International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 10 | Oct - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Neuro-Holography: Translating Brain Signals into 3D Visuals

Adharsh S. K.
Dept.of Electronics and Communicaton Engineering,NCERC
Thrissur,India
adharshskncerc005@gmail.com

Safa P. V.
Dept. of Electronics and Communication Engineering,NCERC
Thrissur,India
safapanikkaveettil71097@gmail.com

Shankar V. Padmakumar
Dept. of Electronics and Communication Engineering,NCERC
Thrissur,India
shankarpadmakumar@gmail.com

Nanda Kishor S.
Dept. of Electronics and Communication Engineering,NCERC
Thrissur,India
nk8641947@gmail.com

Vysak Valsan
Dept. of Electronics and Communication
Assistant Professor,NCERC
Thrissur,India

Abstract— This research presents Neuro-Holography, a multi-stage Brain–Computer Interface (BCI) framework designed to translate Electroencephalography (EEG) signals into assistive commands and visual representations. Traditional human–computer interaction relies heavily on physical input devices, which can be inaccessible for individuals with severe motor impairments. The proposed system addresses this limitation by interpreting neural activity patterns through a structured processing pipeline consisting of signal preprocessing, feature extraction using the Common Spatial Pattern (CSP) method, and classification using machine learning algorithms. In this study, two classifiers—Support Vector Machine (SVM) and Random Forest (RF)—were evaluated to determine the most effective model for motor imagery classification. The system is implemented through two main modules: a MATLAB-based Assistive Control Simulation that converts classified motor imagery signals into directional commands, and a Python-based Brain-to-AI Visualization module that maps interpreted EEG patterns to an alphabetic interface for generating visual outputs through artificial intelligence models. Experimental evaluation using the BCI Competition IV Dataset 2a demonstrates the effectiveness of the approach, where the SVM classifier achieved the highest classification accuracy of 85.46%, outperforming the Random Forest model. The proposed framework highlights the potential of combining BCI signal decoding with AI-driven visualization to support assistive technologies and advance intuitive human–computer interaction systems.

Keywords— Brain–Computer Interface (BCI), Electroencephalography (EEG), Motor Imagery, Feature Extraction, Machine Learning, Support Vector Machine (SVM), Random Forest, Neural Visualization.

INTRODUCTION

Human–computer interaction traditionally relies on physical input devices such as keyboards, mice, and controllers. While these interfaces are effective for most users, they can present significant challenges for individuals with severe motor disabilities. Brain–Computer Interface (BCI) technology provides an alternative communication pathway by enabling direct interaction between the human brain and external systems. This is achieved by capturing neural activity using non-invasive techniques such as **Electroencephalography (EEG)**, which measures electrical signals generated by brain activity.

By analyzing patterns within EEG signals, it is possible to interpret user intentions without requiring physical movement. **Motor imagery–based BCI systems** are particularly useful in this context, as imagining specific movements can produce distinct neural patterns that can be decoded using signal processing and machine learning techniques. These decoded signals can then be mapped to functional commands for assistive technologies.

Despite significant advancements in EEG signal decoding, many existing BCI systems are limited to simple control tasks and do not provide intuitive ways to represent interpreted neural activity visually. The ability to translate brain signals into meaningful visual outputs could significantly enhance human–computer interaction and improve communication mechanisms for users with physical impairments.

To address this challenge, this research introduces **Neuro-Holography**, a system designed to interpret EEG signals and convert them into both assistive control commands and visual representations. The proposed framework utilizes signal preprocessing, feature extraction using the **Common Spatial Pattern (CSP)** method, and machine learning–based classification to identify motor imagery patterns. In this study, two classifiers—**Support Vector Machines (SVM)** and **Random Forest (RF)**—are evaluated to determine the most effective model for EEG signal classification.

The classified signals are then applied in two modules: an **assistive control simulation module** for mobility-related commands and a **brain-to-AI visualization module** that generates visual outputs from interpreted neural activity. The proposed system demonstrates how EEG-based brain signal interpretation can be combined with artificial intelligence to develop interactive systems capable of translating neural patterns into functional commands and visual outputs, thereby expanding the possibilities of Brain–Computer Interface applications.

