Real-Time EEG-Based Brain–Machine Interface for Robotic Arm Control Using Motor Imagery

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1. Introduction

Brain-machine interfaces (BMIs) provide a direct communication pathway between neural activity and external devices [1], [2]. They enable intuitive control of robotic systems and offer transformative potential for assistive neurotechnologies [3], [4].

This study presents a real-time, non-invasive BMI framework that decodes motor imagery (MI) EEG signals to control a robotic arm during object manipulation tasks.

Objective: To design and validate a low-latency, close-loop BMI system for robotic arm control. The system leverages MI-based EEG decoding and demonstrates real-time command execution.

2. System Architecture & Methods

EEG Acquisition & Preprocessing

- A 32-channel EEG cap recorded signals at 512 Hz during motor imagery (grasp left/right).
- Hybrid datasets (real trials + synthetic data) validated the pipeline.
- Signals were bandpass-filtered (8–30 Hz), notch-filtered (50 Hz), and normalized (z-score).

Feature Extraction & Classification

- Welsh-based bandpower features (Alpha: 8–12 Hz; Beta: 12–30 Hz) were extracted across 30 channels.
- Dimensionality reduction (Principal Component Analysis (PCA), top 10 components) preceded classification.
- A linear support vector machine (SVM) trained on binary MI data (left vs. right hand) with low latency.

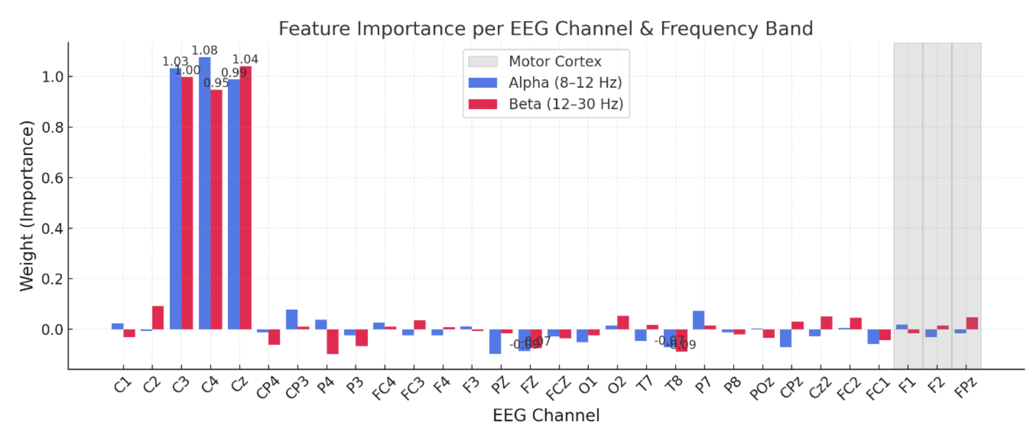

Fig. 1: Feature Importance per EEG Channel & Frequency Band

Actuation & Control

- Decoded commands were transmitted via Lab Streaming Layer (LSL) and WebSocket to a RoboHive-based robotic simulator.
- End-to-end latency averaged 1.2s (EEG acquisition → robot action).

