WEP Warwick Evans Publishing

Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 11
TPCEE 2025

Research on Signal-to-Noise Ratio Comparison and Optimization of EEG Signals in Brain-Computer Interface Systems

Jiancheng Ma *

Department of biomedical engineering, Hainan University, Hainan, 570100, China

* Corresponding Author Email: 20233008293@hainanu.edu

Abstract. Electroencephalogram (EEG) signals are widely used in brain-computer interface (BCI) systems due to their high temporal resolution and non-invasive nature. However, their low amplitude, susceptibility to noise, and poor spatial resolution often lead to inaccurate classification of brain intentions. To address these limitations, this study explores a multimodal approach that integrates functional near-infrared spectroscopy (fNIRS) with EEG to enhance signal quality and classification accuracy. The complementary advantages of EEG's millisecond-level temporal resolution and fNIRS's high spatial resolution enable more robust and interpretable decoding of brain activities. Furthermore, we propose the potential integration of transcranial focused ultrasound (tFUS) technology, which offers precise neuromodulation capabilities, for future multimodal BCI systems. Experimental results demonstrate that the EEG-fNIRS combination significantly improves classification performance compared to single-modal EEG, with higher accuracy and reduced noise interference. This research highlights the promising direction of multimodal signal fusion for developing more reliable and efficient non-invasive BCI systems, with broad applications in medical rehabilitation, assistive technology, and cognitive neuroscience.

Keywords: EEG; fNIRS; tFUS; signal.

1. Introduction

In 1924, Hans Berger first recorded brain waves. Then, in 1929, the first successful human brain EEG was recorded [1]. Since then, EEG has evolved from a basic research tool to a core means for clinical diagnosis (such as epilepsy) and frontier exploration. It achieves efficient interaction between humans and machines by directly decoding brain activity signals, and shows great potential in medical rehabilitation, disability assistance, and intelligent control fields. As a non-invasive brain signal acquisition technology, it is widely used in neuroscience research and clinical diagnosis due to its high temporal resolution and low cost. However, EEG signals have the characteristics of weak amplitude and susceptibility to noise interference, resulting in a low signal-to-noise ratio (SNR). These noises include physiological noises such as electrooculogram, electromyogram, electrocardiogram, and environmental noises such as power frequency interference and equipment electromagnetic radiation.

A single signal, such as an EEG signal, sometimes cannot accurately distinguish between motor imagination and emotional intention. Using a multimodal complementary approach can increase the accuracy of signal classification and reduce the noise interference of the signal. Signals obtained through the combination of EEG-fNIRS can improve the accuracy of the signal, and the technology is relatively mature. It can also be combined with tFUS technology to obtain more accurate signals or integrated stimulation of the brain. This paper investigates whether combining different modal signals can improve the classification accuracy of the signals [2].

2. Basic theory analysis

2.1. Signal processing procedure of the brain-computer interface system

The signal processing flow of the brain-computer interface system is a systematic process aimed at converting the original brain signals into effective control instructions. It mainly consists of several key stages.

Firstly, signals are collected using EEG electrodes placed on the scalp, capturing the weak electrical activities generated by the discharges of brain neurons. The collected analog signals are then converted into digital signals through analog-to-digital conversion for subsequent processing [3].

The next stage is the preprocessing stage, which is crucial for improving the signal quality. This step mainly focuses on removing various noises and artifacts. Traditional artifact removal algorithms include regression, wavelet transform, empirical mode decomposition, and blind source separation, which separate artifacts based on the time-frequency characteristics of the signal or the statistical characteristics between signals. They have played an important role in the development of electroencephalogram applications. In the actual process, the most difficult-to-separate physiological artifacts that have a significant impact on the EEG signals are mostly electrooculogram, electrocardiogram, and electromyogram [4].

After preprocessing, feature extraction is carried out, extracting distinctive features from the processed EEG signals. Common features include time-domain features (such as amplitude, variance), frequency-domain features (such as power spectral density in different frequency bands, such as delta waves, theta waves, alpha waves, and beta waves), and time-frequency domain features (such as features extracted using wavelet transform). These features can effectively represent the differences in brain activity patterns under different mental states.

