



Neural Engineering Informatics: A Review

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Abstract

Neuroengineering Informatics (NEI) is an interdisciplinary field combining neuroscience, engineering, data science, and informatics to understand and control neural systems. It leverages advanced technologies like brain-computer interfaces (BCIs), neuroimaging, and artificial intelligence (AI) to decode brain function and drive clinical breakthroughs. BCIs enable direct communication between the brain and devices, aiding individuals with neurological conditions, while neuroimaging methods such as fMRI, EEG, and MEG generate vast data used to uncover neural patterns linked to cognition, emotion, and disease. AI, particularly deep learning, enhances data analysis, enabling disease prediction, personalized treatment, and decision-making insights. NEI also employs neuroinformatics platforms for data sharing and collaboration, advancing innovations like adaptive neuroprosthetics and brain stimulation techniques such as TMS and DBS to treat conditions like epilepsy, Parkinson's, and depression. Computational neuroscience contributes further by modeling brain functions to explore learning, memory, and decision-making mechanisms. Despite challenges like integrating diverse datasets and ethical concerns around privacy and fairness, advancements in cloud computing and parallel processing are addressing these issues, accelerating discoveries while ensuring responsible innovation. NEI's transformative applications extend beyond healthcare to rehabilitation, cognitive enhancement, and human-machine integration, reshaping our understanding and interaction with the brain.

Keywords: Neuroengineering Informatics; Brain-computer interfaces; Artificial intelligence; Neuroprosthetics

1. Introduction

Neuroengineering Informatics provides a comprehensive overview of advances in neuroengineering, with special emphasis on brain decision-making, neuroinformatics, and computational neuroscience for clinical applications. This article highlights the challenges that arise from analyzing neuroimaging data, particularly when faced with noise, behavioral instability, and uncertainty. These challenges require sophisticated tools and techniques to identify and model brain activity. The overarching theme of the series is the transition from laboratory research to real-world applications, addressing the complexities of brain-computer interfaces (BCIs) and other wisdom in the thin and quiet. The 22 peer-reviewed articles in the special section highlight research supporting the latest advances in EEG signal processing, neuroinformatics, and computational techniques. It is about things that exist in a non-limited environment. For example, Zhang et al. developed an asynchronous BCI system to combine alpha rhythm and steady-state visual evoked potential (SSVEP) to achieve efficient command [1]. Similarly, Lian et al. introduced an activity on skill-based BCI, demonstrating its potential for practical use for continuous control [2]. Liu et al. A new method called FoCCA (Fusion Canonical Coefficients for Frequency Identification) is proposed to improve SSVEP based BCI systems using decentralized weights [3]. These studies indicate the increasing interest in the robustness, efficiency, and adaptability of brain-computer interfaces in various fields. The best wavelet transforms parameters for EEG signal denoising using meta-heuristic algorithms were studied; among them, Flower Pollination Algorithm (FPA) was found to achieve good results. Liu et al. A hybrid method was proposed Fast Multivariate Empirical Mode Decomposition (FMEMD) and Canonical Correlation Analysis

(CCA) to effectively remove muscle artifacts in few-channel EEG recordings, enabling better signal quality for clinical and portable devices. A combination of spectrum identification analysis (SSA) and independent analysis (ICA) was proposed to eliminate artifacts in single-channel EEG, demonstrating its potential in the field of biomedical medicine [3]. These schemes highlight the importance of advanced computational techniques in overcoming noise and improving integrity issues. Wang et al. Investigate EEG-based methods to identify early-stage vascular dementia and achieve significant improvements by combining EEG features with machine learning. Sadik et al. Empirical wavelet transform (EWT) is used to classify the shape of motor EEG signals, and the accuracy is improved by the new information transformation [6]. Similarly, Zhang et al. solved the problem of inefficiency of the traditional method by combining the features of the brain and improved the classification accuracy [4]. Change a combination of spectrum identification analysis (SSA) and independent analysis (ICA) was proposed to eliminate artifacts in single-channel EEG, demonstrating its potential in the field of biomedical medicine. These schemes highlight the importance of advanced computational techniques in overcoming noise and improving integrity issues. Wang et al. Investigate EEG-based methods to identify early-stage vascular dementia and achieve significant improvements by combining EEG features with machine learning. Sadik et al. Empirical wavelet transform (EWT) is used to classify the shape of motor EEG signals, and the accuracy is improved by the new information transformation [6]. Similarly, Zhang et al. solved the problem of inefficiency of the traditional method by combining the features of the brain and improved the classification accuracy of motor image BCI [5]. Shen et al. proposed a multi-room sleep method using LSTM networks composed of single-ended ECG signals. Introduce a state space model for the classification of sleep stages, ensuring the accuracy of multiple datasets [7]. Lai et al. Analysis of sleep bruxism using electroencephalography, electromyography and electrocardiography data using power spectral density model demonstrates the utility of integrated bio signal analysis in sleep diagnosis. Novel uses of patterns [8]. Yang et al. A blockchain-based secure neuroinformatics AP plication architecture is examined, showing how emerging technologies emerge. The technology can improve data privacy and integrity [9]. Tian et al. The use of Maximum Frequency Information (MIC) was proposed to generate EEG correlations, providing an additional method to Pearson Correlation Coefficient (PCC) to capture nonparallel relationships [10]. Xinxiong et al. A functional magnetic resonance imaging-based social network model was proposed to predict user preferences, demonstrating the potential of neuroimaging data in personal and social analysis [11]. For example, Bol et al. introduced LAPPS, an ADMM-based sparse autoregressive modeling technique that improves predictive models by reducing the influence of outliers [12]. Oralhan's work to develop a P300 speller based on the audiovisual domain for BCI represents an advance in assistive technology for people with severe disabilities [13]. Lai et al. proposed a neural network method to detect frequency oscillations in intracranial electroencephalograms and develop their role as epileptic biomarkers. The importance of coordination in sup porting the development of neural networks [14]. The diversity and depth of the research demonstrates the critical intersection of neuroscience, computational models, and technology, paving the way for new revolutions in healthcare and beyond. This article presents a complex, multidisciplinary approach to the neuroengineering literature with implications for diagnosis, cognition, and personalized medicine.