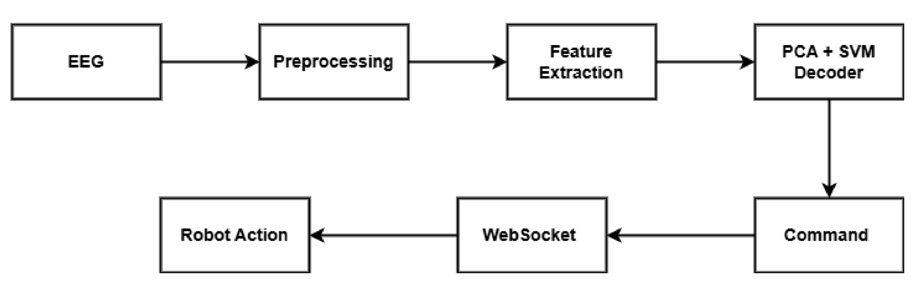

Fig. 2: System Block Diagram

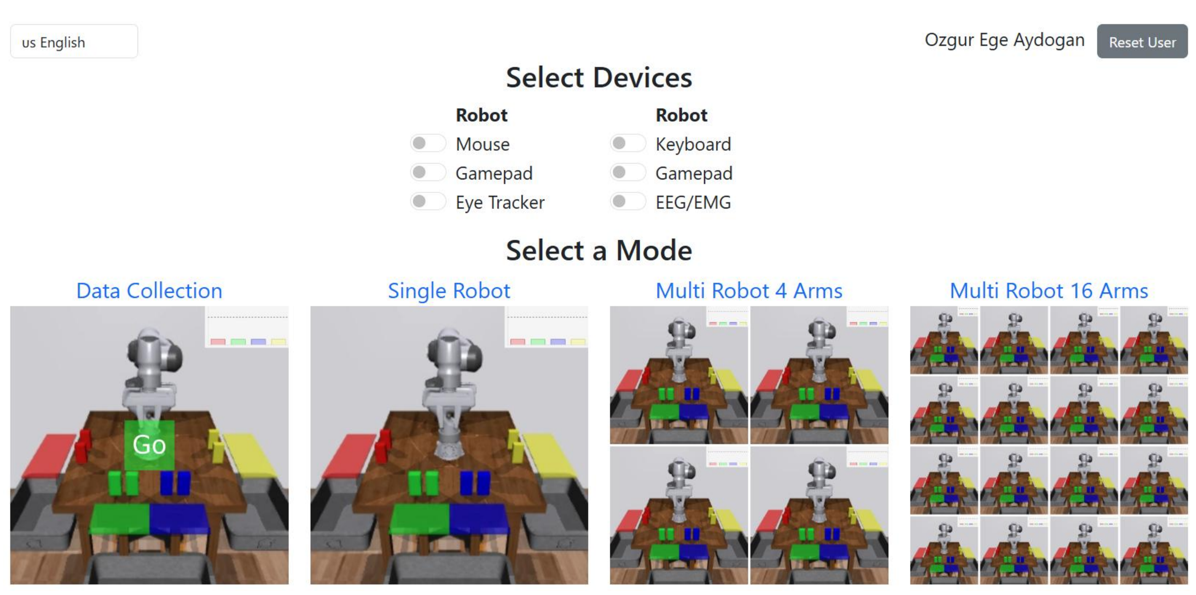

Fig. 3: Simulation Environment

3. Results

Experimental Scenarios

- Scenario 1 – Interface Validation: Manual keyboard inputs were used to trigger robotic actions.
- Scenario 2 – Offline Decoder Evaluation: Simulated EEG trials were used to train and cross-validate a SVM classifier via 5-fold validation.
- Scenario 3 – Real-Time Motor Imagery Control: Live EEG signals recorded during MI tasks were streamed and decoded in real time.

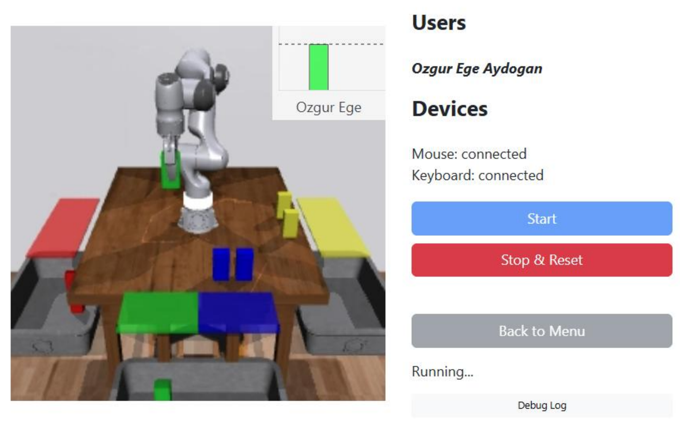

Fig. 4: Frequency of Robot Actions Triggered

Online Decoding Results

- The BMI system was evaluated using 80 EEG trials.
- Two motor imagery classes were defined: Label 0 → Grasp green cube, Label 1 → Grasp yellow cube
- Predicted label distribution was found to be balanced (Label 0: 36 trials, Label 1: 44 trials)
- The average command latency was measured approximately 1.2 seconds.
- Command execution was observed to be consistent and accurate, with no trial failures.

