Estimating People's Subjective Experiences of Robot Behavior

Andrew Sutcliffe and **Joelle Pineau**
School of Computer Science, McGill University,
McConnell Engineering Bldg. Room 318,
3480 University, Montreal, Qc, Canada, H3A 0E9

Daniel Grollman
Vecna Technologies
36 Cambridgepark Dr,
Cambridge, MA 02140

Introduction

Progress in general HRI metrics, while significant, is often in the form of post-experiment questionnaires or expert video analysis (Joosse et al. 2013; Bartneck et al. 2008; Weiss et al. 2009). This is a significant hurdle for any intelligent system that aspires to interact with its social environment. In the case of social navigation, robots must react to a dynamic environment. Socially aware robot behavior requires real time quantitative metrics of human subjective experience. This is a vast topic, which we approach by trying to measure how predictable robot actions are from its impact on the paths taken by passers-by. We chose predictability as a first metric because it can be modelled in terms of efficiency, and it affects safety. Thus, it serves as an interesting proof of concept.

Related work that focuses on proxemics has tried to understand discomfort through proximity(Torta, Cuijpers, and Juola 2013). Our work is similar in that it tries to correlate a subjective experience to a measurable metric, yet it differs on one important aspect. The relationships we are trying to observe are not of cause and effect, but of mutually occurring effects.

Since we assume that differences in the subjective perceptions and expectations of those who interact with a robot can be traced to individual differences(Dragan, Lee, and Srinivasa 2013), cultural differences(Hall 1969), and/or differences in the robot's appearance (Walters et al. 2009), we believe that measuring the impact a robot has on the people around it offers a more feasible method for evaluating and improving robot behavior.

Methodology

In order to assess the impact of unpredictable robot movements on a passer-by's path, we devised an experimental protocol where participants must pass a delivery robot moving down a hallway. In the first scenario, the robot avoids a visible obstacle; in the second scenario, it avoids an invisible obstacle. In both cases, the robot follows the same path. In accordance with observations made by Morales et al. on how people walk side by side(Morales et al. 2012), we hypothesize that passers-by who see the obstacle understand that the robot will go around it and smoothly adjust their trajectory accordingly; passers-by who do not see the obstacle react more abruptly (see Figure 1). We will quantify this difference in passer-by behaviors and define a real time metric for the predictability of robot movement. Questionnaires will help test our hypothesis and control for confounds.

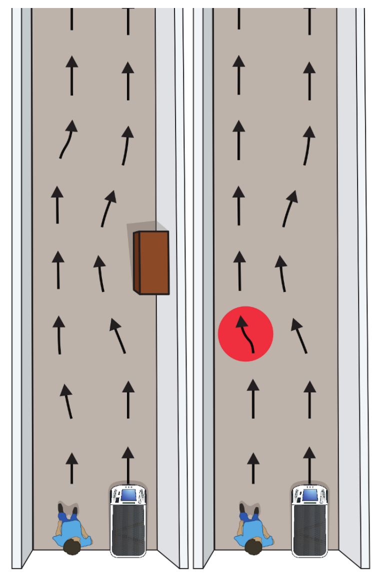

Figure 1: *A potential scenario showing the predictable case (left) and the unpredictable case (right) with the area of interest highlighted in red.*

Our pilot study used an intelligent powered wheelchair (IPW) equipped with turn signals. Participants had to pass an oncoming IPW to reach the hallway's other end. We observed results similar to Lu and Smart(Lu and Smart 2013), where legibility, or the conveying of intent(Dragan, Lee, and Srinivasa 2013), led to measurable differences in passer-by paths. We also observed statistically significant improvement in participant time to completion ($11.2s$ vs $11.7s$, $p < 0.005$). These results correlated with participants reporting that they were able to start avoiding the robot earlier when it used turn signals. This study focuses on predictability and legibility, although in this instance it might not be possible to disambiguate the two concepts. In both scenarios, the robot follows a preprogrammed path; any extrapolation by passers-by is based on subjectively attributing rational behavior to the robot(Dragan, Lee, and Srinivasa 2013). Our approach facilitates development of person-specific algorithms. Moreover, real time quantitative metrics will greatly reduce the cost of evaluating different navigation algorithms, which is presently based on questionnaires and expert ratings.

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