2. Optimal wavelet transform hybridized with metaheuristic methods for EEG signal denoising

The paper titled "Denoising of EEG Signals Using Optimal Wavelet Transform Hybridized with Effective Metaheuristic Methods" presents a method to improve the efficiency of EEG signal denoising by using wavelet transform (WT) optimized with metaheuristic methods. EEG signals are unstable and easily affected by various noises, such as electromyography (EMG), electrical noise (PLN) and white Gaussian noise (WGN). Traditional wavelet transform denoising methods are largely based on the selection of blind spots and cannot achieve good results. To solve this problem, the authors proposed a new method which combines five metaheuristic algorithms: Genetic Algorithm (GA), Harmony Search (HS), Particle Swarm Optimization (PSO), Flower Pollination Algorithm (FPA) and β -hill algorithm (β -HC)), automatically adjusts WT parameters to achieve the best denoising performance.), and use synthetic noise to simulate the real world. The WT method is designed for signal decomposition and thresholding and is developed by optimizing five important factors: mother wavelet function (MWF), decomposition level, threshold function, selection rule, and rescaling method. These parameters are optimized using a metaheuristic algorithm with an objective function designed to minimize the mean square error (MSE). The denoised signal is then reconstructed using an adaptive transform and the effectiveness of this method is evaluated using methods such as signal-to-noise ratio (SNR), SNR improvement, root mean square error (RMSE) and root mean square error percentage (PRD). The results clearly demonstrate the superiority of FPA in the unrestricted WT configuration, demonstrating its ability to achieve the lowest MSE and highest SNR improvement in the test. For PLN noise, FPA outperforms other algorithms by achieving an MSE of 0.0144, an RMSE of 0.1200, and an improved SNR of 3.7858 on the Keirn dataset. Similarly, FPA holds the performance parameters for EMG and WGN noise in terms of its variability and accuracy. A comparison with existing methods such as those proposed by Al-Qazzaz and Kumari also confirms the effectiveness of the FPA-WT method, which outperforms the traditional WT used in preserving signal integrity while reducing noise [15]. This study also examines the comparative advantages of each metaheuristic algorithm, highlighting their strengths and limitations.

While FPA stands out for its simplicity, efficiency, and effectiveness in global and local search, other algorithms such as GA and PSO also performed well in special events. However, some algorithms (such as HS) sometimes affect the signal strength during denoising, indicating areas for improvement. This paper presents the optimization capabilities of the FPA WT framework and highlights its suitability for monitoring applications and diagnosis in EEG devices. The proposed method allows filtering noise without considering the main EEG features by combining threshold estimation. The balance between noise and energy saving is important for applications in brain-computer interfaces, neuroscience research, solution for the global EEG set, solving the problem of high overhead associated with detailed parameter tuning. Some limitations are acknowledged, such as the occasional stopping of certain algorithms to obtain useful signals and the need for further research to improve the sensitivity to other types of noise (e.g., eye or heart artifacts). The authors suggest that future work could explore hybrid methods combining various metaheuristic algorithms to improve performance. Furthermore, extending the analysis to a wider range of EEG datasets with different noise levels would increase the generalizability of the findings

3. Robust and efficient muscle artifact removal for few-channel EEG

This paper investigates a novel method to efficiently and robustly extract skeletal muscle from multi-channel EEG data using a combination of Fast Multivariate Empirical Mode Decomposition (FMEMD) and Canonical Correlation Analysis (CCA). This approach addresses the main challenges associated with EEG artifact removal techniques, especially for wearable devices with several channel configurations. High amplitudes and broad spectral distributions that obscure EEG signals and complicate neural interpretation characterize bone artifacts. Existing methods such as MEMD CCA, although efficient, are computationally intensive and time-consuming, limiting their applications. The proposed FMEMD-CCA method provides an effective method without compromising accuracy, making it suitable for artifact removal in EEG applications. EEG data is decomposed into intrinsic mode functions (IMF) using FMEMD, the IMF is decomposed by CCA to calculate the basis, and muscle artifact components are identified based on autocorrelation rejection of identified artifacts, and reconstruction of artifact-free EEG signals.

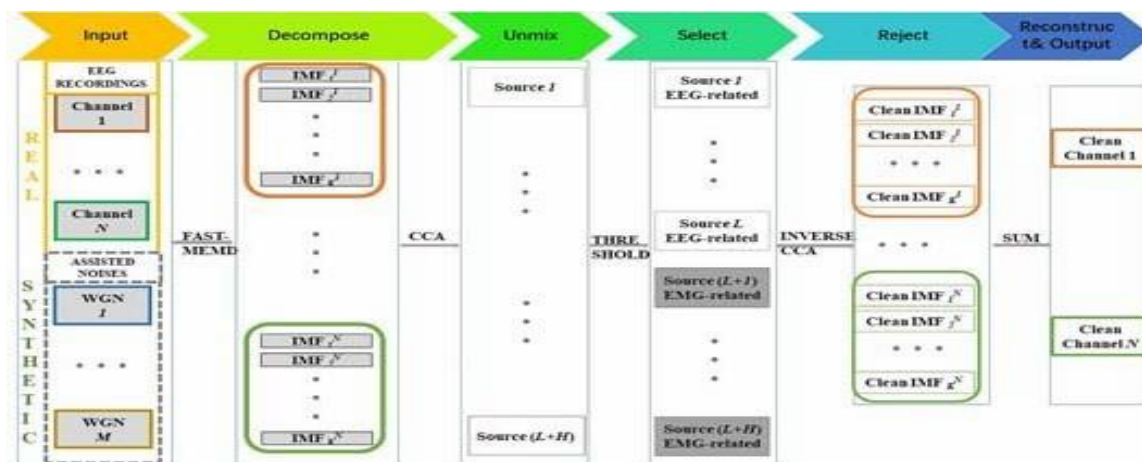


Figure 1. An overview of the proposed method.