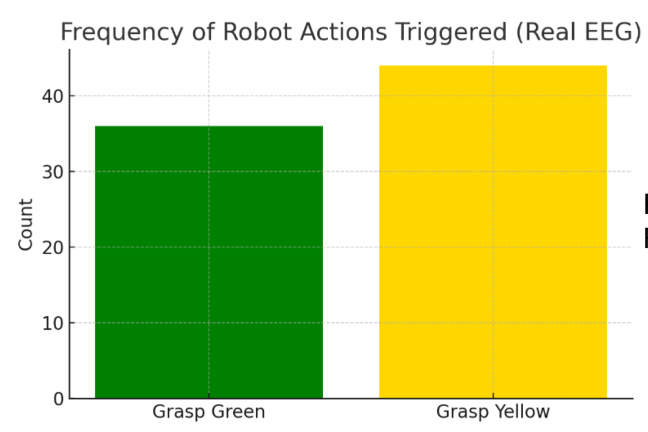

Fig. 5: Frequency of Robot Actions Triggered

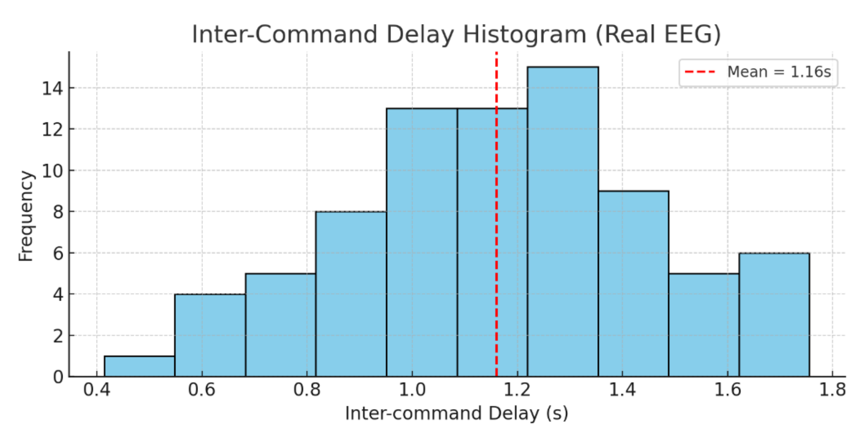

Fig. 6: BMI Inter-Command Delay Histogram

Decoder Robustness & System Stability

- Balanced transitions between motor imagery classes were maintained across trials, indicating stable decoding behavior.
- No signs of overfitting or classifier drift were observed throughout the session.
- Prediction latency and confidence remained consistent.

