Correcting Robot Mistakes in Real Time Using EEG Signals

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

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

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

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

Secondary Errors:

misclassification of ErrP signal in online closed loop setting

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: https://ieeexplore.ieee.org/document/7989777
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: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7140110
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


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.
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

* In ⅞ trials. In ⅛ trials Baxter was right 70% of the time.
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*

* 1 of the 5 individuals was in a meditative state (?)
Subject Selection

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

* 1 of the 5 individuals was in a meditative state (?)
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
- \textit{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.

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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.

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Signal Classification Pipeline

1. **Pre-Process:** every 800ms, reduce dimensionality of all 48 EEG channels to 9 channels

2. **Feature Extraction:** XDAWN filter → 190 features, Correlation indexes → 9 features

3. **Classifier:** Elastic Net (lasso and ridge regression), $\alpha = 0.5$ and $l1_{\text{ratio}} = 0.0002$

4. **Threshold:** $\arg \min \sqrt{0.7 \left(1 - \text{sensit.}\right)^2 + 0.3 \left(1 - \text{specif.}\right)^2}$

5. **Decision:** 0 indicates to ErrP is present vs. 1 indicates ErrP is present → 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
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<tr>
<th>Session Type</th>
<th>Accuracy Mean</th>
<th>Accuracy Std. Dev.</th>
<th>Chance</th>
<th>Above Chance</th>
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<tr>
<td>Closed-loop Offline</td>
<td>64.17</td>
<td>06.56</td>
<td>56.49</td>
<td>07.68</td>
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<td>Open-loop Offline</td>
<td>65.06</td>
<td>01.75</td>
<td>58.91</td>
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<td>Second. ErrP (II+CI)</td>
<td>73.99</td>
<td>07.64</td>
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<td>83.49</td>
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<td>Second. ErrP (CI)</td>
<td>86.51</td>
<td>05.03</td>
<td>58.41</td>
<td>28.10</td>
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</table>
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?