takayama, L., & Pantofaru, C. (2009, October). Influences on proxemic behaviors in human-robot interaction. In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 5495-5502). IEEE.

Approaching Behaviour



Results

- Experience with owning pets decreases the personal space that people maintain around robots
- Experience with robots decreases the personal space that people maintain around robots
- A robot “looking” at people in the face (versus at their legs) influences proxemics behaviours → women maintain larger personal spaces from robots that are “looking” at their faces than men

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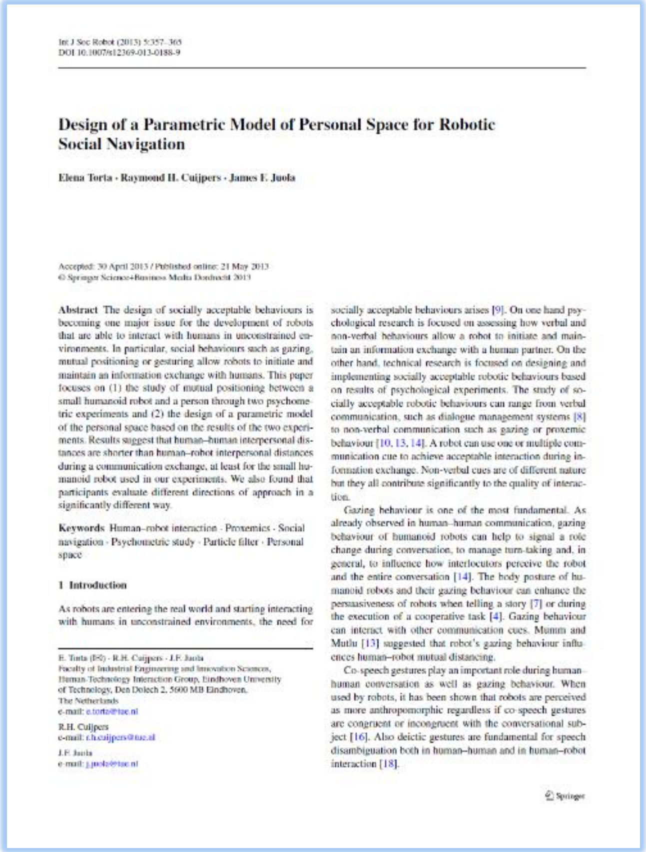

Int J Soc Robot (2013) 5:357–365
DOI 10.1007/s12369-013-0188-9

Design of a Parametric Model of Personal Space for Robotic Social Navigation

Elena Torta · Raymond H. Cuijpers · James F. Juola

Accepted: 30 April 2013 / Published online: 21 May 2013

Abstract The design of socially acceptable behaviours is becoming one major issue for the development of robots that are able to interact with humans in unconstrained environments. In particular, social behaviours such as gazing, mutual positioning or gesturing allow robots to initiate and maintain an information exchange with humans. This paper focuses on (1) the study of mutual positioning between a small humanoid robot and a person through two psychometric experiments and (2) the design of a parametric model of the personal space based on the results of the two experiments. Results suggest that human–human interpersonal distances are shorter than human–robot interpersonal distances during a communication exchange, at least for the small humanoid robot used in our experiments. We also found that participants evaluate different directions of approach in a significantly different way.

Keywords Human–robot interaction · Proxemics · Social navigation · Psychometric study · Particle filter · Personal space

1 Introduction

As robots are entering the real world and starting interacting with humans in unconstrained environments, the need for socially acceptable behaviours arises [9]. On one hand psychological research is focused on assessing how verbal and non-verbal behaviours allow a robot to initiate and maintain an information exchange with a human partner. On the other hand, technical research is focused on designing and implementing socially acceptable robotic behaviours based on results of psychological experiments. The study of socially acceptable robotic behaviours can range from verbal communication, such as dialogue management systems [8] to non-verbal communication such as gazing or proxemic behaviour [10, 13, 14]. A robot can use one or multiple communication cue to achieve acceptable interaction during information exchange. Non-verbal cues are of different nature but they all contribute significantly to the quality of interaction.

Gazing behaviour is one of the most fundamental. As already observed in human–human communication, gazing behaviour of humanoid robots can help to signal a role change during conversation, to manage turn-taking and, in general, to influence how interlocutors perceive the robot and the entire conversation [14]. The body posture of humanoid robots and their gazing behaviour can enhance the persuasiveness of robots when telling a story [7] or during the execution of a cooperative task [4]. Gazing behaviour can interact with other communication cues. Mumm and Mutlu [13] suggested that robot's gazing behaviour influences human–robot mutual distancing.

Co-speech gestures play an important role during human–human conversation as well as gazing behaviour. When used by robots, it has been shown that robots are perceived as more anthropomorphic regardless if co-speech gestures are congruent or incongruent with the conversational subject [16]. Also deictic gestures are fundamental for speech disambiguation both in human–human and in human–robot interaction [18].

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Torta, E., Cuijpers, R. H., & Juola, J. F. (2013).