Finally, the extracted features are input into classification algorithms (such as support vector machines, artificial neural networks, or linear discriminant analysis) for pattern recognition. The classification results are then mapped to specific control instructions to achieve interaction between the human brain and external devices, such as controlling cursor movement, prosthetic actions, or communication devices. The processing flow is shown in Fig.1.

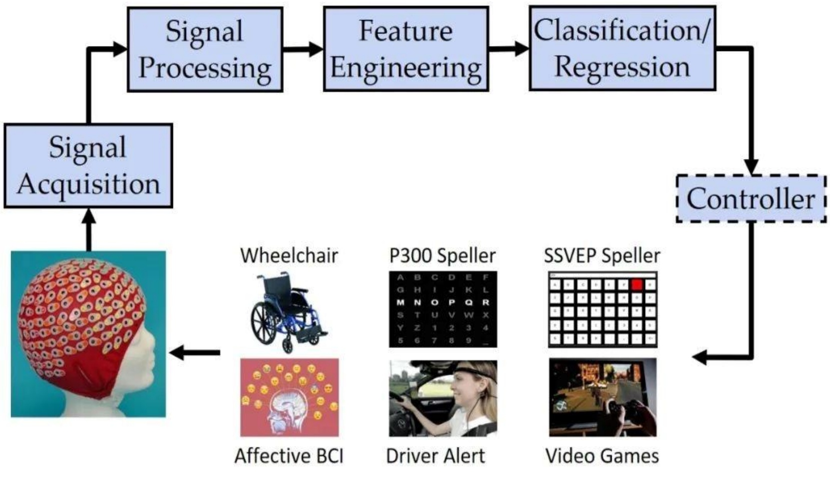

Figure 1. Signal processing procedure (Picture credit: Original)

2.2. The characteristics of EEG signals

EEG signals possess several notable characteristics, which pose significant challenges for their effective application in brain-computer interface systems. Firstly, they exhibit low amplitude, with the amplitude of scalp EEG typically ranging from 10 to 100 microvolts. This makes them highly susceptible to various noises, making it difficult to distinguish the effective signals from the background interference. The low signal intensity necessitates the use of highly sensitive recording equipment and powerful noise reduction algorithms to separate the valid signals from the background noise.

Secondly, EEG signals show non-stationarity, meaning their statistical properties change over time. This is because brain activity is dynamic and is influenced by factors such as mental state, fatigue, and external stimuli. The non-stationarity of EEG signals complicates feature extraction and classification, as the patterns observed at one time point may not be consistent at another time point.

Another key characteristic is individual variability. Due to differences in brain structure, physiological conditions, and cognitive habits among individuals, EEG signals vary significantly in amplitude, frequency components, and spatial distribution. This variability makes it challenging to develop a universal model that can be directly applied to all users, often requiring time-consuming calibration and adaptation processes for each individual.

Furthermore, EEG signals are susceptible to various artifacts and noises, including physiological artifacts (such as blinking, eye movement, muscle contraction, and electrocardiogram signals) and environmental noises (such as electromagnetic interference from electronic devices and 50 or 60 hertz power frequency noise). These noises severely distort EEG signals, leading to inaccurate feature extraction and decreased classification performance, which is one of the most critical challenges in EEG-based brain-computer interface research [5]. The Common types of brain waves is shown in Fig. 2.