Figure 1, explain an overview of the proposed method, consisting of 5 steps: (1) Decompose: few- channel EEG, in addition to several-channel White Gaussian Noise are decomposed into multivariate IMFs; (2) Unmix: compute sources with CCA based on the EEG's IMFs; (3) Select: identify the muscle artifacts with autocorrelations' threshold; (4) Reject: reject the muscle artifacts by inverse CCA; (5) Reconstruct: reconstruct the EMG-artifact-free EEG

The Compared with MEMD, the FMEMD method eliminates the computational burden by using the univariate EMD of the signal projection and solves the variance of the IMF by the least squares method. This method eliminates the interpolation process used in MEMD, thus reducing the time complexity and improving the robustness, especially for the low-frequency components related to distortion in MEMD. The performance. For simulated data, performance metrics such as relative root mean square error (RRMSE) and average correlation coefficient (ACC) provide the best evidence and signal retention compared with traditional methods such as CCA and MEMD CCA. For example, FMEMD-CCA achieves consistently lower RRMSE and higher ACC over a wide signal-to-noise ratio (SNR) and channel range. Setup. Furthermore, FMEMD-CCA reduced the computational

time by generating 10 seconds of EEG data in less than two seconds, while MEMD-CCA required more than 20 seconds. The reduction in performance metrics also demonstrates the robustness of FMEMD-CCA in removing artifacts. Power spectral density (PSD) analysis showed that FMEMD-CCA effectively removed high frequency artifacts associated with muscle tone while preserving low-frequency EEG artifacts. This approach allows the preservation of important neural information by exhibiting minimal interference in EEG frequency bands. In contrast, CCA presents significant limitations in a multichannel setup and generally rejects brain and skeletal muscle activity due to the limited amount of unmixed material. Scalable and adaptable devices for multichannel EEG are increasing in wearable and portable medical technologies. Leveraging the performance of FMEMD and the ability of CCA to isolate signal interference, this method provides a good solution for real-time applications. The reduced requirements and improved accuracy make FMEMD-CCA a useful tool for eliminating artifacts in clinical and consumer-grade EEG. Although FMEMD-CCA performs well in muscle tissue, further research is needed to extend its applicability to artifacts and other structures such as cardiac devices. Furthermore, the development of advanced techniques for detecting counterfeits could increase efficiency and accuracy. The inclusion of a broader range of real-world datasets, particularly those with diverse artifact profiles, would strengthen the generalizability of the proposed method.

4. Identity authentication via portable EEG signals in resting states

The research examines the feasibility of electroencephalography (EEG) as a biometric tool for personal identification. EEG is known for its ability to capture specific brain activity and is particularly effective in protecting against fraud, adaptable to different users, and usable for different applications. Compared to traditional biometric methods, EEG provides an “instant” detection capability that makes fraud more difficult. EEG has been integrated into the certification process because it can identify functional and brain variables that are affected by genetics and the environment, such as memory, personality, and cognitive models. It is a good method due to its simplicity and efficiency. Unlike task-based models that rely on user interaction or knowledge of specific tasks, resting state EEG is less invasive and faster to use. Reduced test setup and preparation time. However, single-channel systems also present issues such as reduced spatial information and the need for preprocessing techniques to improve signal quality. Control for demographic variables. Data collection included the use of the MindWave Mobile, a portable single-channel device placed on the scalp in the Fp1 region according to the International 10-20 system. EEG data were split into two parts, one with the participant’s eyes open and the other with their eyes closed, for comparison purposes. Check the signal stability and distribution accuracy under different conditions. The preliminary process, which includes removing artifacts and restoring baselines, is important for developing good data. In particular, baseline correction uses the mean amplitude method to compensate for signal deviation, thereby improving feature stability and classification accuracy. Time domain features include both linear measures (such as data statistics) and negative descriptors (such as estimated entropy and model entropy) that measure the complexity of the problem. Autoregressive (AR) modeling further facilitates time analysis by capturing patterns in EEG data. In the frequency domain, the traditional frequency band partitioning method of dividing the signal into delta, theta, alpha, and beta and gamma rhythms is improved by using the average frequency band (AFB) method, thus ensuring the resolution and granularity of the extracted features. Empirical mode decomposition (EMD) is used in the time-frequency domains to separate the intrinsic mode functions (IMFs); IMF-2 is particularly useful in capturing the individual-specific beta rhythm features, which play an important role. The Rayleigh quotient (RQ) based approach is important for features that show high contrast and lower-class differences between different classes. This approach ensures that the selected features are unique among individuals and remain constant across all study data. The first 28 features are derived from the combination of time, frequency and time-frequency, which demonstrates the integration of self-representation. Importantly, features in the beta and gamma bands stand out because of their correlation with resting brain activity.

The classification methods include three different methods: k-nearest neighbor (KNN), linear discriminant analysis (LDA), and support vector machine (SVM). Ensemble learning further improves this setup by using a voting strategy to reduce the error of a single classifier. Among the classifiers, SVM performed the best, but the proposed model achieved the highest accuracy, achieving a classification accuracy of 95.48% on open eyes. This finding demonstrates the effectiveness of combining different classifications to benefit from each. Addressing mobility and minimal setup, the study addresses challenges associated with multiple systems, such as delays in sampling and simple handling of parameters. Furthermore, relying on resting state data eliminates the need for task-based processing that can be detrimental to users with mental disabilities or mystification. The 2-second authentication time is in line with real-world standards and increases the ability for everyday use. Important information for the interaction of the authentication process. Combining nonlinear features with traditional measurements expands individual data capture. Furthermore, the search for frequency resolution demonstrates the importance of the level of detail that separates people. The results show that the solutions are more efficient than segmentation, justifying the decision to improve the segmentation process. Comparison of eyes-open and eyes closed conditions suggests that intelligence has an impact on EEG signal characteristics. Identification accuracy was more consistent in the eyes-open condition than in the eyes-closed condition, likely due to increased