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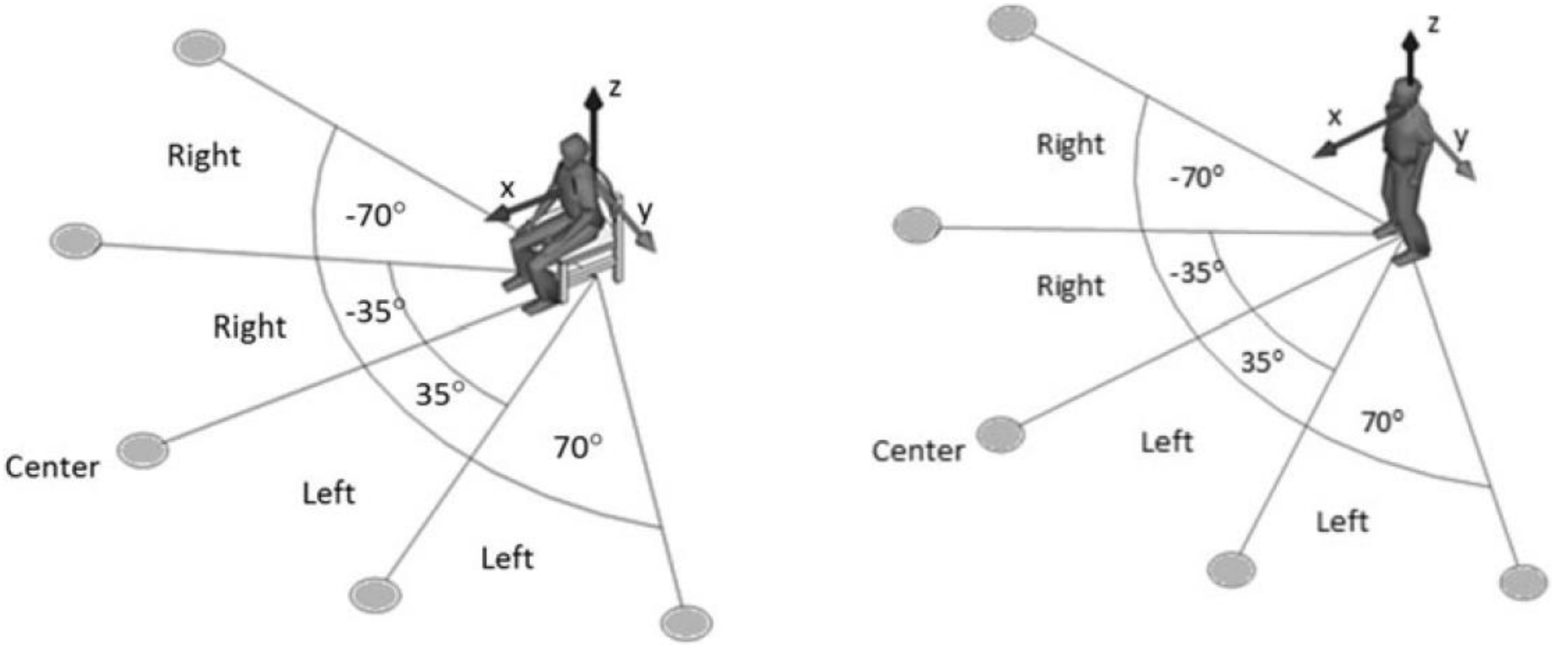
International Journal of Social Robotics, 5(3), 357-365.

Approaching Behaviour



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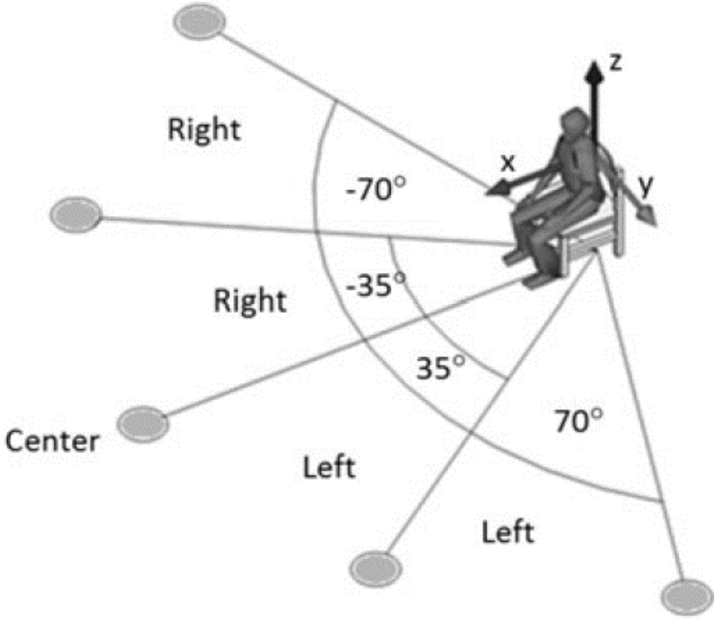
Approaching Behaviour



Conditions

- Optimal: Human stops robot when it is at the **optimal position** to have a comfortable conversation
- Close: Human stops robot when it is at the **closest position** to have a comfortable conversation
- Far: Human stops robot when it is at the **furthest position** to have a comfortable conversation

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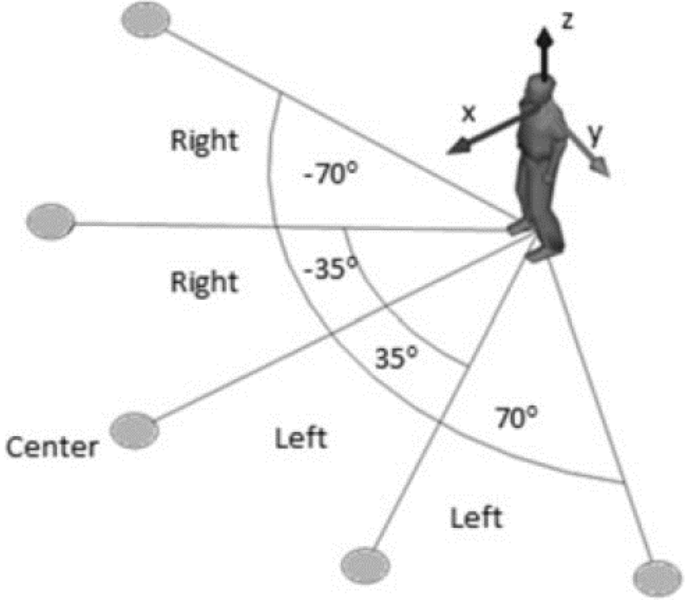

Conditions

- Optimal: Human stops robot when it is at the **optimal position** to have a comfortable conversation

Torta, E., Cuijpers, R. H., & Juola, J. F. (2013). Design of a parametric model of personal space for robotic social navigation. *International Journal of Social Robotics*, *5*(3), 357-365.

