Multimodal Integration of Motor Imagery Brain-Computer Interface (BCI) with Adaptive Virtual Reality (VR) Environments for Assistive Robotics

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Abstract

High-density Electroencephalogram (EEG) setups hinder practical deployment of motor-imagery (MI) brain-computer interface (BCI) in virtual reality–robotic rehabilitation due to portability, computation, and inter-subject variability constraints. We propose CHDECW, a *Collaborative Hierarchical Density–Entropy aware Channel selection* framework augmented with a cognitive-workload detector, which prioritizes informative (hard, high-entropy) trials during channel selection and weights trial contributions by workload state; evaluated on cross-subject rehabilitation MI tasks, CHDECW maintains decoding performance while substantially reducing electrode count, enabling more portable and personalized BCI–VR–robot interventions.

Introduction

Electroencephalogram-based motor-imagery (MI) decoding is central to brain–computer interface (BCI) applications in virtual reality-assisted and robotic rehabilitation, but conventional high-density electrode setups increase computational load, reduce portability, and hinder clinical adoption [1]. Channel selection can alleviate these issues, yet existing approaches struggle with inter-subject variability, task-dependent regional effects, and the masking of hard, informative trials by easier ones [2, 3]. To address these gaps, we introduce CHDECW: a hierarchical channel-interaction model that uses a density–entropy collaborative optimization strategy to prioritize discriminative, high-entropy trials, coupled with a cognitive workload detector that guides trial selection and adapts VR/robot training intensity. Evaluated on rehabilitation-oriented cross-subject MI tasks, CHDECW preserves decoding performance while reducing electrode requirements, thereby advancing portable, adaptive MI-BCI solutions. Future work will focus on extending the framework for low-latency, real-time decoding to improve responsiveness in closed-loop training.

Objective 1 Cognitive Load Detection

Early motor imagery experiments found increased cognitive workload hindered stable motor imagery performance. This necessitated a generalized, real-time cognitive workload detection approach to enable adaptive task difficulty adjustment under high workload [4].

High Cognitive Load - Inefficient Trial

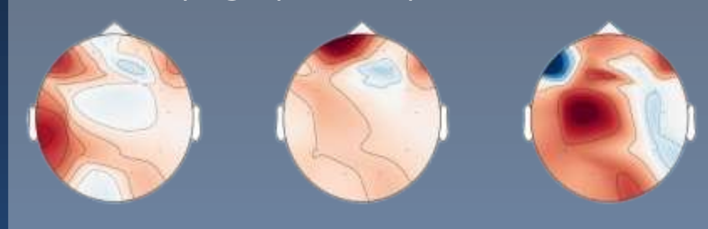
Experiment 1 Setup

Aim Develop a real-time method to detect cognitive load for adapting task difficulty.

Participants 8 healthy subjects (no prior BCI experience, average age 21).

Task Setup Tasks with three difficulty levels to induce cognitive loads: Low 0 / Medium 1 / High 2.