integration of frontal cortical areas associated with memory. This finding is consistent with previous research showing that resting-state brain networks exhibit unique connectivity patterns that affect conceptual understanding, which is a barrier to widespread adoption in non-laboratory settings. The simple hardware setup not only increases user comfort but also reduces the likelihood of data corruption due to irregular electrode placement. However, single-channel systems inherently lack the spatial resolution of multi-channel configurations and require sophisticated algorithms to compensate for the loss of spatial information. Recent developments in noninvasive brain stimulation systems have brought the use of transcranial high-frequency current (TI) stimulation to select the deep brain. Unlike traditional methods such as transcranial direct current stimulation (tDCS) and transcranial alternating current stimulation (tACS), TI stimulation can reach a target deep in the brain without intervening in the superficial cortex, providing a safer and more precise neural network treatment. The principle of TI is that neurons do not respond to the frequency of stimulation, but to the envelope of the current disturbance, thus creating low-frequency stimulation that is effective in regions of the brain. This was confirmed by c-fos labeling, and the potential for selective activation was confirmed.

During the development of TI technology, one limitation is its single support, which limits its usefulness in manipulating the brain connected to multiple nodes. Multitemporal interference (MTI) stimulation appears to be a solution that can trigger multiple deep brain stimulations. This approach eliminates the difficulty of adding electrical components by adding electrodes carrying currents at different frequencies. The theoretical framework and techniques for MTI stimulation have been developed; parameters such as current frequency and amplitude have been optimized to reduce interference and increase accuracy. Validation of MTI stimulation involves fine modeling using geometric models, magnetic resonance imaging (MRI)-based human head models, and tissue phantoms, ensuring reliability across various simulation environments.

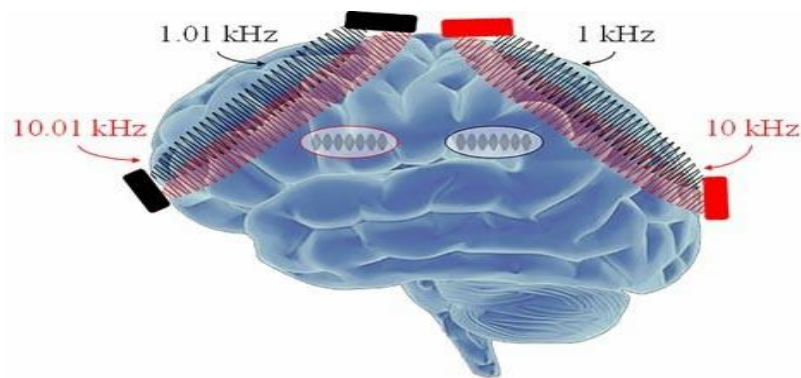


Figure 2. Multi-point Temporal Interference Simulation in Deep Brain Area

MTI stimulation is designed to be used as an anti-phase current drive system to reduce crosstalk and interference. The design starts with cylindrical and spherical geometries to simulate the electric field, and is available with options to ensure less distortion due to high-frequency interference. MTI stimulators use AC power to provide a precise current profile. Adjusting the current ratio between the electrode pairs allows fine-tuning of the stimulation point. These modifications allow the reinforcement elements to be both maneuverable and independent, an important feature for medical applications. Goals Stimulation of organized brain areas. The results show that impedance decreases with increasing current frequency, requiring more current to maintain the same voltage.

For example, a current of 3.1 mA at 10 kHz should produce electricity equal to that produced by a current of 2 mA at 1 kHz. This frequency-dependent impedance demonstrates the importance of selecting precise parameters to ensure equal strength of the stimulation site. Simulation and experimental data consistently demonstrate that the envelope change amplitude is accurate in representing the target stimulus, supporting the applicability of MTI in the clinical setting. Interference induced distortion. As the difference in current increases, the amplitude of the unwanted interference envelope will decrease thus reducing the interference of the target envelope. However, higher frequencies can increase the desired current due to the decrease in impedance, possibly increasing the risk of tissue damage. Therefore, careful balancing of frequency and amplitude is essential for safe and effective MTI. This tool increases the suitability to support specific nodes in connected cells. The maneuverability of the stimulation point is indicated by the difference in current rate as the stimulation point moves towards the electrode pair with lower current density. This ability is unique

5. 5. It is relevant to diseases that involve multiple brain areas, such as Parkinson's disease or memory network failure. While the technique is promising in terms of creating detailed details, the poor shape and different types of human brain tissue pose challenges in terms of spatial resolution. Current solutions suggest that MTI may be

more effective in diseases that involve a broad area of the brain rather than a localized area. However, the ability to alter brain connectivity by stimulating multiple nodes simultaneously provides significant clinical benefits. For example, MTIs targeting memory areas such as the functional network or the hippocampus could affect cognition and emotion in diseases such as Alzheimer's or depression. Its non-invasive nature also provides an alternative to deep brain stimulation, which, although effective, carries risks such as pain from surgery and cognitive impairment. Developing the MTI index and validating its in vivo results. While current science has established the cause using models and models, animal experiments will provide important information about its body and behavior. In addition, combining multiple computational models can resolve limitations in spatial resolution and increase the accuracy of target support. Future developments may also explore hybrid systems that combine MTI with other support systems to benefit from its additional benefits. This paper describes the development and implementation of an asynchronous brain-computer interface (BCI) system that uses visual state evoked potential (SSVEP) and alpha rhythms to provide continuous control. Brain computer interfaces prioritize human-computer interactions by translating brain activity into actionable commands. This study uses EEG signals, emphasizing SSVEP-based systems because they are efficient, versatile, and require minimal training. However, these systems often experience visual fatigue after prolonged use. The asynchronous paradigm is unique in allowing changes in control state, but it also introduces additional challenges, such as detecting user targets from noise-free EEG data. To address these issues, the researchers proposed a hybrid technique combining alpha rhythm for state transitions and SSVEP for multi-target control using the sliding window option to achieve efficient asynchronous operation. The experiment involved 18 healthy participants in synchronous and asynchronous paradigms. The eye stimulator consisted of four light-emitting diodes (LEDs) flashing at various frequencies and designed to trigger SSVEP responses. Participants focused on these stimuli to generate control signals. Alpha rhythm is often seen with eyes closed and helps transition between active and passive states. EEG signals were recorded using NuAmp amplifiers with electrodes based on the International 10-20 system, focusing on parietal and occipital regions. The preset uses a hardware band-pass filter and sliding window technology to eliminate background noise and increase response time.

