UNIVERSITY OF TECHNOLOGY SYDNEY

Planning and Sequential Decision Making for Human-Aware Robots

by

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A thesis submitted in partial fulfilment for the degree of Doctor of Philosophy

in the
Faculty of Engineering
Mechatronics and Intelligent Systems

May 2012

Declaration of Authorship

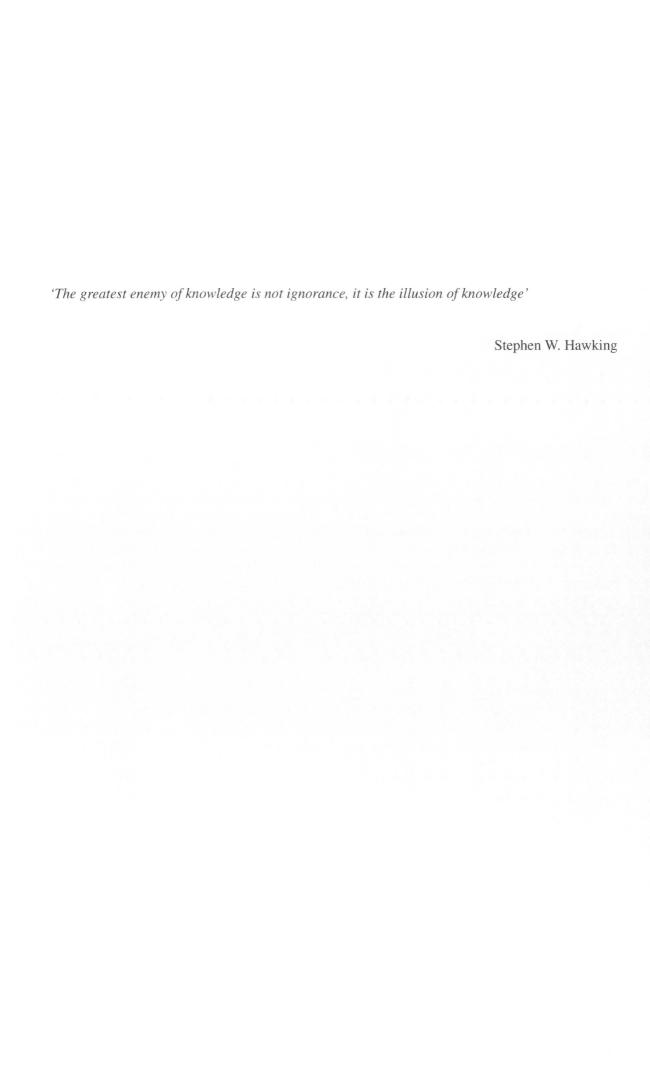
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Abstract

Faculty of Engineering
Mechatronics and Intelligent Systems

Doctor of Philosophy

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This thesis explores the use of probabilistic techniques for enhancing the interaction between a human and a robotic assistant. The human in this context is regarded as an integral part of the system, providing a major contribution to the decision making process and is able to overwrite, re-evaluate and correct decisions made by the robot to fulfil her or his true intentions and ultimate goals and needs. Conversely, the robot is expected to behave as an intelligent collaborative agent that predicts human intentions and makes decisions by merging learned behaviours with the information it currently possesses. The work is motivated by the rapid increase of the application domains in which robotic systems operate, and the presence of humans in many of these domains. The proposed framework facilitates human-robot social integration by increasing the synergy between robot's capabilities and human needs, primarily during assistive navigational tasks.

The first part of the thesis sets the groundwork by developing a path-planning/re-planning strategy able to produce smooth feasible paths to address the issue of navigating a robotic wheelchair in cluttered indoor environments. This strategy integrates a global path-planner that operates as a mission controller, and a local reactive planner that navigates locally in an optimal manner while preventing collisions with static and dynamic obstacles in the local area. The proposed strategy also encapsulates social behaviour, such as navigating through preferred routes, in order to generate socially and behaviourally acceptable plans.

The work then focuses on predicting and responding to human interactions with a robotic agent by exploiting probabilistic techniques for sequential decision making and planning under uncertainty. Dynamic Bayesian networks and partially observable Markov decision processes are examined for estimating human intention in order to minimise the flow of information between the human and the robot during navigation tasks. A framework to capture human behaviour, motivated by the human action cycle as derived from the psychology domain is developed. This framework embeds a human-robot interaction layer, which defines variables and procedures to model interaction scenarios, and facilitates the transfer of information during human-robot collaborative tasks.

Experiments using a human-operated robotic wheelchair carrying out navigational daily routines are conducted to demonstrate the capacity of the proposed methodology to understand human intentions and comply with their long term plans. The results obtained are presented as the outcome of a set of trials conducted with actor users, or simulated experiments based on real scenarios.

Acknowledgements

This work was made possible by many people other than myself, and I am extremely grateful for their encouragement and support.

Firstly, I would like to thank my supervisors, Dr Jaime Valls Miró and Professor Gamini Dissayanake, for their support, guidance and encouragement.

I would also like to thank all the bright minds who were around me at the Centre of Excellence for Autonomous Systems, for all the intelligent conversations, coffee breaks and research culture. Nathan Kirchner, Gavin Paul, Stephan Sehestedt and Weizhen Zhou, your presence around helped more than you can imagine.

Many thanks to Professor Raymond Apthorpe for his words of wisdom and support, and Christer for bearing with me during my intense times.

I would also like to acknowledge Dr Lisa Lines for her editorial intervention, which was restricted to Standards D and E of the Australian Standards for Editing Practice.

I would like to reserve my final thanks to my parents for their years of blessings and motivation.

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Abbreviations

ADD Algebric Decision Diagrams

AI Artificial Intelligence

AMCL Adaptive Monte-Carlo Localisation

BDD Binary Decision Diagrams

BN Bayesian Network

CAS Centre of Autonomous Systems

CPT Conditional Probability Table

CSTEP Controlled Sampling and Time Efficient Planner

CVM Curvature Velocity Method

DAC Digital to Analog Converter

DBN Dynamic Bayesian Network

DWA Dynamic Window Obstacle Avoidance

EM Expectation Maximisation

GDWA Global Dynamic Window Approach

HRI Human Robot Interaction

ITE If-Then-Else

MDP Markov Decision Processes

MSE Mean Square Error

ND Nearness Diagram

POMDP Partially Observable Markov Decision Processes

PRM Probabilistic Road Maps

RRT Rapidly-Exploring Random Trees

VFH Vector Field Histogram

Dedicated to my parents