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Prediction-Error Negativity in Physical Human-Robot Collaboration

by

Stefano Aldini

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

Supervisor: Dist. Prof. Dikai Liu

Co-supervisor: Dr. Marc Garry Carmichael

at the

Robotics Institute

Faculty of Engineering and Information Technology

University of Technology Sydney

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Certificate of Original Authorship

I, Stefano Aldini, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Mechanical and Mechatronic Engineering 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

Robotic systems for physical Human-Robot Collaboration (pHRC) are often controlled using control systems based on the admittance or impedance of the system. The interaction forces exchanged between the robot and the human co-worker during pHRC may affect the human cognitive state. In pHRC systems, the human cognitive state is often neglected. It is hypothesised that admittance dynamics of the robot have an effect on the human co-worker's cognitive state which can be used to estimate the predictability of the robot behaviour, or simply called the robot predictability. By using an electroencephalogram (EEG) device, the brain activity of the human co-worker can be measured. A feature, called Prediction-Error Negativity (PEN), that can be found in the EEG signal and is visible in the Event-Related Potentials (ERP) has the potential to be used to objectively assess the robot predictability. This thesis addresses the following research question: can the human cognitive state be used to assess and improve the robot predictability during physical human-robot collaboration?

Firstly, the relationship between PEN and changes in the robot admittance is investigated. Changes in the robot admittance were the result of the introduction of resistive forces with first-order dynamics. An analysis of the ERP is performed in the time-domain, to determine whether different admittance dynamics result in different PEN amplitudes. It is found that admittance dynamics can modulate PEN and thus robot predictability. Secondly, six different machine learning classifiers are then compared for classification of PEN by using the data sets collected. A two-class classification problem and a three-class classification problem are formulated for the comparative study.

A Convolutional Neural Network (CNN) is found to perform best in both the formulated classification problems, when compared to the other classifiers tested. Thirdly, a singularity avoidance strategy is implemented in a practical pHRC robot and is chosen to assess whether PEN can be detected during pHRC in real applications. The relationship between PEN and human preferences is also investigated and confirmed. Finally, a PEN-based closed-loop control is implemented and it is found that this can reduce PEN by automatically tuning parameters in a singularity avoidance strategy.

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Acronyms & Abbreviations

1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
ADL	Activity of Daily Living
ANOVA	Analysis of Variance
ASR	Artifact Subspace Reconstruction
BCI	Brain-Computer Interface
BMI	Brain-Machine Interface
BRI	Brain-Robot Interface
cHRI	Cognitive Human-Robot Interaction
CNN	Convolutional Neural Network
DDPG	Deep Deterministic Policy Gradient
DOF	Degree-of-Freedom
DLS	Damped Least Squares
EDLS	Exponentially-Damped Least Squares
EEG	Electroencephalogram
ERN	Error-Related Negativity

ERP	Event-Related Potential
ErrP	Error-Related Potential
FRN	Feedback-Related Negativity
FIR	Finite Impulse Response
GSR	Galvanic Skin Response
GPR	Gaussian Progress Regression
HR	Heart Rate
HRI	Human-Robot Interaction
IC	Independent Component
ICA	Independent Component Analysis
L-BFGS	Limited-memory Broyden-Fletcher-Goldfarb-Shanno
L-SVM	Linear Support Vector Machine
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LSD	least Significant Difference
LSL	Lab Streaming Layer
ML	Machine Learning
MLP	Multi-Layer Perceptron
MoBI	Mobile Brain/Body Imaging
MSE	Mean Square Error
NN	Neural Network
PEN	Prediction-Error Negativity

pHRC	Physical Human-Robot Collaboration
pHRI	Physical Human-Robot Interaction
PSD	Power Spectral Density
RBF-SVM	Support Vector Machine with Radial Basis Function
RL	Reinforcement Learning
ROS	Robot Operating System
SD	Standard Deviation
SDA	Series Damper Actuators
SEA	Series Elastic Actuators
SEM	Standard Error of Means
sEMG	Surface Electromyography
SVM	Support Vector Machine
SVD	Singular Value Decomposition
VIA	Variable Impedance Actuator
vMMN	Visual Mismatch Negativity

Glossary of Terms

Admittance	Measure of how easily a force causes motion of a structure or system.
Class	Set of data having a property or attribute in common.
Cognitive	Related to mental processes.
Collaboration	The action of working with another human or robot to complete a task.
Collaborative robot	Robot designed to work in collaboration with a human operator.
Control system	System that directs and regulates the behaviour of robots.
Closed-loop system	System that is directed or regulated by a control system with an active feedback loop.
Data processing	The action of carrying out operations on data.
Data set	Collection of data.
Experiment	Scientific procedure to test a hypothesis.
Interaction	Reciprocal action or influence.
Interface	Device or program enabling the interaction between two systems.
Kinematic singularity	Robot configuration resulting in a non-invertible Jacobian matrix.
Operator	Person operating a robot system.
Negativity	Negative peak in the event-related potentials.
Participant	Person who takes part in the experiment.
Physiological signal	Signals generated by the human body.
Pipeline	Linear sequence of operations.
Predictability	The ability to be predicted.
Prediction error	Result of a mismatch between expected and real outcomes of a task.

Stimulus	Action that causes a reaction or response.
Target	Goal of the task.
Task	Work to be completed by human and/or robot.