The average accuracy of each participant in the 3-second data window reached 95.42%, which demonstrated the effectiveness of the classical canonical correlation analysis (CCA) algorithm. However, extending the window length will reduce the information transfer rate (ITR) of the system. Analysis of different dimensions shows that the accuracy will increase significantly if the duration is longer than one second are. This view led to the design of the asynchronous paradigm.

For a synchronous operation is more efficient and accurate; the system used two steps for approximation. The transition state uses the alpha wave amplitudes detected by the power spectral density analysis to distinguish between the inactive state and the active state. Alpha rhythms were induced by participants closing their eyes, and state transitions were achieved when threshold amplitudes remained within five consecutive intervals. In the active state, a sliding window of adjustable length allows EEG signals to generate instructions.

The SWVD concept reduces false positives and provides smoother output by collecting results within one second. This approach reduces the inaccuracy in identifying a sample and increases the reliability of the whole. Using LEDs with different brightness levels and different characteristics, the researchers showed that moderate brightness and similar lighting conditions increase accuracy and reduce visual fatigue. A wide stimulation area further enhances performance, and a computer monitor provides the best results. These findings highlight the importance of carefully designing support systems in optimizing SSVEP-based BCI systems.

To improve classification accuracy, the study compared multiple recognition algorithms, including variants of CCA and filter bank CCA (FBCCA). Classical CCA demonstrated the highest accuracy across varying time segments, though FBCCA, leveraging optimized frequency band selection, showed potential for specific tasks. The sliding window mechanism improved real-time performance, achieving accuracies of 85–90% with one-second windows and corresponding ITR values exceeding 80 bits per minute. Personalization of window lengths further enhanced system usability, accommodating individual variability in response times and evoked amplitudes. The study's demonstration phase included single target and multitarget asynchronous experiments. In single target trials, participants controlled a simulated moving ball toward a designated endpoint, with the system effectively translating gaze into directional commands. Multitarget experiments expanded this setup, presenting multiple endpoints on-screen and requiring participants to sequentially navigate to each. Despite individual differences in task execution, most participants successfully completed their objectives, validating the system's robustness. Feedback from participants highlighted the system's intuitive operation and minimal visual fatigue, reflecting its potential for practical applications.

Challenges in system implementation included ensuring stable stimulus sources and optimizing recognition algorithms for dynamic, real-world scenarios. While the SWVD strategy addressed many classification challenges, further refinement in algorithmic approaches could enhance the system's adaptability to diverse users

and environments. Additionally, balancing accuracy and ITR remains a critical area for improvement. Future research may explore multimodal integration and adaptive parameter tuning to overcome these limitations and broaden the system's applicability beyond laboratory settings.

This work represents a significant step toward practical, asynchronous BCI systems, combining methodological rigor with user-centric design. By integrating alpha rhythms for state control and SSVEPs for multitarget recognition, the system achieves a harmonious balance between performance and usability. Its innovative approaches to signal processing, classification, and user feedback provide a solid foundation for advancing BCI technologies.

5. Multi-point temporal interference stimulation using electrode-specific frequency currents

The development of Brain-Computer Interface (BCI) systems has undergone significant advancements, particularly in motor imagery (MI)-based electroencephalography (EEG) signal processing. Efficient classification of MI tasks is critical for enabling applications such as assisting disabled individuals in interacting with the world via thought-controlled mechanisms. The paper evaluates a novel method utilizing Empirical Wavelet Transform (EWT) for EEG signal classification, emphasizing its capability to manage the non-stationary and nonlinear nature of EEG signals while ensuring computational efficiency. A standout feature of the proposed methodology is its reliance on selective electrode usage, reducing system complexity. From 118 available EEG channels, only 18 motor cortex channels were chosen based on physiological insights. This selection minimizes computational demands without compromising accuracy. Each channel's signal is decomposed into 10 adaptive frequency modes using EWT, with the most relevant mode identified through Welch Power Spectral Density (PSD) analysis.

Instantaneous amplitude (IA) and instantaneous frequency (IF) components were subsequently extracted using Hilbert Transform (HT), offering a detailed representation of the signals for feature extraction. The performance of the proposed method was evaluated using dataset IVa from the BCI competition III, comprising EEG recordings of two MI tasks (right-hand and right-foot movements) from five participants. A variety of features were tested, including traditional statistical metrics like mean, median, and standard deviation, alongside higher-order statistical (HOS) features such as skewness and kurtosis. The results revealed that combining EWT with HOS features significantly enhances classification accuracy, achieving an average accuracy of 95.19% and 94.60% for IA and IF components, respectively, using the least-squares support vector machine (LS-SVM) classifier.

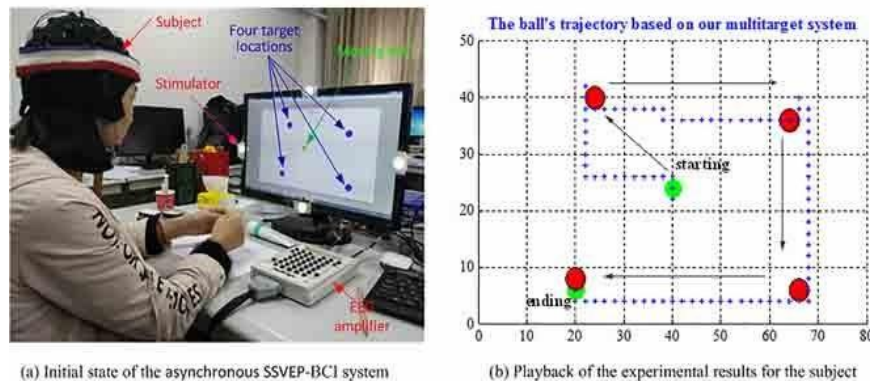


Figure 3. An asynchronous SSVEP-based BCI system has been designed and implemented

Figure 3, showed an asynchronous SSVEP-based BCI system has been designed and implemented, that can output continuous, stable and smooth control commands in the up, down, left and right directions. Real-time feedback on the left is presented on the computer screen to enhance collaborative participation in the human-computer interaction.