Approaching Behaviour

Results

- Mean value of optimal distance of approach is, in both conditions sitting (182 cm) or standing (173 cm), larger than the distance range for human–human communication (indicatively 45 cm–120 cm)
- Central directions of approach are preferred to sidewards directions
- Rightwards directions are preferred to leftwards directions

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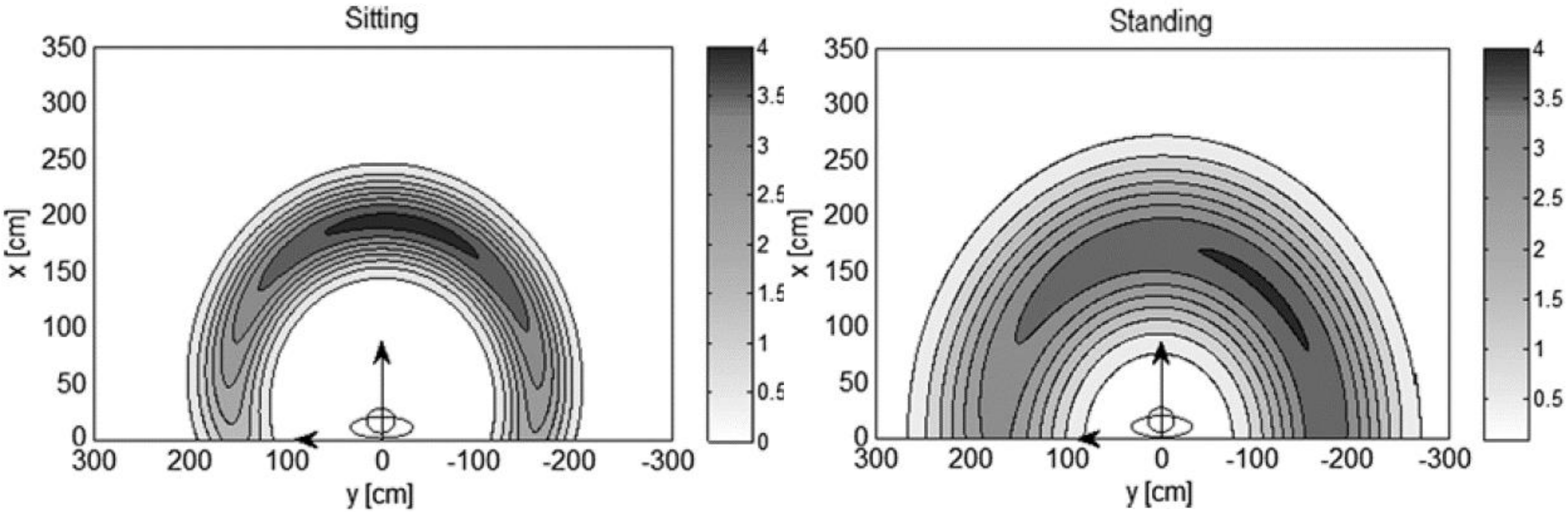
Approaching Behaviour



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Human-Robot Interaction in Handing-Over Tasks

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Abstract— In many future joint-action scenarios, humans and robots will have to interact physically in order to successfully cooperate. Ideally, seamless human-robot interaction should not require training for the human, but should be intuitively simple. Nonetheless, seamless interaction and cooperation involve some degree of learning and adaptation. Here, we report on a simple case of physical human-robot interaction, a hand-over task. Even such a basic task as manually handing over an object from one agent to another requires that both partners agree upon certain basic prerequisites and boundary conditions. While some of them are negotiated explicitly, e.g. by verbal communication, others are determined indirectly and adaptively in the course of the cooperation. In the present study, we compared human-human hand-over interaction with the same task done by a robot and a human. To evaluate the importance of biological motion, the robot human interaction was tested with two different velocity profiles: a conventional trapezoidal velocity profile in joint coordinates and a minimum-jerk profile of the end-effector. Our results show a significantly shorter reaction time for minimum jerk profiles, which decreased over the first three hand-overs. The results of our comparison provide the background for implementing effective joint-action strategies in humanoid robot systems.

I. Introduction

Robots have been successfully employed in industrial settings to improve productivity and perform dangerous tasks. In the near future however, due to the recent remarkable improvements in robotic intelligence and technology, it is expected that robots will also coexist with humans to assist or cooperate with them. Therefore, robots must be able to interact with humans in a safe and user-friendly manner while performing cooperative tasks. Joint action requires understanding the other's actions and intentions [1]. To do so, a possible strategy is to transfer knowledge gained from experiments on human-human interaction to technical systems [2].

One basic constituent of robot-human joint action will be physical interaction, e.g., when the human is teaching the robot to assist him in order to solve a complex task. The blueprint for such an interaction is the relation between the master craftsman and his apprentice. In such interactions, a common task is to hand objects from one person (the apprentice) to the other (the master). In the present work we investigated whether current robot technology allows for intuitive and natural joint-action in a hand-over task which simply consisted of 6 wooden cubes being handed over from the apprentice (either human or robot) to the master (human).

