Correcting Robot Mistakes in Real Time Using EEG Signals¹

Andres F. Salazar-Gomez * Joseph DelPreto † Stephanie Gil † Frank H. Guenther * Daniela Rus †

- † MIT Distributed Robotics Lab
- Boston University Guenther Lab

1: <u>https://ieeexplore.ieee.org/document/7989777</u> 2017 International Conference on Robotics and Automation (ICRA)





2: http://groups.csail.mit.edu/drl/wiki/index.php?title=Correcting_Robot_Mistakes_Using_EEG

Outline of Today's Talk

- I. Introduction
- II. Literature Review
- III. System and Experimental Design
- IV. Training and ErrP Classification
 - V. Results: Primary and Secondary Errors
- VI. Conclusion and Future Work

Introduction

Why is this useful?

- Recent research shows that our brains generate a specific signal when we observe or make a mistake. These signals are called error-related potential signals.

In short, ErrP = mistake signal.

- Now imagine an Amazon warehouse:



"...humans could remotely communicate 'stop' instantaneously when the robot makes a mistake without needing to type a command or push a button." ¹

3: https://www.nytimes.com/2017/09/10/technology/amazon-robots-workers.html

1: https://ieeexplore.ieee.org/document/7989777

Intro to Experiment

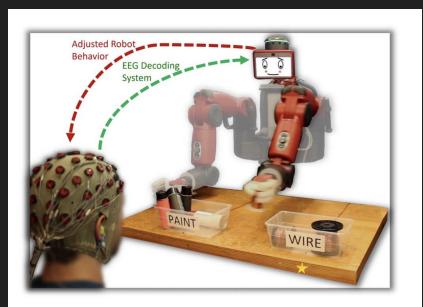


Fig. 1: The robot is informed that its initial motion was incorrect based upon real-time decoding of the observer's EEG signals, and it corrects its selection accordingly to properly sort an object.

Definitions

Secondary Errors:

misclassification of ErrP signal in online closed loop setting

Closed Loop:

Human and robot directly affect each other throughout the task.

change in ErrP = change in Baxter

Open Loop:

Robot performs task without feedback from human.

change in ErrP ≠ change in Baxter

Online Performance:

Real-time ErrP classification. ≈10-30 milliseconds.

Required for a closed loop system.

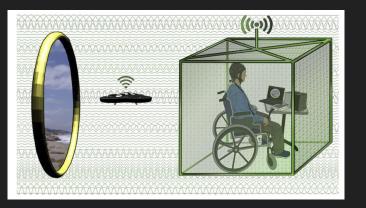
Offline Performance:

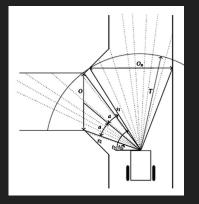
Pre-trained ErrP classifier.

No constraint on computation time often leads to better performance than online.

Literature Review

EEG-based methods for Robot Tasks







4: <u>https://ieeexplore.ieee.org/document/7989777</u> Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface 5: https://www.ncbi.nlm.nih.gov/pubmed/18621580

A brain-actuated wheelchair: asynchronous and non-invasive Brain-computer interfaces for continuous control of robots. 6: <u>https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7140110</u> An Autonomous Robotic Assistant for Drinking

EEG-based methods for Robot Tasks (cont'd)

7: https://www.ncbi.nlm.nih.gov/pubmed/17445904

8: https://www.ncbi.nlm.nih.gov/pubmed/21096199

9: https://www.ncbi.nlm.nih.gov/pubmed/23181009

10: https://www.sciencedirect.com/science/article/pii/S0957417414006903

The Error-Related Potential Signal

11: Interaction Errors - https://www.ijcai.org/Proceedings/05/Papers/0778.pdf

12: Learning Algorithms – https://infoscience.epfl.ch/record/150583/files/chavarriaga-iccn-2007.pdf

13: Noninvasive – <u>https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5491194</u>

14: Real World Driving – <u>https://www.ncbi.nlm.nih.gov/pubmed/26595103</u>

The Error-Related Potential Signal

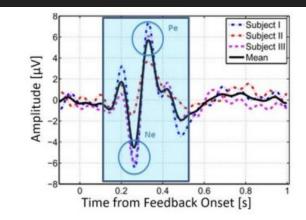


Fig. 2: Error-Related Potentials exhibit a characteristic shape across subjects and include a short negative peak, a short positive peak, and a longer negative tail.

12: Learning Algorithms – https://infoscience.epfl.ch/record/150583/files/chavarriaga-iccn-2007.pdf

System and Experimental Design

Binary Choice Paradigm

- subject is wearing an EEG cap
- subject is seated 50cm from Baxter
- subject judges whether Baxter's *binary choice* is correct
- decoder searches for ErrP signals
- if misclassification occurs, secondary error may be induced
- open loop sessions: EEG signals not controlling Baxter. Baxter was right 50% of the time*
- **closed loop sessions:** Four block trials, one for training and three for testing

Subject Selection

- Approved by:
 - Internal Review Board of Boston University
 - Committee on Use of Humans as Experimental Subjects of MIT

- Total of 12 individuals
 - open loop: 7 individuals
 - closed loop: 5 individuals, but only data from 4 are included*

Subject Selection

- Approved by:
 - Internal Review Board of Boston University
 - Committee on Use of Humans as Experimental Subjects of MIT

- Total of 12 individuals
 - open loop: 7 individuals
 - closed loop: 5 individuals, but only data from 4 are included*
 - Is this enough people?