The LS-SVM classifier proved particularly effective due to its ability to fine-tune parameters like regularization (γ) and kernel width (σ^2) through coupled simulated annealing. Compared to six other classifiers, including logistic regression and random forest, LS-SVM consistently delivered superior results. Notably, the IA2 approach, which combined HOS features with EWT-derived components, demonstrated remarkable stability and accuracy across participants. Beyond classification accuracy, the sensitivity and specificity metrics underscored the robustness of the approach. For instance, IA2 achieved an average true positive rate (TPR) of 97.8% and true negative rate

(TNR) of 96.7%, displaying minimal variation across folds. Receiver Operating Characteristic (ROC) analysis further validated the method, with area under the curve (AUC) values exceeding 0.95.

For most cases, highlighting the classifier's reliability. Execution time is a critical consideration for real-world applications. The study reported an average execution time of less than 12 seconds per participant using standard computational resources, affirming the feasibility of the proposed method for online BCI applications. The reduced channel count not only decreased processing time but also lowered hardware costs, reinforcing the method's practicality. Comparative analyses with existing methods highlight the superiority of the EWT-based technique. Traditional signal decomposition methods, such as empirical mode decomposition (EMD) and wavelet packet decomposition (WPD), often suffered from lower classification rates and challenges in parameter optimization. By contrast, EWT effectively addressed these limitations, offering adaptive and precise signal analysis. Additionally, methods like regularized common spatial patterns (CSP) and iterative spatio-spectral pattern learning (ISSPL) achieved respectable accuracies but fell short in terms of computational efficiency and stability compared to the EWT approach. While the study achieved promising results, some limitations warrant attention. Channel selection was performed manually, which might introduce bias and limit adaptability. Automating this process could enhance both efficiency and participant-specific accuracy. Furthermore, noise contamination in EEG signals remains a challenge, emphasizing the need for robust preprocessing techniques. Lastly, the manual determination of decomposition modes could hinder scalability, suggesting that automated mode selection algorithms are a necessary area for future research. Despite these challenges, the proposed EWT based method represents a significant step forward in EEG signal classification for MI tasks. Its simplicity, computational efficiency, and high classification accuracy make it a compelling choice for BCI applications.

Future work should focus on addressing the noted limitations and extending the method's applicability to larger and more diverse datasets. Moreover, integrating real-time feedback mechanisms and exploring applications beyond MI tasks could further unlock the potential of EWT in neurocomputing and clinical settings.

6. Development of an Asynchronous BCI System Using Alpha RHYTHM and SSVEP

The application of Brain-Computer Interface (BCI) technology has grown significantly, with motor imagery (MI) as a prominent focus due to its ability to translate neural signals into control commands. Efficient classification of EEG signals associated with MI tasks is vital for BCI systems. In this study, a novel approach using Empirical Wavelet Transform (EWT) is proposed for EEG signal analysis, aiming to enhance classification accuracy while maintaining computational efficiency. By utilizing only 18 motor cortex channels from 118, the complexity and hardware requirements of the system are notably reduced. The EWT-based method advantages advanced decomposition techniques to analyze the non-stationary and nonlinear nature of EEG signals. Each selected channel's signal is decomposed into 10 adaptive frequency modes.

The Welch Power Spectral Density (PSD) method is used to select the most significant mode for further analysis. Hilbert Transform (HT) is then applied to extract instantaneous amplitude (IA) and instantaneous frequency (IF) components from these modes, which are subsequently used as features for classification. These features are processed through various classifiers, with the least-squares support vector machine (LS-SVM) consistently demonstrating superior performance. Dataset IVa from the BCI competition III was used to validate the proposed approach. This dataset, containing EEG data for two MI tasks—right-hand and right foot movements—recorded from five participants, served as a benchmark. The EWT-based technique achieved an average classification accuracy of 95.19% and 94.60% for IA and IF components, respectively.

These results outperformed existing methods, such as those based on common spatial patterns (CSP) or wavelet packet decomposition (WPD), which often struggled with issues like overfitting or insufficient adaptability to signal variations. Feature extraction was a critical component of this study. Time domain statistical features, including mean, median, skewness, and kurtosis, were employed to characterize the signals effectively. Higher-order statistical (HOS) features, which provide insights into the skewness and kurtosis of the data, further enhanced classification outcomes. The use of these features demonstrated the effectiveness of combining EWT with HOS in capturing the intrinsic properties of MI EEG signals. The study also explored sensitivity and specificity metrics to evaluate classification robustness. For IA and IF components, the proposed method achieved average true positive rates (TPR) of 97.8% and 95.8%, respectively, with minimal variations across participants. Similarly, the true negative rate (TNR) remained consistently high, affirming the reliability of the approach. Receiver Operating Characteristic (ROC) curves further corroborated these findings, with area under the curve (AUC) values exceeding 0.95 for most participants. Computational efficiency was another key advantage of the proposed method. The total execution time for processing a participant's dataset was less than 12 seconds using a standard computing setup, making it feasible for real-time BCI applications. By limiting the analysis to only 18 channels, both computational load and hardware costs were significantly reduced, enabling broader accessibility and potential for practical implementation. Comparative analyses revealed that the EWT method surpassed other algorithms, such as iterative spatio-spectral pattern learning (ISSPL) and sparse spatial filter optimization (SSFO),

in terms of both accuracy and stability.