Single-handed human multi-joint movements for pointing or reaching are well-studied and various mathematical models have been proposed to describe their kinematics (for review see [3]) based on some optimization criterion, e.g. minimum-jerk [4] or minimum-variance [5]. Studies of the kinematics of grasping similarly revealed characteristic patterns of behavior [6], [7], [8]. Some of these results have already been implemented in robot environments to simulate human behavior [9]. However, studies about cooperative strategies and behavior in humans, specifically concerning manual joint-action, are relatively new. There exist only few examinations about different action pattern for competitive and cooperative behaviors [10], the transfer of objects in joint action [11], or cooperative lifting of objects [12]. Extending these results to the field of robot-human cooperation raises new questions about acceptance and efficiency. Latest results in this field of research is reported in [13], [14].

In the present work we focus on the comparison of timing in a hand-over task between two humans or a robot and a human. Even though the overall task of receiving a fixed number of objects by hand-over is known to the test subject, many parameters of the exact execution are not specified by the instruction. These parameters, such as position of the hand-over or timing of the movements, depend on the giving subject and become evident by observation during the first few hand-over actions. We assumed that the human receiver flexibly adapts to these parameters and interaction becomes smoother and more rapid within a few repetitions. In the present work, we examined our assumption by tracking hand movements during a human-human hand-over task. Additionally, we show that basic principles known from human motor control such as smooth velocity profiles and accuracy-dependent velocity scaling of arm movements can also be observed during cooperative action. We then compared human-human to human-robot joint action using the same basic task. In the human-robot experiment, we used two different velocity profiles to drive the end-effector of a humanoid robot. The average movement duration was adapted to that of the previous human-human experiment.

II. Experimental Setup

A. Human-Human Hand-Over Experiment

We measured hand movements in human subjects during a hand-over task using the magnet-field based motion tracking system *Polhemus Liberty*. The two test subjects were sitting opposite to each other at a table (width 100 cm). The hand positions of the subjects were recorded by the tracking system. Tracking sensors were placed on the back

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Robot-To-Human Handover

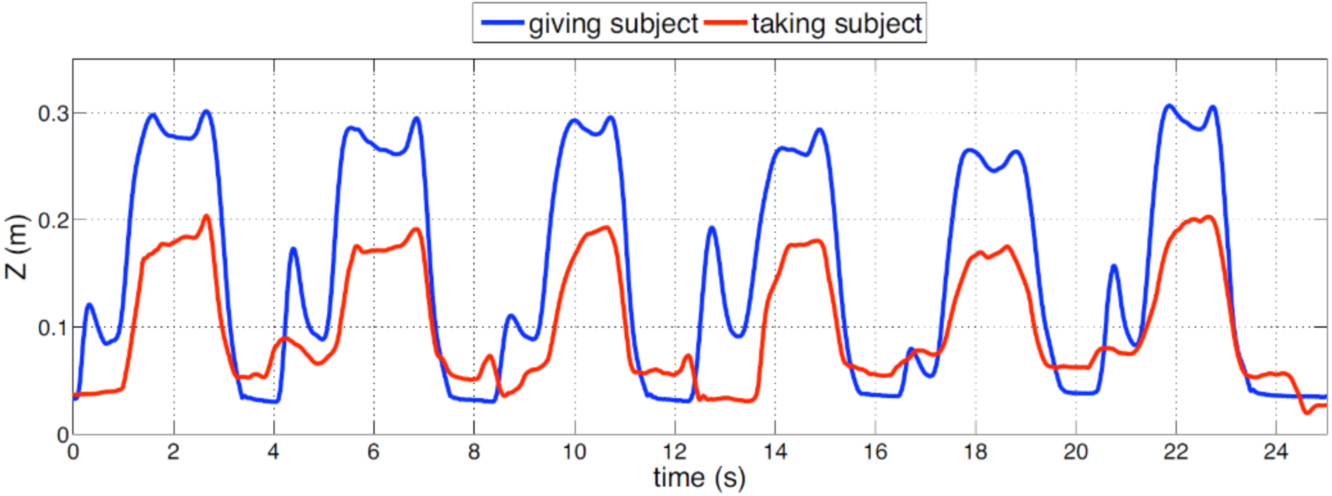

Fig. 3. Typical trajectory of hand movements during the hand-over task. The height of the hand over the table is plotted over the time. Blue: giving subject, red: taking subject.

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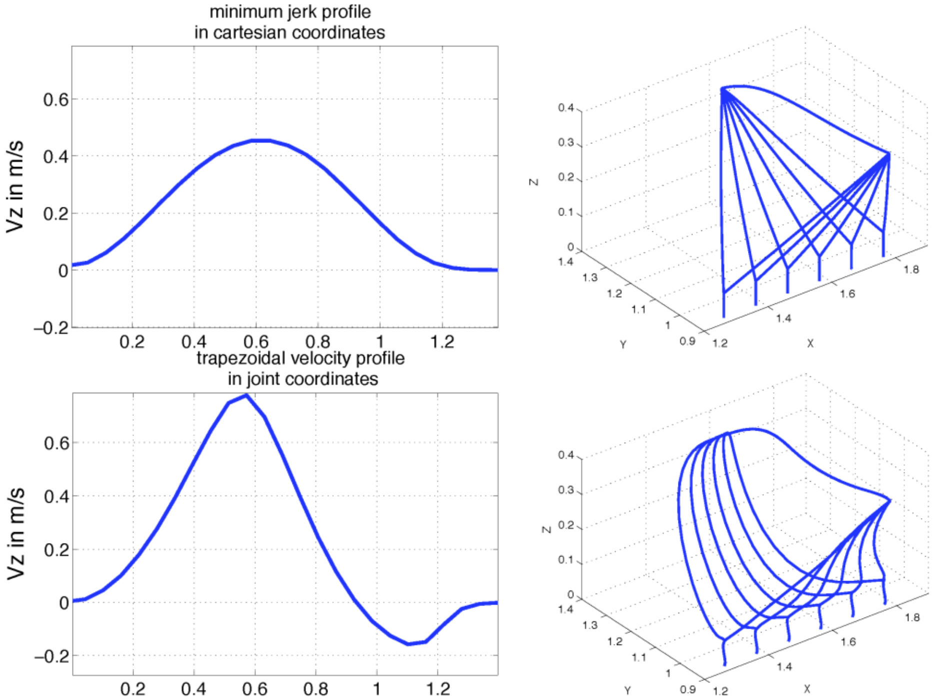