RELATED WORK

System / Reference	Year	Technique Used	Advantages	Limitations
DreamDiffusion (Bai et al.)	2023	Diffusion-based generative model aligning EEG signals with image and text embeddings	Produces high-quality visual outputs; integrates advanced generative AI methods	Requires large datasets; computationally intensive; sensitive to EEG noise
Cross-Subject EEG Feedback (de la Torre-Ortiz et al.)	2024	GAN-based framework using EEG feedback from multiple subjects	Enables multi-user neural feedback; improves diversity of generated visual outputs	Requires calibration; expensive EEG equipment; limited real-time usability
EEG2Image (Singh et al.)	2023	Conditional GAN with contrastive learning for EEG-to-image reconstruction	Works with smaller datasets; demonstrates feasibility of EEG-based image reconstruction	Produces low-resolution images; sensitive to signal noise
High-Resolution Transcranial Optical Imaging (Lefebvre et al.)	2024	Digital holographic interferometry for neural activity imaging	Provides high spatial and temporal resolution	Complex optical setup; high equipment cost
fMRI-to-Image Reconstruction Survey (Guo et al.)	2025	Encoding–mapping–generation pipeline for neural image reconstruction	Provides comprehensive taxonomy of reconstruction methods	High system complexity; limited EEG-focused implementations
Proposed Neuro-Holography System	2026	EEG preprocessing, CSP feature extraction, SVM classification, assistive control simulation, and AI-based visualization	Integrates brain signal decoding with assistive control and neural visualization in a unified framework	Currently simulation-based; requires real-time EEG hardware integration

PROPOSED METHODOLOGY

The proposed Neuro-Holography system is designed as a multi-stage processing framework that converts Electroencephalography (EEG) signals into functional commands and visual outputs. The system consists of several sequential stages including EEG data acquisition, signal preprocessing, feature extraction, classification, and two output modules for assistive control and neural visualization.

A. EEG Data Acquisition

The first stage of the system involves acquiring EEG signals for analysis. In this research, motor imagery EEG data from the **BCI Competition IV Dataset 2a** is used. The dataset contains recordings from multiple subjects performing four mental tasks: imagining movements of the **left hand, right hand, feet, and tongue**.

These motor imagery signals activate the motor cortex region of the brain and generate distinguishable EEG patterns. Using a publicly available dataset allows the system to be tested under controlled conditions and provides labeled data for training and evaluation.

B. Signal Preprocessing

Raw EEG signals often contain noise and artifacts caused by muscle activity, eye movements, or external electrical interference. Therefore, preprocessing is required to improve signal quality.

The following preprocessing steps are applied:

- **Band-pass filtering (8–30 Hz)** to capture the mu and beta frequency bands associated with motor imagery activity.
- **Signal normalization** to maintain consistent amplitude levels across recordings.
- **Segmentation** of continuous EEG data into smaller time windows for feature extraction.

These preprocessing steps help isolate meaningful neural activity from unwanted noise.

C. Feature Extraction Using Common Spatial Pattern (CSP)

After preprocessing, the **Common Spatial Pattern (CSP)** algorithm is used to extract discriminative features from the EEG signals.

CSP identifies spatial filters that maximize the variance of one class while minimizing the variance of another class. This allows the algorithm to highlight spatial patterns that distinguish different motor imagery tasks.

The feature vector is obtained using the log-variance of the spatially filtered EEG signals:

$$f_i = \log\left(\mathrm{Var}(W_i^T X)\right)$$

where:

- Xrepresents the EEG signal matrix
- $W_i$represents the spatial filter
- $f_i$represents the extracted feature

These features are then used as inputs for the classification stage.

D. Signal Classification Using Machine Learning

The extracted features are classified using machine learning algorithms to identify the corresponding motor imagery task. In this study, two classifiers were evaluated: **Support Vector Machine (SVM)** and **Random Forest (RF)**.