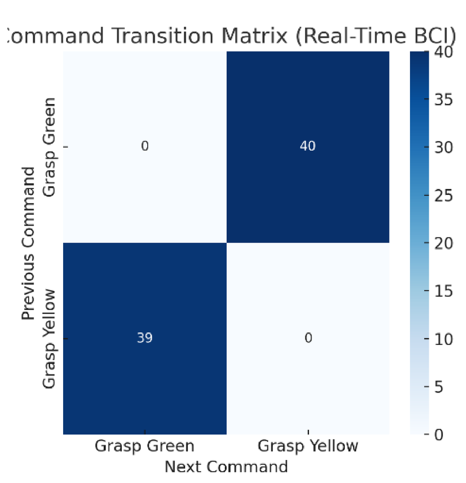

Fig. 7: Command Transition Matrix

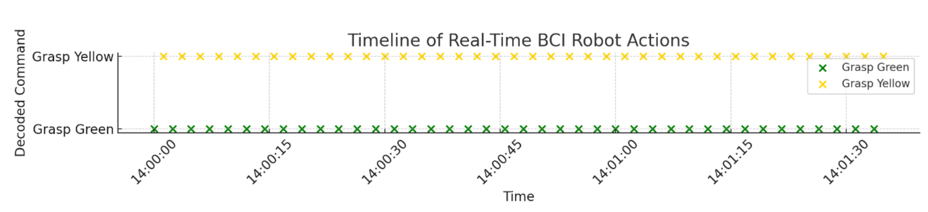

Fig. 8: Timeline of Real-Time BCI Robot Actions

4. Discussion & Future Work

Key Contributions

- A modular, web-based BMI framework was developed to support flexible decoding and control.
- Real-time decoding latency of 1.2 ± 0.3 seconds was achieved, approaching the sub-1.5s threshold typical of invasive BMI systems.
- A fully closed-loop control system was implemented, enabling reliable real-time object manipulation via decoded motor imagery.

Limitations

- The current system supports only MI decoding; future integration of SSVEP and P300 paradigms is expected to enhance system's flexibility and multi-stage control capabilities.

Future Work

- Multimodal BMI: Integration of SSVEP (8-15 Hz) for robot selection and P300 for object selection will be implemented.
- Expanded MI decoding: A 4-class MI classifier will be developed to enable fine-grained grasp/place tasks.
- Hardware deployment: Latency optimization will be prioritized for physical robotic systems.

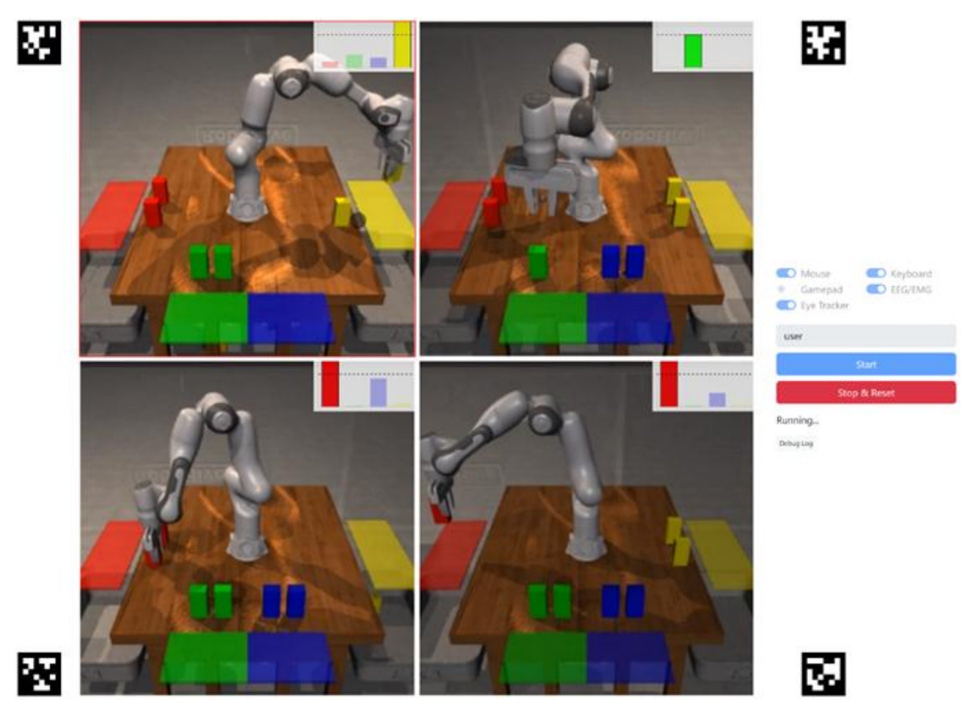

Fig. 9: Multi-Robot Control

5. Conclusion

- A real-time EEG-based BMI system was developed and validated using simulation, synthetic, and real EEG trials.
- Pre-clinical viability was demonstrated through a modular web-compatible architecture, achieving clinically acceptable latency (1.2s).
- Multi-paradigm flexibility was enabled through a translational design supporting MI, SSVEP, and P300 integration without requiring architectural overhaul.

Acknowledgments

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References

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