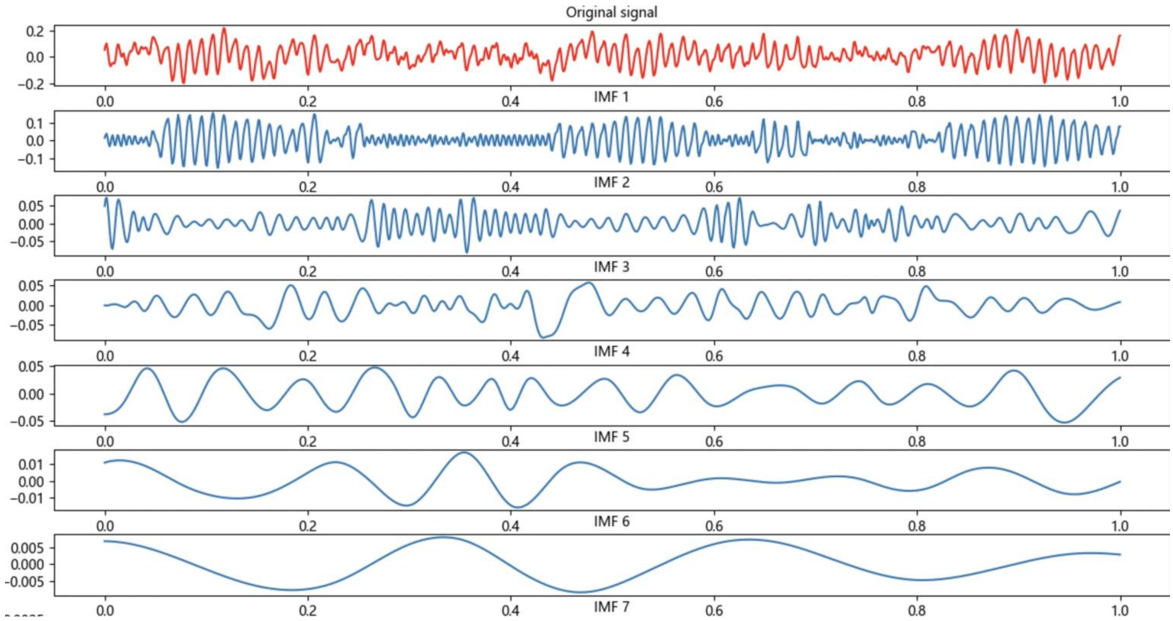

Figure 2. Different waves [5]

3. Optimization of EEG Signal Processing

3.1. FNRIS Technology

3.1.1. Definition Principle.

FNRIS - EEG Integration System is a multimodal neural signal acquisition and processing technology that combines fNIRS technology with EEG technology. Its core principle is to fully utilize the complementary advantages of the two technologies to overcome the limitations of a single modality in signal acquisition [6].

A FNRIS imaging device generally consists of a light source, a light source detector, a data collector, etc. It is lightweight and portable and can be carried around. The light source emits near-infrared light to a specific brain region through light-emitting diodes or fiber optic bundles that match the subject's head shape. The light scatters along a banana-shaped path, and the light detector 2-7 cm away from the light beam can collect the light scattered back by the tissue.

When the human brain is stimulated and in a local active state, the balance between oxygen supply and consumption is disrupted. The increase in human metabolic rate leads to an increase in oxygen demand, so the demand for oxygenated hemoglobin increases, and a large amount of deoxygenated hemoglobin is required for conversion. Therefore, the concentration of deoxygenated hemoglobin in the blood increases [3].

Therefore, brain activity affects the blood oxygen level, and the blood oxygen level affects its optical properties. The main components of blood (water, oxygenated hemoglobin, and deoxygenated hemoglobin) have very little absorption of near-infrared light of 600-900nm and have good scattering properties. Within the 600-900nm spectral window, the sensitivity of near-infrared light at around 760nm and 850nm to oxygenated hemoglobin and deoxygenated hemoglobin is different. The former is sensitive to deoxygenated state, and the latter is more sensitive to oxygenated state.

Because the number of scatterings in different cortical layers of the head does not change due to neural activity, the attenuation caused by cortical tissue scattering is considered constant. Therefore, the changes in attenuation measured during cognitive activities are considered to be due to changes in absorption, and this change is caused by the changes in oxygenated hemoglobin and deoxygenated hemoglobin in the brain activity tissue. Thus, by measuring the intensity of scattered light from the cerebral cortex in the brain activity area, the changes in blood oxygen and blood volume in that area can be inferred [3]. The fNIRS schematic diagram is shown in Fig.3.

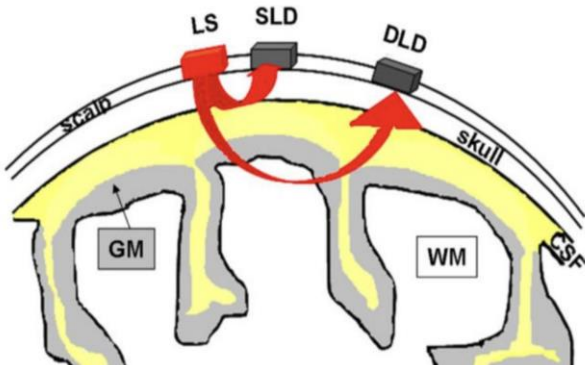

Figure 3. Schematic diagram (Picture credit: Original)

The absorption coefficients of three types of biological tissues for different wavelengths of light is shown in Fig.4.