Baxter Robot

- Baxter interfaces with experiment controller using ROS
- Controller provides trajectories for Baxter's left 7 DOF arm
- Image is projected onto Baxter's face
 - if ErrP is detected, face sentiment changes

EEG System

- 48 passive electrodes
- located according to the 10/20 international system
- sampled at 256 Hz using the g.USBamp EEG system
- Matlab and Simulink used to capture, process, and classify signals
- function success : signal \rightarrow { 0 , 1 }

System Design

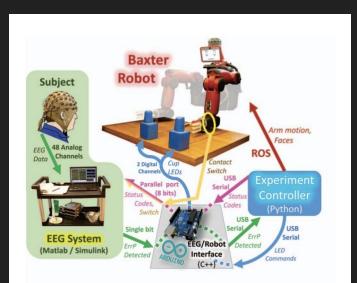


Fig. 4: The system includes a main experiment controller, the Baxter robot, and an EEG acquisition and classification system. An Arduino relays messages between the controller and the EEG system. A mechanical contact switch detects arm motion initiation.

Training and ErrP Classification

Signal Classification Pipeline

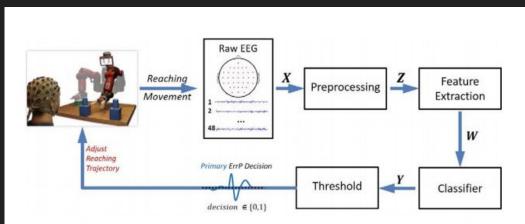


Fig. 6: Various pre-processing and classification stages identify ErrPs in a buffer of EEG data. This decision immediately affects robot behavior, which affects EEG signals and closes the feedback loop.

Signal Classification Pipeline

- 1. **Pre-Process:** every 800ms, reduce dimensionality of all 48 EEG channels to 9 channels
- **2.** Feature Extraction: XDAWN filter \rightarrow 190 features, Correlation indexes \rightarrow 9 features
- **3.** Classifier: Elastic Net (lasso and ridge regression), $\alpha = 0.5$ and $11_{ratio} = 0.0002$
- 4. Threshold: arg min $\sqrt{0.7\left(1-sensit.\right)^2+0.3\left(1-specif.\right)^2}$
- **5. Decision:** 0 indicates to ErrP is present vs. 1 indicates ErrP is present \rightarrow Baxter changes

Results: Primary and Secondary Errors

Trials

- **1. online closed-loop:** real time error detection and trajectory update
- 2. offline closed-loop: pre trained error detection and trajectory update
- 3. offline open-loop: pre trained error detection and no trajectory update
- 4. offline secondary error: same as 3, but an additional classifier is trained for secondary errors after an initial round of passive classification to generate labeled data

TABLE I: Offline Classification Performance (Percentages)

Session Type	Accuracy Mean	Accuracy Std. Dev.	Chance	Above Chance
Closed-loop Offline	64.17	06.56	56.49	07.68
Open-loop Offline	65.06	01.75	58.91	06.15
Second. ErrP (II+CI)	73.99	07.64	58.16	15.83
Second. ErrP (II)	83.49	01.64	73.19	10.30
Second. ErrP (CI)	86.51	05.03	58.41	28.10

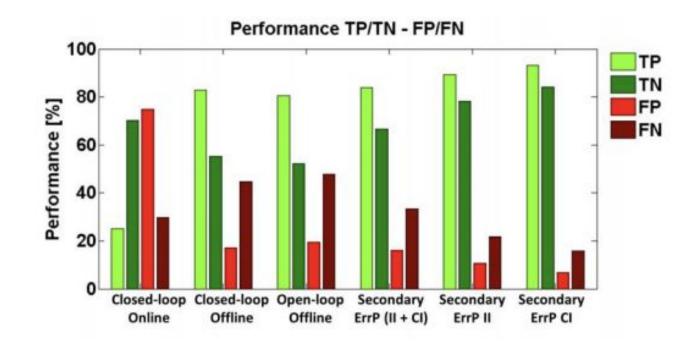


Fig. 12: Using secondary ErrPs in the classification loop greatly increases true positive and true negative classification rates.

Conclusion and Future Work

Conclusion and Future Work

- Research:

- scale testing far beyond 12 people
- improve results for binary choice setting
 - better signal classification pipeline
- explore non-binary choice settings
- explore non-ErrP brain signals
- Industry:
 - hopefully use cases that directly help humans
 - more disability-focused solutions
 - Musk?
- Far Future:
 - seamless human computer interaction
 - thoughts drive environmental behavior
 - enabled by IoT



Questions?