Error-related potentials-based human-robot intelligent system

Xiaofei Wang

School of Computer Science

Faculty of Engg. & IT

University of Technology Sydney

NSW - 2007, Australia

Error-related potentials-based human-robot intelligent system.

by Xiaofei Wang

A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy
in
Software Engineering

Principle Supervisors: Professor Chin-Teng Lin

Co-Supervisors: Dr. Tim Chen, and Dr. YK Wang

School of Computer Science
Faculty of Engineering and Information Technology
University of Technology Sydney

February 2022

Certificate of original authorship

I, *Xiaofei Wang* declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *Computer Science*, *Faculty of Engineering and Information Technology* at the University of Technology Sydney, Australia, 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. This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

Production Note:
Signature removed prior to publication.

SIGNATURE: ______________________

[Xiaofei Wang]

DATE: 4th July, 2022

PLACE: Sydney, Australia

Abstract

Brain-Computer Interface (BCI) is an emerging technology that provides natural and direct communication between humans and machines. Recent BCI works aimed to create accurate and reliable BCI systems in the field of Human-Robot Interaction (HRI). Of these, the BCI paradigm based on error-related potentials (ErrPs), a cognitive phenomenon derived from EEG signals, is particularly promising. ErrPs are involuntarily evoked when a person perceives unexpected errors in the environment. Unlike other BCI paradigms that require users to actively imagine the mental commands or engage with additional visual stimuli, ErrPs depends on the user's experience on assessing the correctness of the robot behaviours. The ErrP-based BCI does not require additional training and does not interrupt the user's original workflow. This thesis presents two novel ErrP-based BCI systems:

First, a novel robotic design for ErrP-based BCI that allows humans to evaluate the robot's intentions continuously. Current ErrP-based BCI cannot handle interaction sequences that involve continuous robot movements. For example, it is difficult to extract a time-locked event when the user detects an unexpected error while the robot arm is already in motion. The high classification accuracy (77.57%) from the first system confirmed that the proposed ErrP-based BCI paradigm allows continuous evaluation of robot intentions in real-time and thus enable earlier intervention before the robot commits an error.

Second, ErrP-based shared autonomy via deep recurrent reinforcement learning.

Current BCI systems use ErrP as either an implicit control signal to the agent or a reward signal in reinforcement learning (RL). Our novel framework proposed using ErrP as an input feature in the trained RL model, which enables human intervention with a trained autonomous agent. In a simulation with 70% ErrP accuracy, agents completed the task 14.1 % faster. In the real-world experiment, agents completed the navigation task 14.9% faster. The evaluation results confirmed that the shared autonomy via deep recurrent reinforcement learning is an effective way to deal with uncertain human feedback in a complex HRI task.

These two novel BCI systems advance the current ErrP-based BCI capabilities and enable a wide range of new interaction possibilities between human and robot. This thesis represents an important step toward a BCI-based shared autonomy between humans and robots.

Acknowledgments

I want to express my sincere gratitude to my principle supervisor, Professor CT Lin, for the guidance, motivation and weekly feedback during these years. He has always motivated and guided my work in the right directions. Without those, I don't think I would have been able to finish this project. It is my great honor to be supervised by Professor CT Lin. I would also like to thank my co-supervisor, Tim Chen. Thank you for the hard work and endless support. Whenever there is a problem in research or outside the school environment, he always tries his best to help. Thank you for all the help, guidance, and mentoring received during these years. I would also like to thank my co-supervisor, Dr. YK Wang. Thank you for the weekly discussion. Thank you for the help on papers and thesis.

I want to thank all the CIBCI lab members for all the help and knowledge they provided during my years. Special thanks to Carlos Tirado, Fred Chang, Tien-Thong Do, Avinash Kumar Singh, Howe Zhu, Jia Liu, Jie Yang, Sai Kalyan Ranga, Yanqiu Tian, and Liang Ou.

I want to thank all my friends in Techlab. Thank all the friends since the first day I came to Techlab. And thank all the friends outside the school environment. The green mountain won't change, the flowing water is endless. See you around!

I want to thank the Australian Research Council (ARC) for its financial support.This work was supported in part by the ARC under discovery grant DP180100656 and DP210101093. I also want to thank the UTS International Research Scholarship for covering my tuition fees.

Last but not least, I want to thank my family for their constant love and support. Without their support and motivation, I would not be where I am now. No words can express how thankful and grateful as being one of the members in my family. I love you all!