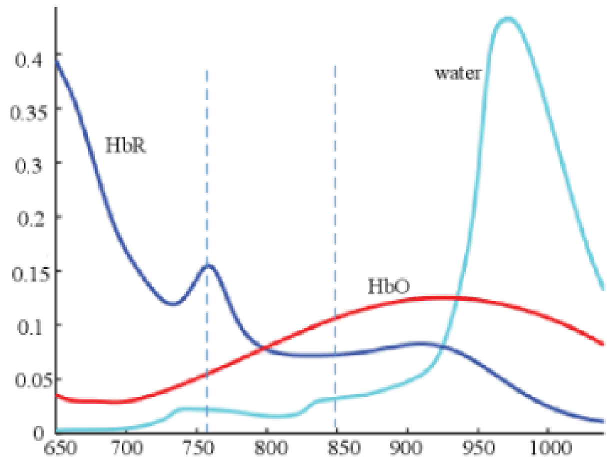

Figure 4. Absorption coefficients [3]

3.1.2. Processing procedure.

In order to fully utilize fNIRS and EEG in clinical diagnosis and research, it is necessary to simultaneously collect fNIRS signals and EEG signals. This requires that the two different types of sensors, namely light and electricity, be located at the same position, and two independent acquisition devices must be synchronized. Synchronous acquisition can be achieved through hardware connections or providing parallel input to the two systems to trigger pulses in real time. The same position sensing requires the miniaturization and fixation of existing electrodes and photodiodes on the scalp. Additionally, to overcome the problem of limited available space for signal acquisition, the acquisition voltage and light intensity probes can be combined into a single sensor.

The fNIRS signals are collected at a sampling frequency of 12.5Hz. The acquisition device is provided by NIRScout and consists of 14 near-infrared light sources and 16 near-infrared detectors. Each near-infrared light source and its adjacent near-infrared detector form a near-infrared physiological channel. Among them, 9 channels are distributed in the frontal lobe area, 12 channels are distributed in the motor-sensory area, and 3 channels are distributed in the visual area. The distance between each light diode is set at 30mm. The near-infrared light diodes and the aforementioned EEG electrodes are fixed in the same elastic fabric cap to achieve synchronous data acquisition. Additionally, data synchronization transmission is achieved through parallel triggering in MATLAB. To eliminate the interference of ambient natural light, the near-infrared spectrometer is in close contact with the subject's scalp. The electrode position diagram is shown as Fig.5.

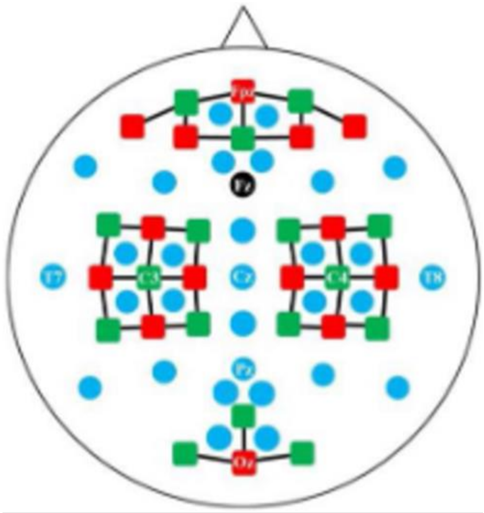

Figure 5. The electrode position diagram [3]

Blue represents EEG acquisition electrodes, black represents grounding, red represents near-infrared light sources, and green represents near-infrared detectors.

3.1.3. Effect.

In 2025, Feng Xianqi used a multimodal parallel deep fusion network to complement the two signals through parallel feature extraction branches, designed feature extraction algorithms for each branch based on the characteristics of the signals, respectively extracted features of EEG and fNIRS signals, utilized the attention module to adaptively allocate weights to achieve feature fusion, and finally completed the classification of the movement imagination task through the classifier [7].