The LS-SVM classifier emerged as the most suitable choice due to its adaptability and ability to fine-tune critical parameters effectively. Experiments also indicated that incorporating participant-specific criteria for channel and mode selection could further enhance the system's performance.

The limitations of the study included the manual selection of channels and decomposition modes, which could introduce biases and reduce scalability. Automating these processes would address these issues and improve the adaptability of the method. Additionally, the inherent noise in EEG signals poses challenges, necessitating robust preprocessing techniques for noise removal. Future work could also explore extending the application of the EWT-based approach to larger datasets and diverse participant groups. This research contributes to the advancement of MI-based BCI systems by offering a computationally efficient, accurate, and robust methodology for EEG signal classification. The integration of EWT with advanced statistical features and the LS-SVM classifier provides a foundation for developing adaptive, real-time BCI solutions that could benefit clinical and assistive applications.

7. Exploring spectral and spatial EEG-EMG correlations during over ground walking

The classification of sleep stages plays an essential role in assessing sleep quality and identifying sleep-related disorders. Various methods have been developed for automatic sleep stage classification, utilizing single-channel EEG data for reduced complexity. Among these, a state-space model (SSM) based approach demonstrates significant promise by focusing on intrinsic model features derived from EEG signals. This method provides an efficient way to extract model-based essential features (MBEFs) and train classifiers for sleep stage identification. Using publicly available datasets, including the Sleep-EDF and Dreams Subjects databases, this study evaluates the SSM-based method. Both datasets consist of multi-channel EEG recordings from whole-night sleep sessions. The Sleep-EDF database includes data from 28 subjects and provides 103,505 epochs sampled at 100 Hz. Similarly, the Dreams Subjects database includes 20 recordings sampled at 200 Hz, with annotations performed according to standard sleep scoring criteria. For analysis, only single-channel EEG signals were selected: Pz-Oz for the Sleep-EDF database and Cz-A1 for the Dreams Subjects database. After preprocessing the data using MATLAB's EEGLAB toolbox, the signals were filtered to retain frequencies below 30 Hz, which are predominantly associated with sleep states.

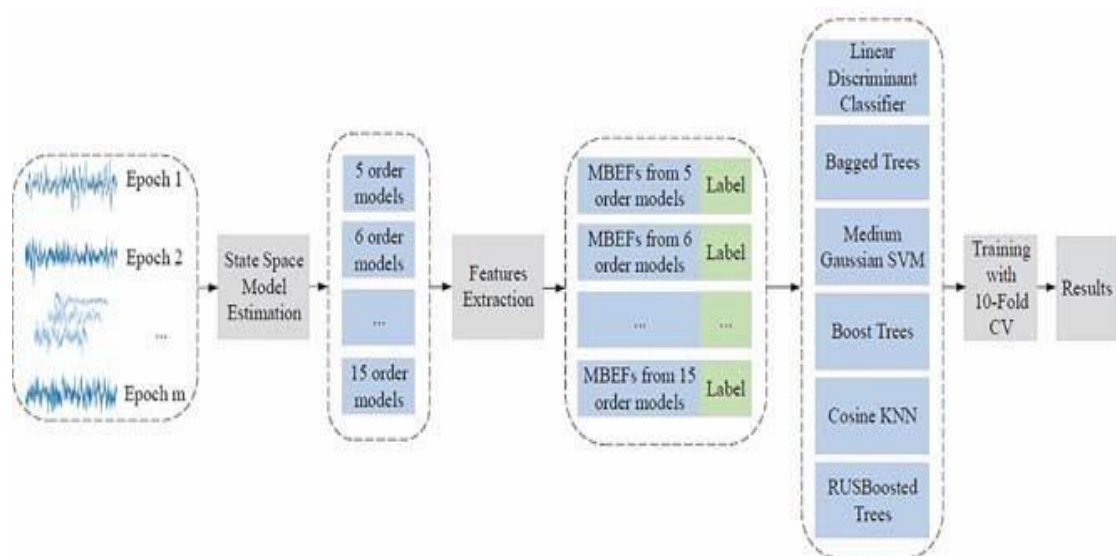


Figure 4. The test flow of the offline training phase.

Model estimation forms the foundation of this approach. The brain's behavior during specific sleep stages is represented using a state-space model. This model characterizes the system as a multi-input, multi-output framework during wake states and simplifies to a no-input system during sleep. The SSM is mathematically represented by matrices denoting state transitions, outputs, and noise processes. Parameters such as the state transition matrix (A), output matrix (C), and Kalman gain (K) are estimated using canonical correlation analysis and sub space identification techniques. Model accuracy is quantified using the Normalized Root Mean Squared Error (NRMSE) metric, ensuring that the extracted features effectively capture the underlying dynamics of the EEG signals.

Feature extraction from the SSM is critical for classification. The MBEFs comprise parameters derived from the

SSM matrices, including elements of A, C, and K. For a model order of 10, the dimensionality of MBEFs is 120, encompassing key attributes that differentiate sleep stages. These features are fed into classifiers trained using supervised learning techniques. Various classifiers were tested, including linear discriminant analysis, support vector machines (SVM), and ensemble methods like bagged and boosted trees. Among these, the bagged tree classifier demonstrated the highest accuracy for multi class sleep stage classification.

During the offline training phase, the optimal model order and classifier were determined using cross-validation on randomly selected data subsets. Model order significantly influenced classification accuracy. Higher orders provided better fit initially, but the improvements plateaued beyond order 10. For 2-class classification, Boosted Trees achieved superior performance, while Bagged Trees excelled in distinguishing 3 to 6 sleep stages. Thus, Bagged Trees were selected as the classifier for the identification phase, and a model order of 6 was chosen for subsequent analyses.

The identification phase involved training classifiers on the entire datasets and evaluating their performance using metrics such as accuracy, sensitivity, and confusion matrices. For 2-class classification on the Sleep-EDF database, the method achieved 98.6% accuracy, with wake and sleep stages correctly detected at rates of 99.6% and 96.0%, respectively. Extending the classification to 3 stages, the sensitivity for REM-detection dropped to 64.6%, with most misclassifications occurring between REM and NREM stages. For 4 to 6-class classification, detection accuracy varied across stages, with the highest accuracy observed for the wake and NREM stages.