DEDICATION

To my father, my mother, and my brothers for their endless love, support and encourage ...

LIST OF PUBLICATIONS

JOURNAL :

1. **X.-F. Wang**, H.-T. Chen, Y.-K. Wang, C.-T. Lin, "Implicit Robot Control using Error-related Potential-based Brain-Computer Interface," IEEE Transactions on Cognitive and Developmental Systems. (accepted)

2. **X.-F. Wang**, H.-T. Chen, Y.-K. Wang, C.-T. Lin, "Error-Related Potential-Based Shared Autonomy via Deep Recurrent Reinforcement Learning". (draft)

3. **X.-F. Wang**, H.-T. Chen, Y.-K. Wang, C.-T. Lin, "Error-Related Potential used to correct robot movement during continuous searching task in a maze". (draft)

Table of Contents

Title ii

Certificate of Original Authorship iii

Abstract vii

Acknowledgments ix

Dedication x

List of Publications xi

Contents xvii

List of Figures xvii

List of Tables xx

1 Introduction 1

1.1 Motivation 1

1.2 Problem definition 3

1.3 Research aim and objective 4

1.3.1 Continuous implicit Robot Control using Error-related Potentials . 5

1.3.2 BCI-based shared control for human-robot interaction 6

1.3.3 Shared autonomy via deep recurrent reinforcement learning 7

1.4 Structure of this Dissertation 7

2 Literature review 9

2.1 Brain-Computer Interface 9

2.1.1 Signal Acquisition 10

2.1.2 Preprocessing 11

2.1.3 Feature extraction 11

2.1.4 Classification 12

2.2 Electroencephalogram (EEG) 13

2.3 BCI applications 16

2.3.1 Brain Controlled Robots 17

2.3.2 Brain-Controlled Mobile Robots 18

2.3.3 ErrP-based human-robots interaction 19

2.3.4 Degree of freedom of BCI applications 22

2.4 Human-Robot Interaction 24

2.5 Shared autonomy in HRI 26

2.5.1 BCI-based shared autonomy 28

2.6 Human-in-the-loop reinforcement learning 29

2.6.1 POMDP in Human-Robot Interaction 30

3 Materials, methods and experiment design 33

3.1 Experiment design of ErrP-based implicit robot control 34

3.2 ErrP-based Shared Autonomy via Deep Recurrent Reinforcement Learning 38

3.2.1 Background 40

3.2.2 Method and experiment design 44

3.3 Shared autonomy validation with real human participants 47

3.3.1 Experiment 47

3.4 EEG processing and classification used for the two experiments 49
3.4.1 EEG recording and preprocessing 49
3.4.2 Electrophysiological analysis 50
3.4.3 Feature extraction 50
3.4.4 Classification 51

4 Evaluation of implicit robot control using ErrP 55

4.1 Experiment overview 55
4.2 Results analysis 56
4.2.1 ERP analysis 56
4.2.2 Classification Analysis 63
4.3 Discussion 69
4.3.1 ErrP observability and decodability for evaluating of the robot's intention 69
4.3.2 Using robot motion as time-locked events for ErrP 72
4.3.3 Interaction sequence effect on ErrP 73

5 Evaluation the feasibility of shared autonomy with simulated ErrP 75

5.1 Experiment overview 75
5.2 Results analysis 76
5.3 Discussion 86
5.3.1 Formula the learning as POMDP with noise ErrP 86
5.3.2 Gradient analysis at different positions 87
5.3.3 ErrP Accuracy threshold for training 87
5.3.4 Adaptive human-robot interaction 88
5.3.5 Efficiency of shared control 88

6 Validation the learned shared autonomy with real human participants 91

6.1 Experiment overview 91

6.2 Results analysis 92

6.2.1 Electrophysiology analysis 92

6.2.2 Classification analysis of ErrP 94

6.3 Discussion 100

6.4 Interaction design 100

7 Conclusions and future work **103**

7.1 Conclusion 103

7.2 Future work 105

Bibliography **107**

List of Figures

Figure **Page**

2.1 Critical steps of BCI system. 10

2.2 Bayesian non-parametric learning in POMDP. 32

2.3 multimodal perception model in POMDP. 32

3.1 (a) LCD mounted on the ground robot. (b) The robot performs a binary target-reaching task. 36