Support Vector Machine is a supervised learning algorithm that determines an optimal decision boundary (hyperplane) that separates different classes in the feature space. It is widely used in EEG classification due to its effectiveness in handling high-dimensional data.

Random Forest is an ensemble learning method that constructs multiple decision trees and combines their predictions to improve classification robustness. It is capable of handling complex nonlinear relationships in data.

Both classifiers were trained using the CSP-extracted feature vectors obtained from the EEG signals. The models were designed to distinguish between four motor imagery classes:

• Left Hand → Left
• Right Hand → Right
•Feet → Forward
• Tongue → Stop

Experimental evaluation showed that while both classifiers were capable of identifying motor imagery patterns, the **SVM classifier achieved higher classification accuracy compared to the Random Forest model**. Therefore, SVM was selected as the primary classifier for the proposed Neuro-Holography system.

E. Assistive Control Simulation

In the first output module, the classified motor imagery signals are converted into directional commands for assistive control simulation. Each mental task corresponds to a specific command:

• Left Hand → **Left**
• Right Hand → **Right**
• Feet → **Forward**
• Tongue → **Stop**

These commands are used to simulate the navigation of an assistive device such as a wheelchair within a virtual environment.

F. Brain-to-AI Visualization Module

The second output module focuses on generating visual outputs based on interpreted neural activity. The classified EEG patterns are mapped to an **alphabetic grid interface** where specific signal outputs correspond to characters.

The generated characters combine to form meaningful words, which are then used as prompts for an **AI-based image generation system**. The system produces visual outputs corresponding to the interpreted neural activity, demonstrating the concept of translating brain signals into digital visual representations.

RESULTS AND DISCUSSION

A. Dataset Description

To evaluate the proposed Neuro-Holography framework, experiments were conducted using the **BCI Competition IV Dataset 2a**, which is a widely used benchmark dataset for motor imagery classification.
The dataset contains EEG recordings from **9 subjects**, each performing four motor imagery tasks:

- Left Hand Movement
- Right Hand Movement

- Feet Movement
- Tongue Movement

Each recording consists of **22 EEG channels** with a sampling frequency of **250 Hz**. For every subject, **288 trials** were recorded, with each class containing **72 trials**.

This dataset provides a well-structured benchmark for evaluating EEG signal processing and classification algorithms.

B. Implementation Environment

The proposed system was implemented using a combination of **MATLAB and Python environments**.

- **MATLAB** was used for EEG signal preprocessing, CSP feature extraction, and SVM-based motor imagery classification.
- **Python** was used for implementing the Brain-to-AI visualization module, which converts interpreted neural patterns into AI-generated visual outputs.

The experiments were conducted on a standard computing system equipped with sufficient processing capability for machine learning and signal processing tasks.

C. Performance Evaluation

The performance of the proposed system was evaluated using classification accuracy obtained from the SVM classifier.

The results indicate that the CSP-SVM pipeline effectively distinguishes between the four motor imagery classes. The highest classification accuracy achieved in the experiments was **85.46%**, demonstrating the capability of the proposed framework to interpret EEG signals reliably.

D. System Output Demonstration

The effectiveness of the proposed Neuro-Holography framework was validated through two output modules: assistive control simulation and AI-based visualization. These modules demonstrate how classified EEG motor imagery signals can be converted into functional commands and visual representations.

Assistive Control Simulation

In the first module, the classified motor imagery signals are translated into directional commands that control a simulated assistive mobility system. Each mental task corresponds to a specific movement command:

• Left Hand → **Left**
• Right Hand → **Right**
• Feet → **Forward**
• Tongue → **Stop**

These commands are applied within a simulated wheelchair navigation environment, demonstrating how brain signals can be used to control assistive mobility devices without physical input.