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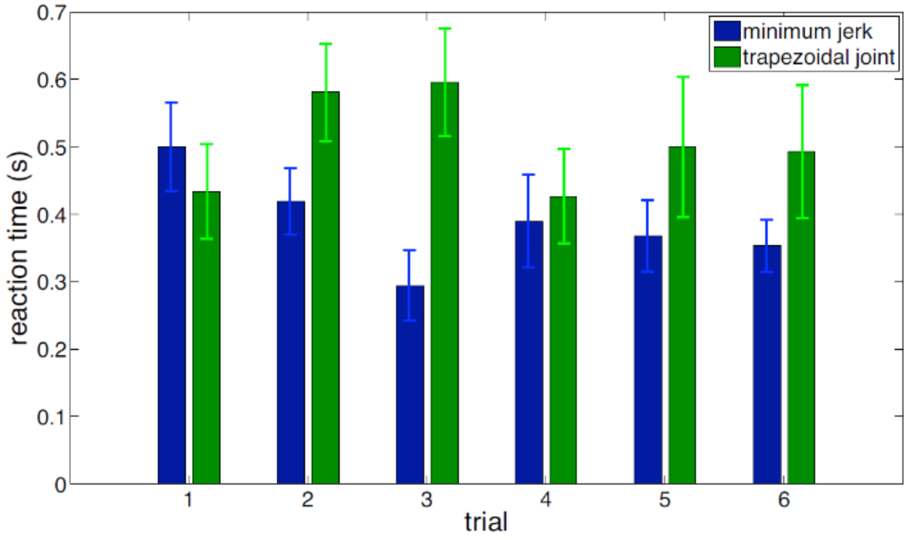

Fig. 8. Reaction time for the six handovers between the robot and the human. Blue bars show the reaction times for the minimum jerk velocity profile, green bars for the trapezoid velocity profile. Error bars show standard deviation.

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Robot-To-Human Handover

Fig. 9. Interview of the subjects after the experiments: the subjects had to answer (from 1 to 5) how human-like they thought the robot movement was and how safe they felt during the experiment.

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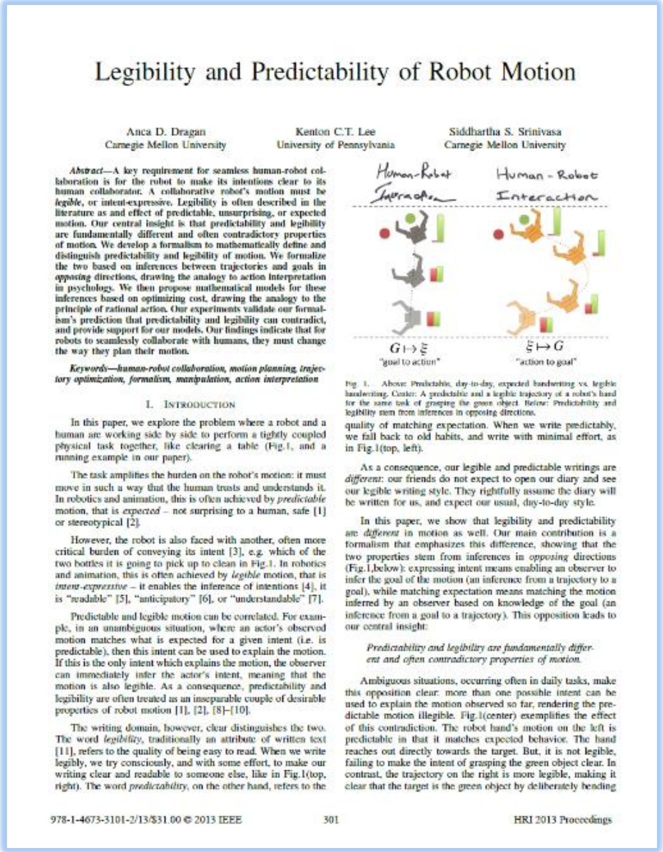

Legibility and Predictability of Robot Motion

Anca D. Dragan, Carnegie Mellon University
Kenton C.T. Lee, University of Pennsylvania
Siddhartha S. Srinivasa, Carnegie Mellon University

Abstract—A key requirement for seamless human-robot collaboration is for the robot to make its intentions clear to its human collaborator. A collaborative robot's motion must be *legible*, or intent-expressive. Legibility is often described in the literature as and effect of predictable, unsurprising, or expected motion. Our central insight is that predictability and legibility are fundamentally different and often contradictory properties of motion. We develop a formalism to mathematically define and distinguish predictability and legibility of motion. We formalize the two based on inferences between trajectories and goals in *opposing* directions, drawing the analogy to action interpretation in psychology. We then propose mathematical models for these inferences based on optimizing cost, drawing the analogy to the principle of rational action. Our experiments validate our formalism's prediction that predictability and legibility can contradict, and provide support for our models. Our findings indicate that for robots to seamlessly collaborate with humans, they must change the way they plan their motion.

Keywords—*human-robot collaboration, motion planning, trajectory optimization, formalism, manipulation, action interpretation*

I. Introduction

In this paper, we explore the problem where a robot and a human are working side by side to perform a tightly coupled physical task together, like clearing a table (Fig.1, and a running example in our paper).

