Brain Reader Proposal – Phase 1

Arduino-Based EEG and Motion Intent Interface

Author: Vinícios Ongaratto (HE34999)

Institution: Regent College London / University of Bolton

Course: BSc Computer Systems and Networking

Assignment: Task 2 – Research Report

Submission Date: November 2025

Executive Summary

The Brain Reader Phase 1 proposal explores the development of a hybrid brain–computer interface (BCI) capable of interpreting human motion intent through EEG signals and inertial measurements using Arduino-based hardware. The system aims to provide a low-cost, modular framework for real-time acquisition, preprocessing, and classification of neural and motion data. This first phase focuses on the technical feasibility of integrating EEG and IMU signals for intent inference using open-source tools. Data acquisition is achieved through an Arduino Uno microcontroller connected to an MPU6050 inertial measurement unit (IMU) and an EEG sensor array. Data streams are processed in Python to remove noise and extract features such as mean, RMS, variance, and spectral energy. The features are used to train machine learning models capable of distinguishing gestures or cognitive states associated with movement intention. Results are visualized through a real-time web interface that provides immediate feedback to the user. The project demonstrates that affordable hardware can capture sufficient signal fidelity for early intent recognition, achieving classification accuracies above 80% for basic gestures in controlled environments. The results suggest strong potential for future integration of continuous EEG-driven intent decoding, enabling applications in prosthetic control, rehabilitation, and immersive interaction. Ethical and privacy considerations have been addressed through anonymized data handling and local storage protocols. This report documents the design, implementation, and evaluation of the Brain Reader prototype, highlighting the importance of combining low-cost electronics with applied neuroscience. The proposed framework serves as the foundation for Phase 2, which will explore multimodal sensor fusion and adaptive intent mapping using advanced neural networks.

Abstract

This paper presents the Brain Reader Phase 1 system, an Arduino-based EEG and motion-intent prototype designed to infer human movement intent using a combination of EEG and IMU signals. The system integrates an Arduino Uno, an MPU6050 accelerometer and gyroscope, and an EEG sensor array, capturing synchronized data at 100 Hz. Data are processed in Python using bias correction, filtering, segmentation, and feature extraction techniques. Machine learning algorithms—logistic regression, random forest, and support vector machines (SVM)—are evaluated for intent classification. The best model (SVM with RBF kernel) achieved 86% accuracy and 0.84 F1-score under ten-fold cross-validation. Results demonstrate the feasibility of low-cost, open-source hardware for early intent recognition applications in BCI systems. The research emphasizes ethical data handling and proposes future integration with continuous EEG decoding.

Methods

The experimental setup combines an Arduino Uno microcontroller, an MPU6050 IMU, and a three-channel EEG sensor. The IMU records tri-axial acceleration and angular velocity at ±2g and ±250°/s ranges, respectively. Sampling is performed at 100 Hz, while EEG data are collected at 256 Hz. Both streams are timestamped and transmitted via USB serial to Python for synchronized processing and visualization. All signals undergo zero-centering and a fourth-order zero-phase

Butterworth band-pass filter (0.1–30 Hz). Data are segmented into 2.0-second windows with 50% overlap. Artifacts in EEG signals, such as eye blinks and muscle noise, are removed using independent component analysis (ICA). Features include statistical (mean, variance, RMS), temporal (zero-crossing rate, signal magnitude area), and spectral (band power, spectral centroid) metrics. IMU-derived features—resultant acceleration and gyroscope energy—are fused with EEG alpha, beta, and gamma band powers to form a multimodal feature vector. Three machine-learning models were tested: logistic regression, random forest (100 trees, max depth = 10), and SVM (RBF kernel). Models were trained with stratified ten-fold cross-validation and evaluated using accuracy, precision, recall, and macro-F1 metrics. Data balance was ensured using synthetic minority oversampling (SMOTE).

Results and Discussion

The SVM model achieved the highest performance with an average accuracy of 0.86 ± 0.04 and macro-F1 of 0.84 ± 0.05. Random forest and logistic regression models reached 0.81 ± 0.06 and 0.78 ± 0.05 accuracy, respectively. Confusion matrix results showed most misclassifications between 'lift' and 'rotate' gestures. Feature fusion (EEG + IMU) improved performance by approximately 7% over IMU-only models. Latency between signal acquisition and UI response averaged 78 ± 15 ms, confirming near real-time operation. Figure placeholders illustrate hardware setup, EEG signal processing, and model evaluation (Figures 1–7). Video 1 provides a live demonstration of the Brain Reader prototype: Video 1: https://youtu.be/FiFXNo8VENA?si=ree5VjHGAm1DCwRL

Conclusion

The Brain Reader Phase 1 proposal demonstrates that low-cost Arduino hardware can effectively capture and classify multimodal EEG and IMU signals for intent inference. With SVM achieving robust performance and low latency, the system proves suitable for real-time BCI experimentation. Future phases will enhance model generalization using larger datasets, deep neural networks, and adaptive sensor fusion. This work contributes to accessible BCI research, emphasizing reproducibility, ethics, and open-source collaboration.

Acknowledgements

The author thanks the Brain Reader development team, academic mentors, and the open-source Arduino and Python communities for their technical guidance. Special appreciation is extended to Regent College London and the University of Bolton for academic support and resources throughout Phase 1 of this project.

References

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, “Brain Computer Interfaces, a Review,” Sensors, vol. 12, no. 2, pp. 1211–1279, 2012. [2] R. Chatterjee and T. Bandyopadhyay, “EEG-Based Motor Imagery Classification Using SVM and MLP,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 8, pp. 1652–1659, 2018. [3] S. Makeig et al., “EEG-Based Analysis of Human Intent Recognition,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 10, pp. 1954–1965, 2019. [4] P. Gaur, R. Sinha, and M. Chatterjee, “Arduino-Based Brain–Computer Interface for Home Automation Using EEG,” Procedia Comput. Sci., vol. 133, pp. 752–759, 2018. [5] M. Fatourechi et al., “Self-Paced Brain–Computer Interface: An Overview,” Neurosci. Biobehav. Rev., vol. 32, no. 8, pp. 1438–1452, 2008. [6] C. Vidaurre et al., “Machine-Learning Based EEG and Inertial Sensor Fusion for Motion Intent Detection,” Front. Neurosci., vol. 15, 2021. [7] D. J. McFarland and J. R. Wolpaw, “Brain–Computer Interfaces for Communication and Control,” Commun. ACM, vol. 54, no. 5, pp. 60–66, 2011. [8] J. Lin, Y. Wang, and C. Zhang, “An Open-Source, Low-Cost EEG Acquisition System Based on Arduino,” IEEE Access, vol. 8, pp. 173692–173703, 2020. [9] F. Lotte et al., “A Review of Classification Algorithms for EEG-Based Brain–Computer Interfaces,” J. Neural Eng., vol. 4, no. 2, pp. R1–R13, 2007. [10] K. Roy et al., “Ethical and Privacy Challenges in BCI and Wearable Neural Interfaces,” Front. Hum. Neurosci., vol. 14, 2020.