

Towards Personalised Robotic Assessment and Response during Physical Human Robot Interactions

by Yujun Lai

Thesis submitted in fulfilment of the requirements for
the degree of

Doctor of Philosophy

under the supervision of Dr. Gavin Paul and Dr. Marc
Carmichael

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Faculty of Engineering and Information Technology

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Certificate of Original Authorship

I, YUJUN LAI, declare that this thesis, is submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy, in the School of Mechanical and Mechatronics Engineering, Faculty of Engineering and Information Technology (FEIT) at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

The exponential growth of robotics in human environments have led to an explosion of human robot interactions. These interactions occur in proximity and have exposed the constraints and limitations of traditional models for robotic response which rely on task-centric measures. This has spurred on an area of research which focuses on understanding the capabilities and limitations of the human user during these interactions.

Humans are complex, autonomous agents that are difficult to model, and provide different categories of feedback that derive from biological systems. The current sensory paradigm requires an improved understanding of the limitations, the development of blended-measure models that employ human-centric measures, and a contextually connected biological human understanding into robotic frameworks.

This thesis presents a framework towards personalised robotic assessment and response with considerations on understanding the human user during physical human robot interactions. The framework approaches this by *examining* current limitations, *enabling* personalised models from human-centric measures, and *enhancing* the understanding of the human user through physiological and musculoskeletal models.

The implementation of a robotic system highlights the feasibility and limitations of using task-centric models during Physical Human Robot Interaction (pHRI). Further work

investigates inertial effects of the user during interactions in the context of a prominent predictive model, Fitts' Law. Physical Human Robot Interaction Primitives (pHRIP) extends upon Interaction Primitives (IPs) by incorporating physical interaction forces between the human user and robot, enabling the inference of user intent when generating a personalised robotic response.

Finally, the enhancement of the link between biological human understanding and robotic frameworks is explored. A validation process for a popular musculoskeletal model is conducted, comparing computational results with experimental readings. The limitations for the complex model led to the generation of an empirical model correlating forearm muscle activity and grip strength. This physiological model captured co-contractions for antagonistic muscle pairs and supplemented motion analysis for the musculoskeletal model, enhancing the computational results.

The framework combines the topics which facilitate intuitive and adaptive human-robot interactions. The advancement of such collaborative intelligence enhances complementary strengths between human and robot, and work hand in end-effector towards a safer, more interactive future.

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Acronyms & Abbreviations

AAN	Assistance as Needed
ADL	Activites of Daily Living
ANOVA	Analysis of Variance
BIPs	Bayesian Interaction Primitives
BCM	Bayesian Committee Machine
CNS	Central Nervous System
Cobot	Collaborative Robot
DBN	Dynamic Bayesian Network
DE	Differential Evolution
DLO	Deformable Linear Object
DMP	Dynamic Movement Primitives
DoF	Degrees of Freedom
DTW	Dynamic Time Warping
EEG	Electroencephalogram
EKF	Extended Kalman Filter
EM	Expectation Maximisation

EMG	Electromyogram
FFT	Fast Fourier Transform
FLV	Force-Length-Velocity
GMM	Gaussian Mixture Model
GP	Gaussian Process
GP-BCM	Gaussian Process-Bayesian Committee Machine
GPLVM	Gaussian Process Latent Variable Model
GSR	Galvanic Skin Response
HMM	Hidden Markov Model
HRI	Human Robot Interactions
IID	Independent and Identically Distributed
IMU	Inertial Measurement Unit
IPs	Interaction Primitives
IVM	Informative Vector Machine
LfD	Learning from Demonstration
LWSS	Longest Warping Subsequence
MAP	Maximum A-Posteriori
MDN	Mixture Density Network
ML	Machine Learning
MPs	Movement Primitives
MR	Mixed Reality
MTU	Muscle Tendon Unit

MVC	Maximum Voluntary Contractions
PbD	Programming by Demonstration
PCA	Principal Component Analysis
PDF	Probability Distribution Function
pHRI	Physical Human Robot Interaction
pHRIP	Physical Human Robot Interaction Primitives
POMDP	Partially Observable Markov Decision Process
ProMPs	Probabilistic Movement Primitives
PSD	Power Spectrum Density
RBF	Radial Basis Function
RCT	Randomised Control Trial
RMS	Root Mean Square
RMSE	Root Mean Square Error
RCT	Randomised Control Trial
SE	Squared Exponential
SEA	Series Elastic Actuator
sEMG	Surface Electromyogram
SSE	Sum of Squared Errors
VIA	Variable Impedance Actuator
VR	Virtual Reality

Glossary of Terms

Autonomous	Without human intervention.
Allocentric	Attention centered on other objects or persons. Antonym of <i>egocentric</i> .
Forward Kinematics	The process of translating system joint states into the Cartesian endpoint pose.
Gamification	The process of turning a task into a game.
Human-centric	Derived from or associated with the human.
Human-robot Dyad	A system consisting of one human and one robot.
In-silico	Testing and analysis that occurs in computational models.
In-vivo	Testing that occurs with living organisms (such as humans).
Inverse Kinematics	The process of translating a Cartesian pose into joint states of a system.
Multi-modal	Consisting of multiple <i>modes</i> , or ways.
One-shot	Using a single take or demonstration.
Osseointegration	The process of inserting a prosthetic into the residual bone of an amputee.
Proximate Cause	The immediate apparent cause of a phenomenon.
Semi-autonomous	With some human intervention.
Task-centric	Derived from or associated with the task.
Ultimate Cause	The primitive cause for a phenomenon. Usually proximate causes are the symptom of the ultimate cause.
Unimodal	Consisting of a single <i>mode</i> .