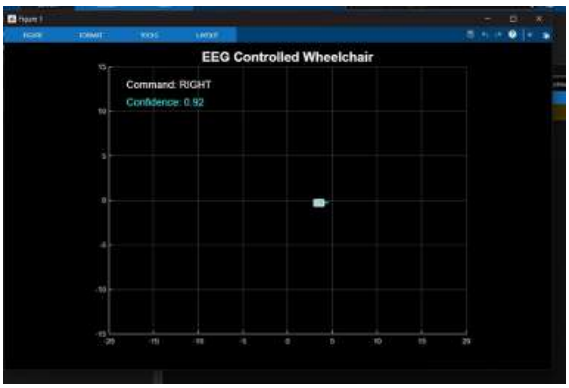


Fig. 1

Fig. 1. Wheelchair navigation simulation controlled using EEG motor imagery classification.

AI-Based Neural Visualization

The second module converts interpreted neural signals into visual representations through an AI-based generation system. In this stage, classified EEG patterns are mapped to an alphabetic grid interface that produces meaningful words representing interpreted neural activity.



Fig. 2

Fig. 2. Text prompt generated from interpreted EEG signal patterns



Fig. 3

Fig. 3. AI-generated visual output corresponding to the interpreted EEG-based prompt.

This module demonstrates how brain signal interpretation can be combined with artificial intelligence to generate visual representations of neural activity.

CONCLUSION

This paper presented **Neuro-Holography**, a Brain–Computer Interface framework designed to interpret EEG signals and convert them into assistive commands and visual outputs. The proposed system integrates EEG signal preprocessing, feature extraction using the **Common Spatial Pattern (CSP)** algorithm, and machine learning–based classification to identify motor imagery tasks such as left hand, right hand, feet, and tongue movements.

Two machine learning classifiers, **Support Vector Machine (SVM)** and **Random Forest (RF)**, were implemented and evaluated for motor imagery classification. Experimental results demonstrated that the **SVM classifier achieved the highest classification accuracy of 85.46%**, outperforming the Random Forest model and confirming the effectiveness of the CSP–SVM pipeline for EEG signal interpretation.

The classified signals were utilized in two output modules: an **assistive control simulation module**, which demonstrates brain-driven wheelchair navigation commands, and a **brain-to-AI visualization module**, which converts interpreted neural patterns into visual outputs using artificial intelligence models.

Although the current implementation operates in a simulation-based environment, the results highlight the potential of integrating EEG signal interpretation with AI-based visualization systems. Future work may focus on integrating **real-time EEG acquisition hardware**, improving classification performance through advanced machine learning techniques, and developing more immersive visualization interfaces.

Overall, the **Neuro-Holography framework** demonstrates how Brain–Computer Interface technology can extend beyond traditional command control to enable intuitive human–computer interaction through neural signal decoding and visual representation.

REFERENCES

1] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, “A Review of Classification Algorithms for EEG-Based Brain–Computer Interfaces,” Journal of Neural Engineering, vol. 4, no. 2, pp. R1–R13, 2007. Available: https://pubmed.ncbi.nlm.nih.gov/17409472/

[2] S. A. A. Shiam, et al., “Motor Imagery Classification Using Effective Channel Selection in EEG-BCI Systems,” Brain Sciences, vol. 14, no. 5, 2024. Available: https://www.mdpi.com/2076-3425/14/5/462

[3] X. Wang, et al., “Deep Learning Methods for Motor Imagery EEG Classification: A Survey,” Artificial Intelligence in Medicine, 2023. Available: https://www.sciencedirect.com/science/article/pii/S093336572300252X

[4] Y. Bai, X. Wang, and Y. Cao, “DreamDiffusion: Generating High-Quality Images from Brain EEG Signals,” arXiv preprint arXiv:2306.16934, 2023. Available: https://arxiv.org/abs/2306.16934

[5] T. Qu, et al., “NeuroVision: EEG-to-Image Reconstruction via Progressive Neural Encoding,” Expert Systems with Applications, 2026. Available: https://www.sciencedirect.com/science/article/abs/pii/S0957417426004392

[6] K. G. R. Atla, et al., “CNN-Based Motor Imagery EEG Classification,” Alexandria Engineering Journal, 2025. Available: https://www.sciencedirect.com/science/article/pii/S1110016825001681