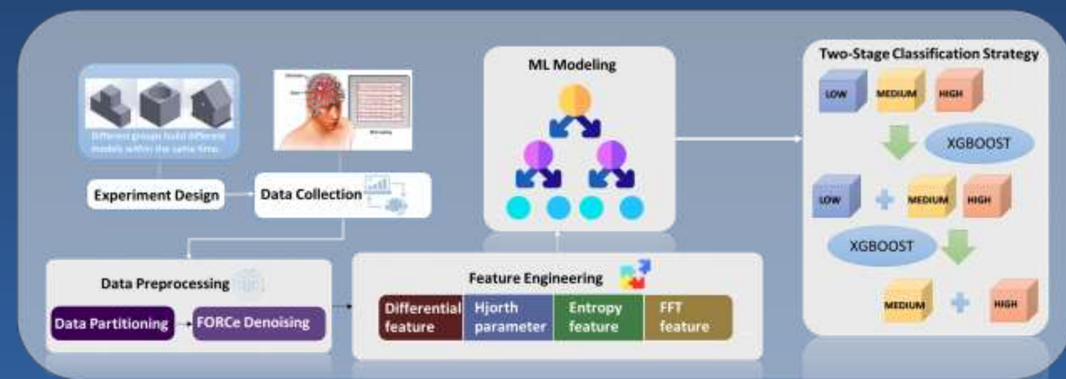
EEG Topographic Maps under 3 Levels



Low Cognition Medium Cognition High Cognition

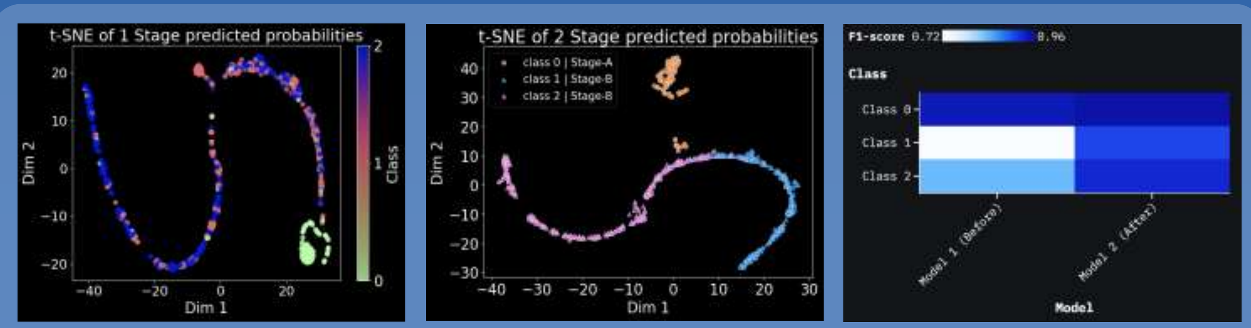
Logic Frame

After preprocessing, XGBoost first isolates *Low* workload using a validation-optimized probability threshold. Remaining samples are reclassified by a second XGBoost with regularization and imbalance handling to better separate *Medium* and *High*.



Results

After selecting key EEG features, XGBoost achieved an initial accuracy of ≈82.5% in classifying three workload levels. By further introducing a **two-stage classification strategy**, the overall accuracy increased by approximately 6%, while the F1-scores for medium and high workload classes improved by about 12%. Moreover, t-SNE visualization further confirmed that this hierarchical approach yielded clearer separation among cognitive workload clusters.



Cognition Cluster (Before) Cognition Cluster (After) F1 Score Change in 3 Classes

Objective 3 BCI-VR-ROBOT Integration

Objective 3 integrates exoskeletons with VR/BCI (Objectives 1–2): motor imagery from a lightweight BCI enables precise, personalized exoskeleton control (e.g., walking); real-time processing adapts assistance and VR difficulty to cognitive load; channel selection from Objective 2 optimizes BCI reliability. This integration transforms repetitive rehabilitation into interactive challenges, boosting engagement and effectiveness and accelerating recovery for people with physical disabilities.

BCI Signal Preprocessing

Workload detection removes high-cognitive-load trials for stable, low-noise EEG; CHDECS selects optimal channels to enhance relevance and reduce redundancy—boosting classification accuracy and system robustness, and laying the foundation for real-time brain-controlled rehabilitation.

Integrated BCI-VR-Robot Control

Process: The final decoded motor imagery signals are used to simultaneously control virtual avatars in a VR environment (e.g., walking, leg raising, kicking) and drive the movements of a robotic exoskeleton in the real world. The system dynamically adjusts the VR training difficulty based on the user's cognitive workload, ensuring participants engage in training under optimal conditions that match their mental and physical capabilities [5].

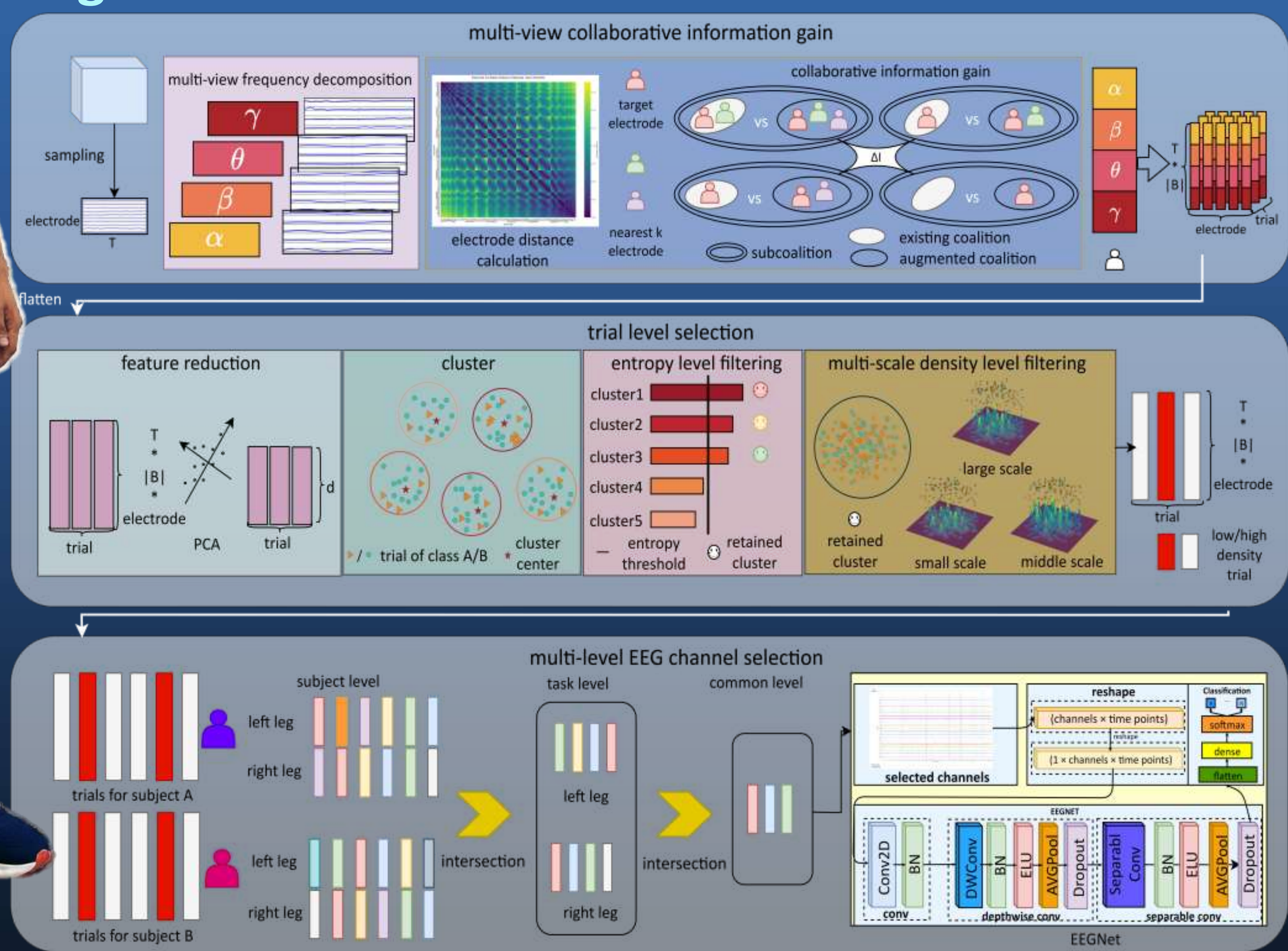
Function: The robotic exoskeleton provides physical support, assisting users with limited mobility in performing movements. Meanwhile, the VR environment creates an engaging experience, turning repetitive rehab exercises into interactive, personalized challenges. This dual approach motivates users through real-time, brain-controlled feedback and adaptive training.