The task amplifies the burden on the robot's motion: it must move in such a way that the human trusts and understands it. In robotics and animation, this is often achieved by *predictable* motion, that is *expected* – not surprising to a human, safe [1] or stereotypical [2].

However, the robot is also faced with another, often more critical burden of conveying its intent [3], e.g. which of the two bottles it is going to pick up to clean in Fig.1. In robotics and animation, this is often achieved by *legible* motion, that is *intent-expressive* – it enables the inference of intentions [4], it is "readable" [5], "anticipatory" [6], or "understandable" [7].

Predictable and legible motion can be correlated. For example, in an unambiguous situation, where an actor's observed motion matches what is expected for a given intent (i.e. is predictable), then this intent can be used to explain the motion. If this is the only intent which explains the motion, the observer can immediately infer the actor's intent, meaning that the motion is also legible. As a consequence, predictability and legibility are often treated as an inseparable couple of desirable properties of robot motion [1], [2], [8]–[10].

The writing domain, however, clear distinguishes the two. The word *legibility*, traditionally an attribute of written text [11], refers to the quality of being easy to read. When we write legibly, we try consciously, and with some effort, to make our writing clear and readable to someone else, like in Fig.1(top, right). The word *predictability*, on the other hand, refers to the

Fig. 1. Above: Predictable, day-to-day, expected handwriting vs. legible handwriting. Center: A predictable and a legible trajectory of a robot's hand for the same task of grasping the green object. Below: Predictability and legibility stem from inferences in opposing directions.

quality of matching expectation. When we write predictably, we fall back to old habits, and write with minimal effort, as in Fig.1(top, left).

As a consequence, our legible and predictable writings are *different*: our friends do not expect to open our diary and see our legible writing style. They rightfully assume the diary will be written for us, and expect our usual, day-to-day style.

In this paper, we show that legibility and predictability are *different* in motion as well. Our main contribution is a formalism that emphasizes this difference, showing that the two properties stem from inferences in *opposing* directions (Fig.1,below): expressing intent means enabling an observer to infer the goal of the motion (an inference from a trajectory to a goal), while matching expectation means matching the motion inferred by an observer based on knowledge of the goal (an inference from a goal to a trajectory). This opposition leads to our central insight:

Predictability and legibility are fundamentally different and often contradictory properties of motion.

Ambiguous situations, occurring often in daily tasks, make this opposition clear: more than one possible intent can be used to explain the motion observed so far, rendering the predictable motion illegible. Fig.1(center) exemplifies the effect of this contradiction. The robot hand's motion on the left is predictable in that it matches expected behavior. The hand reaches out directly towards the target. But, it is not legible, failing to make the intent of grasping the green object clear. In contrast, the trajectory on the right is more legible, making it clear that the target is the green object by deliberately bending

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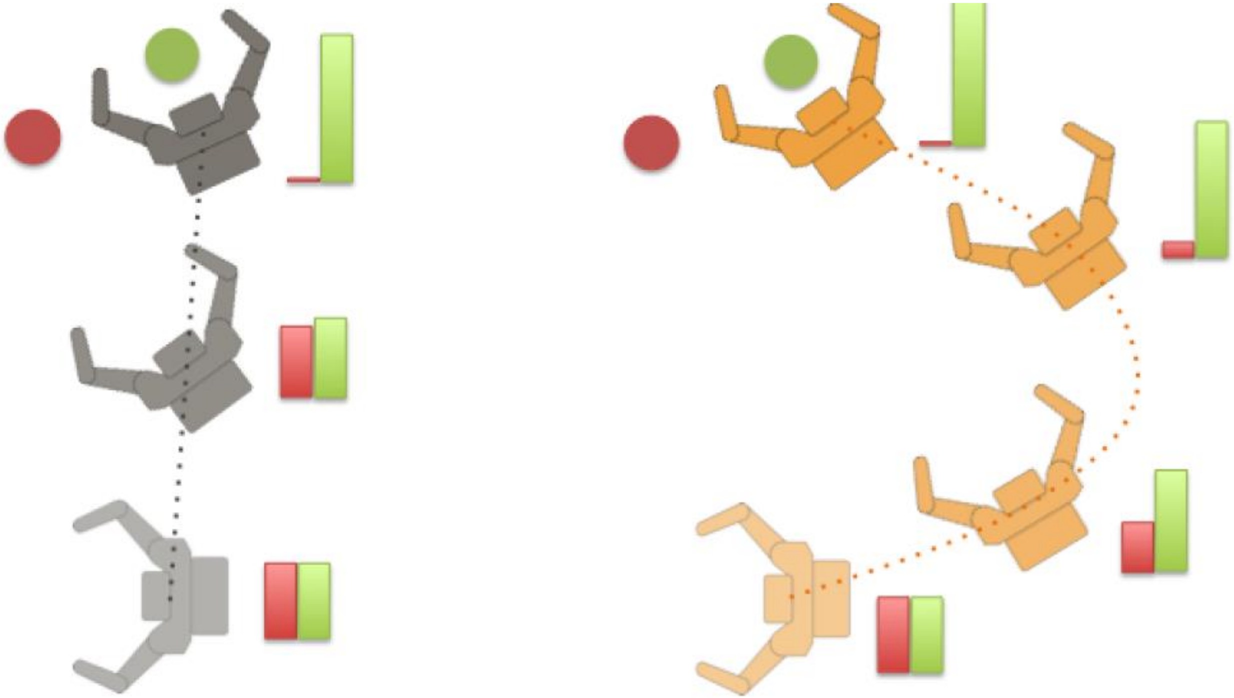
Predictability vs. Legibility of Motions



