

Increased Task Perception for Adaptable Human-Robot Collaboration

by

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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

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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

NAIST Nara Institute of Science and Technology

PMD powered mobility device

RBFN Radial Basis Function Network

UTS University of Technology Sydney

YOLO You Only Look Once v2