Outcome: This integrated framework enhances user motivation and adherence to rehabilitation programs. It accelerates recovery, improves motor function, and ultimately enhances the quality of life for individuals with physical disabilities, providing a more effective and enjoyable rehabilitation process [6].

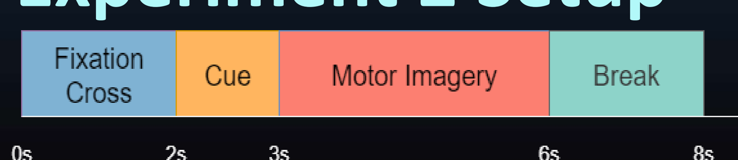
Objective 2 Collaborative Hierarchical Density-Entropy Aware Channel Selection

We propose CHDECS, a novel framework that integrates: (1) multi-view collaborative information gain, which establishes local electrode relationships from a game-theoretic perspective; (2) trial-level selection using density-entropy optimization to emphasize boundary trials; and (3) multi-level EEG channel selection via a hierarchical model that captures task-, subject-, and group-level patterns.

Logic Frame

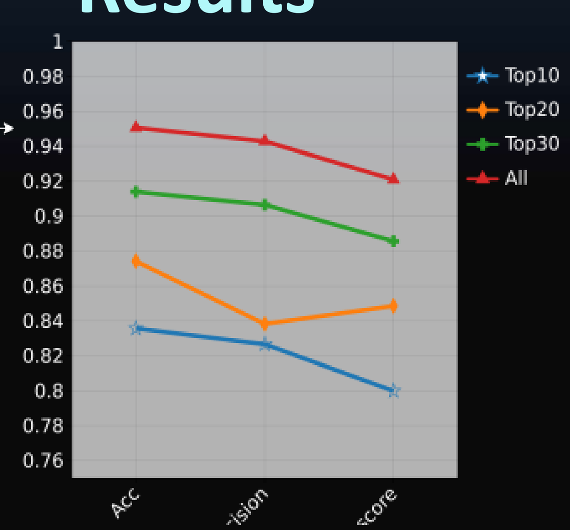


Experiment 2 Setup



During each trial, the subject sits comfortably in front of a screen. A fixation cross appears at the start (t = 0 s), accompanied by an auditory cue. At t = 2 s, a left or right arrow is displayed for 1 s, prompting the subject to imagine the corresponding leg movement. The imagination task continues until the cross disappears at t = 7 s, followed by a 3 s break.

Results



We compared the performance of our CHDECS-selected top 10, 20, and 30 channels against using all channels (left figure). Our method maintains high accuracy with far fewer channels, significantly reducing computation.

Conclusion

This project presents an end-to-end framework that integrates workload-aware trial filtering, hierarchical channel selection, and BCI-VR-robot control. Objective 1 ensured stable input data quality, while Objective 2 (CHDECS) optimized channel subsets for improved cross-subject decoding. Objective 3 then combined the enhanced BCI with VR and robotic exoskeletons for real-time, brain-driven rehabilitation, adapting to cognitive load and user performance for personalized support. This framework advances scientific understanding by unifying workload awareness with hierarchical modeling, achieving engineering efficiency through a lightweight, portable pipeline that transforms repetitive therapy into immersive and engaging training. However, limitations such as insufficient evaluation of closed-loop latency, long-term stability, and the need for broader validation across larger datasets remain. Future work will focus on low-calibration personalization, multimodal fusion, and clinical safety validation, ultimately paving the way for practical deployment in real-world rehabilitation.

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