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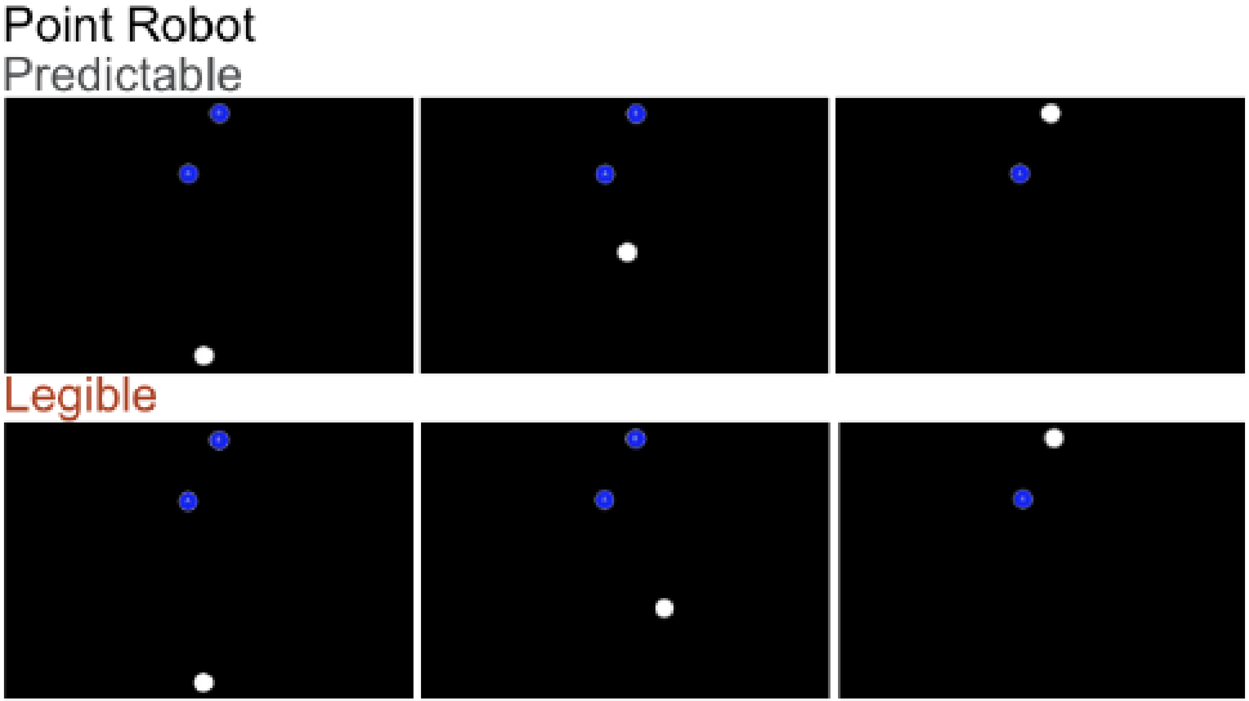

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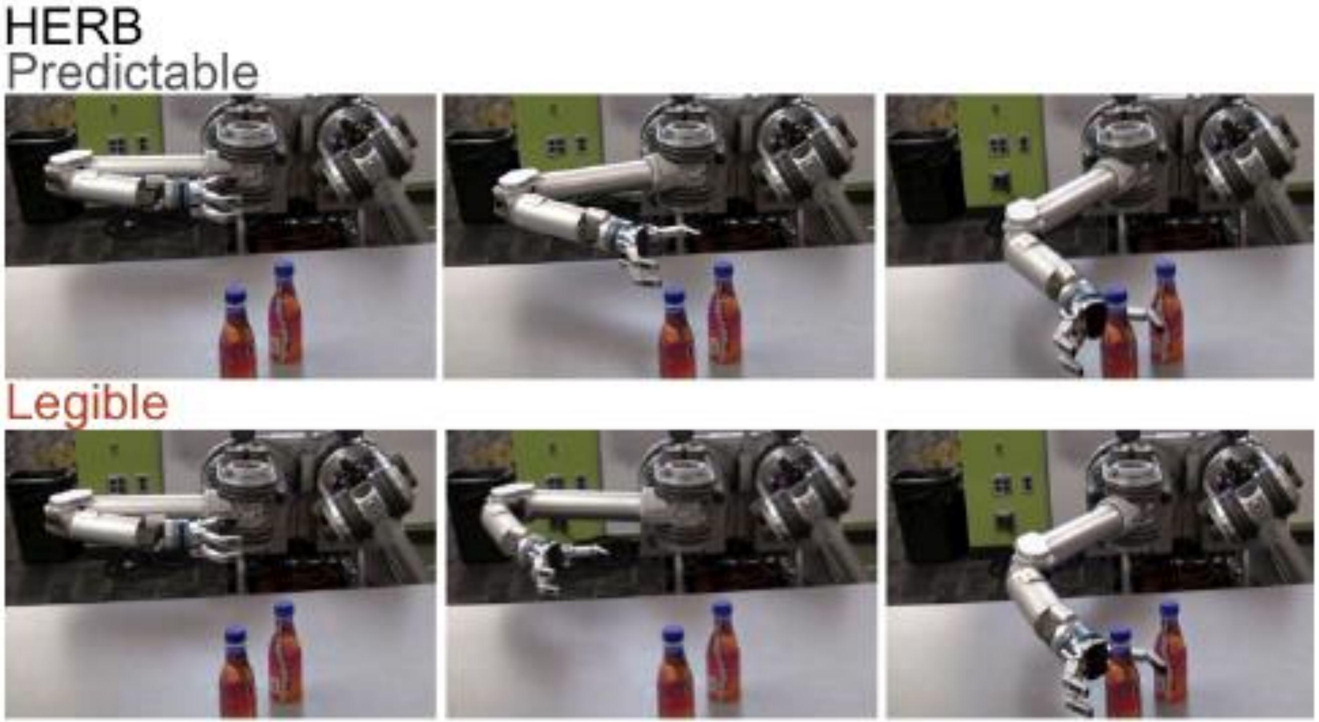

