Introduction

The SmartWheeler project is a multi-disciplinary initiative aimed at integrating state-of-the-art robotic and AI technologies for developing intelligent wheeled mobility platforms. The project is a collaboration between researchers, technicians and clinicians, from the fields of computer science, engineering and rehabilitation. The scientific goals of the project range from a sociological investigation of the needs for high-tech mobility solutions, to the development of machine learning algorithms to achieve robust communication, to AI techniques for socially adaptive path planning, to in-depth validation with clinically-functional outcomes. In this short paper, we outline some of the main contributions of the project in terms of integrating AI in the design and development of the intelligent wheelchair platform.

Overview of robot platform

The robot platform, shown in Figure 1, is built on top of a commercial power wheelchair, and features onboard computers, wireless communication, and a full range of navigation sensors (3 laser range-finders, 1 RGB-D camera, a dozen sonars, wheel-based odometry), as well as multiple communication interfaces (speech recognition/synthesis, joystick, tactile display). The robot’s software architecture is integrated within the widely used Robot Operating System (ROS) architecture. This allows sharing of modules between robotic platform. The processing of information from the navigation sensors (lasers, RGB-D camera, sonars) is integrated within this framework, as is interaction with the touchscreen and speech interfaces. The speech recognition is achieved using the commercially available Dragon system. The robot planning and control system follows the three-layer architecture principle, with a low-level module for obstacle avoidance, a mid-level module for selection of waypoints and trajectories, and a high-level module for goal inference and task planning. At this highest-level of the architecture, we use a POMDP dialogue manager to allow robust selection of goals through the speech and tactile interface.

POMDP-based goal management

In the context of our intelligent wheelchair project, high-level goals are acquired through interactions by the user acquired through the speech interface. It was thus imperative to have a dialogue management system that can offer robustness and flexibility, such as to maximize ease-of-use. We elected to model the dialogue system using the Partially Observable Markov Decision Process (POMDP) framework, which provides a stochastic model for sequential decision-making under uncertainty (Kaelbling, Littman, and Cassandra 1998). One of the advantages of the POMDP paradigm is its ability to optimize strategies contingent on partial state observability, which provides added robustness for handling speech. Indeed, the POMDP model is able to reason about uncertainty in the state (in this case the user’s spoken word and intention) which is crucial to the robustness of the system. In particular, the POMDP model can suggest clarification questions whenever the input received is incomplete or ambiguous. Figure 2 shows a short dialogue between the intelligent wheelchair and a test subject.

At the mid-level, we have developed an approach based on inverse reinforcement learning to achieve socially appropriate navigation strategies. These are two components where the use of AI techniques has had the most impact.

Figure 1: The SmartWheeler robotic wheelchair

Figure 2: A short dialogue between the intelligent wheelchair and a test subject.
Figure 2: Sample dialogue between a test subject and the intelligent wheelchair. The first column shows the user’s actual spoken words. The second column reports the output of the automated speech recognition module. The third column shows the action chosen by the POMDP-based Interaction Manager (entries in italic represent clarification queries; other action choices are transmitted to the Navigation Manager.)

ble. In particular, standard POMDP planning algorithms require a (mathematically) accurate predictive model of the dynamics of the conversation. In general, it is challenging to define such a model a priori, as human behavior is difficult to quantify, and varies substantially between individuals. To address this issue, we leveraged machine learning techniques to build the model directly from observed data (Atrash and Pineau 2009; Png and Pineau 2011). Figure 3 shows the effect of learning on the performance of the Interaction Manager.

Figure 3: Improvement in the quality of actions selected by the Interaction Manager as a function of the observed training data. Results compiled using a simulated user.

Inverse learning of human-like navigation

Once a goal has been extracted via the dialogue manager, a mid-level path planner takes over to find a trajectory from the robot’s current position to the goal position. Traditional methods for path planning use performance criteria such as reaching the goal using the shortest path (or in the shortest time); these lead to effective behaviors in static environments, however they often perform poorly in densely populated environments. Instead, we aimed to develop a framework for socially adaptive path planning in dynamic environments, which is able to generate human-like trajectories. The main technical challenge is the fact that the notion of what is a socially acceptable navigation behaviour is not easily defined as an optimization criteria. Instead, we rely on example paths generated by human experts. Thus the performance criterion for the path planner becomes one of minimizing differences with the behavior of the expert. We can formulate this mathematically using Inverse Reinforcement Learning (IRL) techniques (Henry et al. 2010; Kim and Pineau Submitted). As shown in Figure 4, using data collected in natural situations, this approach is able to achieve driving performance that resembles the human driver when encountering pedestrians.

Figure 4: Average trajectories executed by human driver (white), inverse RL (red), and Dynamic Window Approach (Fox, Burgard, and Thrun 1997) (green). Left figure is when the pedestrian approached the robot and turned right (with respect to the robot) to avoid the robot, and the right figure is when the pedestrian approached the robot and turned left to avoid the robot. Yellow cube represents the goal.

Validation towards a clinically functional outcome

One of the major challenges of the project is to devise a validation procedure that reflects clinical outcomes. In a first stage1, we evaluated the smart wheelchair using an adapted version of the Wheelchair Skills Test (Pineau et al. 2011). This test, composed of a well-defined corpus of atomic tasks, provides a standardized framework for evaluating the capacity and safety of a wheelchair user. The original test is currently used in clinical practice for evaluation purposes. The modified version for robotic wheelchairs provides the first attempt at standardizing evaluation of such platforms. In evaluations with 17 individuals (8 healthy adults, 9 long-term wheelchair users), we found that performance of the intelligent system allowed users to safely and effectively achieve the set of tasks, with few exceptions. To summarize briefly, test subjects achieved 96% task completion rate and 97% safety score (compared to 100% when using conventional joystick control) after only approximately 30min. of experience with the smart wheelchair. Further analysis of these evaluations are available. In the longer term, there are several challenges with defining relevant clinical outcomes for evaluation of the smart wheelchair outside the confines of a laboratory setting. We are currently planning deployment of the smart wheelchair in a downtown shopping mall, where the chair will face substantial challenges in terms of

1The navigation architecture used for this validation is from a previous version of our system described here (Boucher 2010).
navigating in crowds, interacting in noisy surroundings, and dealing with a highly dynamic environment.

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**References**