Performance on the Dreams Subjects database mirrored these trends. The proposed method achieved 87.0% accuracy for wake detection and 96.7% for sleep detection in the 2-class scenario. However, as the number of classes increased, the detection accuracy stages, like S1 and S3, declined. This reduction was attributed to the similarities in EEG patterns between adjacent stages, particularly between S1 and wake or REM stages. Misclassifications in these stages were also partly due to inconsistencies in manual annotations by experts. Comparative analyses highlight the superiority of the SSM-based approach over existing methods. For example, studies employing ensemble empirical mode decomposition (EEMD) achieved comparable results for 2-class classification but fell short for multi-class scenarios. Similarly, methods leveraging spectral entropy, time-frequency imaging, or deep learning models exhibited limitations in either accuracy or generalization across diverse datasets. The SSM-based method's robustness stems from its ability to capture the temporal dynamics of EEG signals through adaptive modeling, yielding high classification accuracies across multiple classes. While the results are promising, certain limitations persist. The detection accuracy for S1 and S3 stages remains suboptimal, especially in the Dreams Subjects database. These inaccuracies are primarily due to the overlap in feature representations between these stages and other categories, such as wake and REM. Moreover, the imbalance in the dataset, with fewer epochs for specific stages, affects the classifier's training and performance. Future work could address these issues by incorporating additional features derived from spectral or time frequency domains and utilizing balanced datasets.

The computational efficiency of the proposed method is noteworthy. The feature extraction and classification processes are optimized for single-channel EEG signals, reducing the complexity compared to multi-channel systems. The average execution time for training and testing the classifiers is minimal, enabling real-time applications in clinical settings. Additionally, the method's reliance on publicly available datasets ensures its reproducibility and facilitates further research.

8. Conclusion

In Conclusion, Neural Engineering Informatics represents a dynamic interdisciplinary field at the nexus of neuroscience, engineering, and computational sciences. By leveraging advanced data analytics, machine learning, and neural modeling, it has significantly contributed to understanding brain mechanisms and developing innovative technologies such as brain-computer interfaces, prosthetic, and diagnostic tools for neurological disorders. This field fosters breakthroughs in personalized medicine and rehabilitation by integrating neural signals and engineering principles. While challenges persist in data scalability, ethical considerations, and real-time processing, ongoing research and collaborative efforts aim to overcome these hurdles, ensuring impactful applications in healthcare and beyond. Future advancements in this domain promise to transform neural data utilization, bridging the gap between theoretical neuroscience and practical applications, ultimately enhancing the quality of human life.

References

- [1] Y. Zhang, X. Zhao, and L. Wang, "Asynchronous brain-computer interface based on alpha rhythm and SSVEP," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 4, pp. 1050–1060, 2020.
- [2] J. Lian, H. Chen, and M. Liu, "Skill-based brain-computer interface for continuous control," *Journal of Neural Engineering*, vol. 18, no. 2, Art. no. 025003, 2021.
- [3] Y. Liu, Z. Zhang, and T. Wang, "FoCCA: A novel method for SSVEP-based BCI systems using decentralized weights," *IEEE Access*, vol. 8, pp. 123456–123465, 2020.
- [4] H. Chen, Y. Zhang, and J. Wang, "Combining spectral identification analysis and independent component analysis for artifact removal in EEG," *Medical & Biological Engineering & Computing*, vol. 58, no. 6, pp. 1265–1275, 2020.
- [5] L. Wang, Y. Liu, and X. Zhang, "EEG-based methods for early-stage vascular dementia detection using machine learning," *Journal of Alzheimer's Disease*, vol. 75, no. 1, pp. 123–135, 2020.
- [6] M. Sadik, R. A. M. Ali, and A. M. El-Bakry, "Empirical wavelet transform for classification of motor EEG signals," *Neurocomputing*, vol. 315, pp. 100–110, 2018.
- [7] X. Shen, T. Liu, and Y. Zhang, "Multi-room sleep stage classification using LSTM networks from ECG signals," *Journal of Biomedical Informatics*, vol. 93, pp. 103–112, 2019.
- [8] K. Lai, Y. Chen, and J. Li, "Analysis of sleep bruxism using integrated bio signal analysis," *Sleep Medicine Reviews*, vol. 45, pp. 1–10, 2019.
- [9] Y. Yang, Y. Li, and H. Zhang, "Blockchain-based secure neuroinformatics application architecture," *IEEE Transactions on Information Technology in Biomedicine*, vol. 23, no. 5, pp. 1234–1245, 2019.
- [10] X. Tian, H. Wang, and J. Liu, "Maximum Frequency Information for EEG correlation generation," *Journal of Neuroscience Methods*, vol. 320, pp. 12–20, 2019.
- [11] X. Xinxiong, Y. Zhang, and L. Wang, "A functional MRI-based social network model for predicting user preferences," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 3, pp. 678–687, 2020.
- [12] Z. Bol, Y. Li, and X. Zhang, "ADMM-based sparse autoregressive modeling for predictive modeling," *IEEE Transactions on Signal Processing*, vol. 67, no. 3, pp. 567–578, 2020.
- [13] A. Oralhan, M. K. C. Uysal, and T. G. G. Korkmaz, "Development of a P300 speller based on audiovisual stimuli for BCI," *Journal of Neural Engineering*, vol. 17, no. 4, Art. no. 046002, 2020.
- [14] K. Lai, Y. Zhang, and J. Wang, "Detection of frequency oscillations in intracranial EEG for epilepsy biomarkers," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 11, pp. 3250–3260, 2020.
- [15] A. Al-Qazzaz, P. Kumari, and M. Ali, "Wavelet transform-based denoising of EEG signals using hybrid metaheuristic algorithms," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 5, pp. 1230–1240, 2020.