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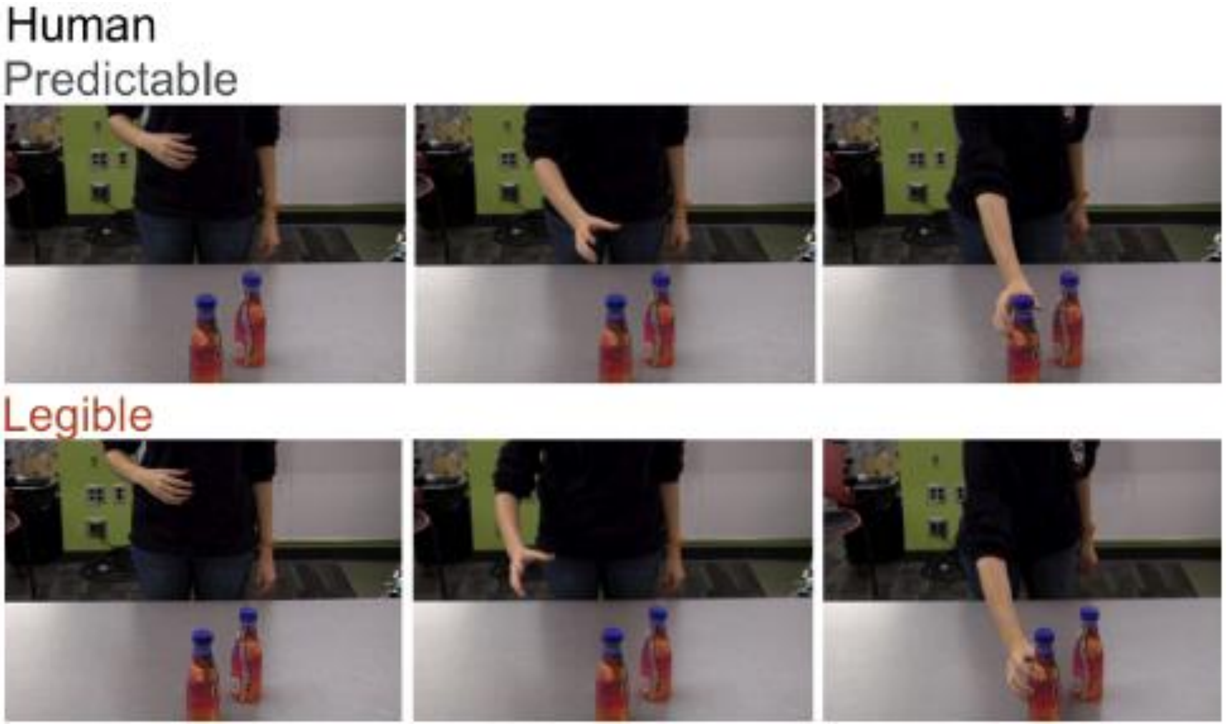

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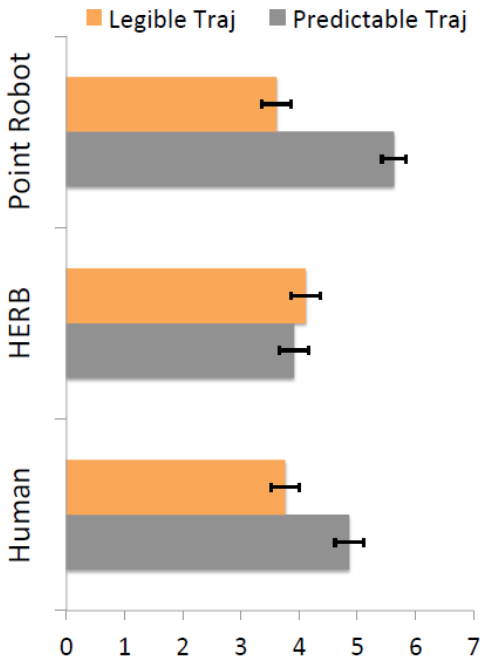
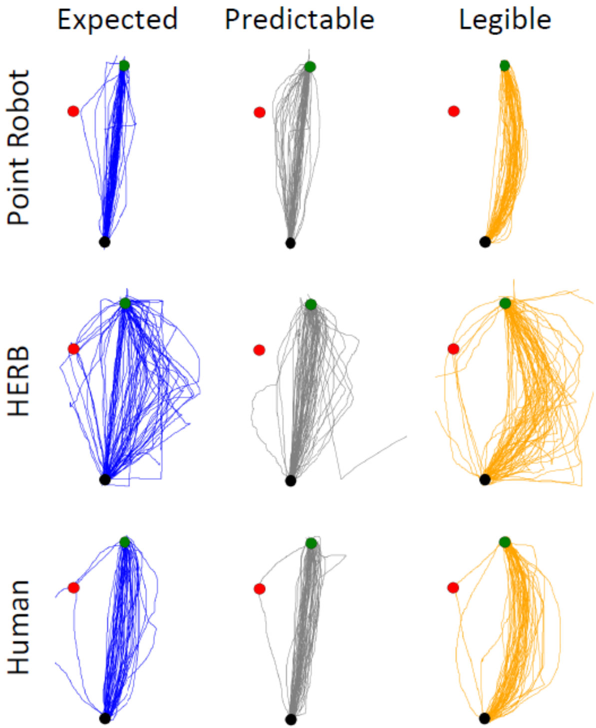


(a) Predictability Rating



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