3.2 (a) Real scenario. (b) The robot signals its intentions ten times at three stages in one run. There were 6 times via LCD at the positions from p1 to p6 at Stage 1, one time at position p7 via turning movement at Stage 2, and three times at positions from p8 to p10 via LCD at Stage 3. 39

3.3 An overview of our method for ErrP-based real-time shared control autonomy and deep reinforcement learning. We evaluated our method in a target search task with real human participants. Here the red dot with an arrow is the agent, and the green square is the target 40

3.4 The environment without obstacles (a) and obstacles (b). 45

3.5 We evaluated our method in a target search task with real human participants (a). The red dot with an arrow is the agent , and the green square is the target (b) 48

4.1 The robot signals its intentions ten times at three stages in one run. There were 6 times via LCD at the positions from p1 to p6 at Stage 1, one time at position p7 via turning movement at Stage 2, and three times at positions from p8 to p10 via LCD at Stage 3. 57

4.2 ERPs of stage1 (a), stage 2 (b), stage 3 (c)) in channel Fz. Statistically significant difference ($p<0.05$) was found at the green area between error and correct conditions using paired permutations test. 59

4.3 ErrP at Stage 1 and Stage 3. Statistically significant difference ($p<0.05$) was found at the green area between error and correct conditions using paired permutation tests. 60

4.4 Grand averaged ERP at Fz, ERP scalp map series at certain latencies of one of the participants at Stage 1 (a), Stage 2 (b), Stage 3 (c). 61

4.5 Grand averaged difference in the ERP waves between the correct trials and error trials at Fz of each stimulus in Stage 1, Stage 2 and Stage 3. 62

4.6 Classification accuracy of four classification methods for offline sessions. . . . 63

4.7 ROC curve of four classification methods for offline sessions. 64

4.8 ACC for Stage 1 (a), Stage 2 (b), and Stage 3 (c). 65

4.9 ACC of the multiple sequence of Stage 1 (a) and Stage 3 (b). ACC of the single sequence of Stage 1 (c) and Stage 3 (d). ACC of the inverse multiple sequence of Stage 1 (e) and Stage 3 (f). 67

4.10 The robot correct rates at three stages of the online session. 68

4.11 True positive and true negative rates at Stage 2 (a) and Stage 3 (b) of online session. 69

5.1 Training curve with 100% correct probability ErrP and no ErrP conditions (a). The averaged step is used to reach the target positions (b). 77

5.2 Average steps during test on different maze size for ErrP and no ErrP conditions. 78

5.3 Training curve with different level probability ErrP and no ErrP conditions (a). The averaged step is used to reach the target positions (b). 80
5.4 The agent search policy with 100% accuracy ErrP. 82
5.5 The agent search policy without ErrP. 83
5.6 The averaged steps to reach the target position on different observation levels with partial and full observation trained model. 84
5.7 ErrP and gradients with different ErrP correct probability. 85
5.8 ErrP gradient distribution at the different positions of two environments. . . 87

6.1 Shared autonomy Frame architecture. We evaluated our method in a target search task with real human participants (a). The red dot with an arrow is the agent , and the green square is the target (b) 92
6.2 ERP analysis for correct and error conditions averaged trials of scenario 1 and scenario 2 (a). ERP analysis for correct and error conditions of scenario 1 and scenario 2, respectively (b). The legend numbers "1" and "2" refer to scenario 1 and scenario 2, respectively. 93
6.3 The averaged steps used among 10000 times of each initial distance between agent start position and target position for two scenarios with no ErrP, 70% accuracy ErrP, and 80% accuracy ErrP. 96
6.4 Success rate to reach the target position within 60 steps for each initial distance with no ErrP, 70% accuracy ErrP, and 80% accuracy ErrP conditions for scenario 1 and scenario 2. 96
6.5 The averaged steps by removing the trials that failed to reach the target positions within 60 steps among 10000 times of each initial distance for two scenarios with no ErrP, 70% accuracy ErrP, and 80% accuracy ErrP. 97
6.6 Steps used for participants in real experiment for scenario 1. 98
6.7 Steps used for participants in real experiment for scenario 2. 99

List of Tables

Table **Page**

2.1 BCI paradigms and controller devices. 22

2.2 Five key factors affect the interactions between humans and robots 25

2.3 ErrP usage in reinforcement learning. 30

3.1 Robot communication channels and observer implicit controls command at different stages. 37

6.1 ErrP training accuracy with 10-fold cross-validation and testing accuracy for the two scenarios. 94

6.2 Table: Success rate and averaged steps in real experiment. 100