Increased Task Perception for Adaptable Human-Robot Collaboration

by

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Submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

at the
Centre for Autonomous Systems
Faculty of Engineering and Information Technology
University of Technology Sydney

August 2018
Declaration of Authorship

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Portions of the research presented in this thesis were undertaken within a series of research exchanges, as part of a collaboration between my primary supervisor and Assoc. Prof. Takamitsu Matsubara at the Intelligent Systems Control Laboratory, Nara Institute of Science and Technology, Japan. As a result, the components of this thesis which were undertaken collaboratively by myself and others within the scope of these exchanges are as follows:

- The work with Gaussian Processes in Section 2.3 was undertaken in collaboration with Daisuke Tanaka during a visit to UTS in October 2014, supported by the Global Initiative Program provided by the Japanese Ministry of Education, Culture, Sports, Science & Technology.

- The Dynamic Policy Programming path planner in Section 3.4 was built together with Yunduan Cui during a visit to UTS from October 2015 to January 2016, supported by the 2015-2017 Japanese Society for the Promotion of Science Bilateral Joint Research Projects (Open Partnership).

- Both Convolutional Neural Networks in Chapter 4 were built together with Yunduan Cui during a visit to UTS in March 2017, again supported by the 2015-2017 Japanese Society for the Promotion of Science Bilateral Joint Research Projects (Open Partnership).
• The work in Chapter 5 was undertaken in collaboration with Yunduan Cui during my visit to NAIST from January to May 2016, and in the immediate months following. My visit was supported by both the New Energy and Industrial Technology Development Organization, Japan, and the UTS Faculty of Engineering & IT Higher Degree by Research Students Research Collaboration Experience.

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Abstract

This thesis presents investigation into enhancing the robustness and adaptability of robot action generation in human-interactive scenarios, by means of a heightened level of task or scene perception which in turn leads to a lessened reliance upon the observed behaviours of the robot’s human counterpart.

In human-robot interaction under the learning from demonstration paradigm, the demonstration is most often carried out by able experts who are capable of performing the task with a very high degree of proficiency while also considering the robot’s physical limitations (movement speed limits, joint singularities, etc.). As a result of this, the actions of the robot’s partner in the obtained training samples can be considered to be near-optimal. A disparity then naturally arises when working with end-users whose performance may be hindered by a range of factors such as disability, inexperience, or fatigue. The lack of task-specific goodness in these observed partner behaviours can then lead to unpredictable or unsafe robot actions in demonstration learning frameworks where an arguably excessive emphasis is placed upon the partner performing their share of the task at a skill level comparable to that of the demonstrators.

As gathering a sufficiently large quantity of training data samples to encompass such a broad scope of human aptitude is generally infeasible, it becomes arguable that a greater emphasis for robot
action modelling should instead be placed upon the task or the work scene that both agents are operating within. An example of this is in collaborative object handling between two humans; one would naturally generate suitable actions for the task by considering the movements of the leader alongside the object and the space they are moving through. The information derived from the latter two observations increases the chance that imperfections in leader behaviour can be adequately compensated for. This allows for an improved adaptability to novel task conditions, and also increased robustness when the observations of partner behaviour are insufficiently informative for safe action planning. These benefits can be primarily attributed to the trained models being more resilient against a lack of informativeness or task goodness in observed partner behaviour, by instead supplementing such missing fine details with information directly drawn from the immediate environment in which the interactive activity is taking place.

This concept of increased task and environmental perception is assessed across two significantly different human-robot interaction paradigms: intelligent wheelchair navigation, and physical humanoid collaboration. For wheelchair navigation, a framework for the generation of expert-stylized short-term paths that can be concatenated for traversal ‘anywhere’ is realized as a flexible adaptation upon the conventional approach of static long-term destinations within known occupancy maps. The reliance upon immediately available on-board sensor data, as opposed to the more conventionally restrictive features such as platform position within the map, allows proactively assisted traversal through settings novel to demonstration data without the need for retraining goal inference models. For physical humanoid collaboration, robust robot action generation is achieved when faced with novel task conditions and ambiguous partner observation, serving as an intuitive extension to action generation postulated solely upon briefly observed partner movements. This is evaluated in a collaborative object covering exercise by a human-humanoid team, where object parameters automatically drawn from visual scene data compensates for uninformative human partner observation.

Thesis Supervisors: Jaime Valls Miro and Gamini Dissanayake
Acknowledgements

First and foremost I would like to express my sincerest thanks to my primary supervisor Prof Jaime Valls Miro for providing me with the abundance of guidance and freedom in exploring a range of interesting research topics over the last several years. The significance of the many opportunities provided to me cannot be understated in what has been a frankly life-changing learning experience, starting from since I was an under-graduate intern and culminating in this body of work. Also from the UTS Centre for Autonomous Systems I would like to thank Dr Gavin Paul, Prof Sarath Kodagoda, and Dr Alen Alempijevic for the casual contracting and teaching opportunities over the course of my graduate study. I have genuinely enjoyed my involvement in your respective courses, and learned many things in doing so. This research was supported by the Australian Government Research Training Program.

My sincere gratitude goes to Prof Takamitsu Matsubara at the Nara Institute of Science and Technology’s Intelligent System Control lab, for our on-going collaboration since late 2014. Particular thanks must be expressed for ISC’s Dr Yunduan Cui, who has become one of my closest friends over the last few years. Thank you for the support and good (and occasionally, not so good) times in Japan; working alongside you at both ISC and CAS, and over the Internet in between, has simply been nothing short of fantastic. I would also like to express gratitude to Mrs Mioko Fukuda at the International Institute for Advanced Studies for providing accommodation during my 2016 exchange visit.

I would like to thank all my colleagues at CAS for your support and advice during my time here; particularly, but in no specific order: Jean Kyle Alvarez, Richardo Khonasty, Karthick Thiagarajan, Christian Reeks, Antony Tran, Julien Collart, Cedric le Gentil, Lei Shi, James Unicomb, David Hunt, Michael Behrens, Mohammad Norouzi, and Freek de Bruijn. Thanks also goes to the entirety of ISC, particularly Prof Kenji Sugimoto, Dr Daisuke Tanaka, Murase Masaki, Haifeng Han, and Juan Rodriguez; thank you all for making my visits to your lab so memorable.

Finally I wish to thank my mother for her support through everything, and my grandfather who never really understood what exactly I was doing but believed in me regardless. And old Kiki, who keeps the clouds away.
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Acronyms

ANN    Artificial Neural Network
CAS    Centre for Autonomous Systems
CNN    Convolutional Neural Network
DMP    Dynamic Movement Primitive
DOF    degree of freedom
DPP    Dynamic Policy Programming
DTW    Dynamic Time Warping
DWA    Dynamic Window Approach
EaIP   Environment-adaptive Interaction Primitive
GP     Gaussian Process
IP     Interaction Primitive
ISC    Intelligent System Control Lab
LfD    learning from demonstration
LIDAR  laser scanner
MDP    Markov Decision Process
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