On May 30, 2025, Wang Wenming used the EEG-fNIRS emotion recognition method based on multi-feature fusion graph convolutional neural network, with FCM-GC-PLI features as the adjacency matrix and DE fusion features as the node features, considering the characteristics of different brain regions and different frequency bands, proposed the MBFA module to further act on the DE fusion features, and then input the adjacency matrix and node fusion features into the feature fusion graph convolutional neural network, finally obtaining the emotion recognition results. Through experiments, it was verified that the recognition results using both EEG and fNIRS signals simultaneously were superior to those using only one signal, with an accuracy rate higher than that of the single EEG signal by 1.35%, and the precision rate, recall rate, and F1 value were also significantly higher than the EEG signal, verifying the effectiveness of multimodal signals [8].

On February 22, 2025, Chen Chongchao conducted feature analysis of fNIRS and EEG signals under different alertness states, obtaining more abundant information related to alertness-related brain mechanisms, and compensating for the shortcomings of a single physiological signal [9].

3.2. tFUS Technology

3.2.1. Definition Principle.

Transcranial focused ultrasound is an emerging non-invasive neural stimulation technology. By utilizing the thermal and mechanical effects generated by ultrasound focusing, it can non-invasively precisely intervene in intracranial tissues or nerves. Compared with electromagnetic non-invasive brain stimulation techniques, transcranial focused ultrasound technology has higher spatial resolution and can reach deep brain structures. Ultrasound, with a frequency greater than 20 kHz, can propagate over long distances in specific media with little energy attenuation and has long been widely used in medical diagnosis and treatment. Focused ultrasound stimulation (FUS) and MRgFUS can also precisely stimulate deeper targets in the body and monitor the treatment process in real time. Low-intensity (2 MHz) stimulation can reversibly block the conduction of peripheral nerves; high-intensity can achieve ablation through thermal effect (650 kHz) or cavitation effect (220 kHz) [10].

3.2.2. Processing procedure.

Most of the tFUS studies treat the skull as a fluid medium. Under this fluid condition, a three-dimensional skull model is constructed based on the pseudo-spectral method, thereby predicting the location of ultrasound focusing within the skull model and its potential impact on the brain [11].

3.2.3. Effect.

In actual measurements, we can utilize the tFUS technology to stimulate the deep brain tissue, and then obtain significantly changed signals in specific brain regions on the EEG. This enables a better classification of EEG signals. It can accurately classify the electroencephalogram signals of different brain regions and has better spatial resolution. tFUS can also treat diseases within the brain through stimulation, such as movement disorders, Parkinson's disease and epilepsy [12]. However, this technology is not yet mature at present. This article believes that this is a developing trend, and it will combine this technology with other non-invasive brain-computer interfaces to create a device that integrates multimodal and multi-functional acoustic, optical and electrical signals.

3.3. Comparison

At the signal attribute level, EEG signals possess abundant time-domain information, while fNIRS has high spatial resolution. The combination of these two types of signals in a multimodal format achieves temporal and spatial complementarity. Moreover, the emerging tFUS technology is expected to detect deep brain tissues and obtain more accurate signal classification [13]. The comparison is shown in table 1.

Table 1. Three types comparison

	EEG	EEG+fNIRS	tFUS
Advantage	Millisecond-level temporal resolution	Millisecond-level temporal resolution and better classification accuracy	It is possible to actively stimulate the brain to obtain modified brainwave signals
Disadvantage	Poor spatial resolution	Signal delay is difficult to handle	technology is under developing

4. Conclusion

In this study, we systematically investigated the limitations of single-modal EEG signals in BCI systems, and explored a multimodal integration approach that combines fNIRS and tFUS technologies to enhance the accuracy and robustness of signal classification. The research results indicated that although EEG signals have high temporal resolution, they have low spatial resolution and are susceptible to noise, which limits their effectiveness in accurately decoding complex brain intentions. By combining the fNIRS, which provides complementary spatial information and hemodynamic responses, with EEG, the combined EEG-fNIRS system demonstrated better classification performance, lower noise interference, and enhanced interpretability of brain activity. Moreover, the emerging tFUS technology shows great potential in actively regulating deep brain structures and optimizing signal acquisition through precise neural regulation.

This multimodal approach not only overcomes the inherent limitations of single-modal systems but also opens up new avenues for non-invasive, high-precision BCI. This integration has significant application potential in medical rehabilitation, assistive technologies, and cognitive neuroscience. Future research should focus on optimizing real-time signal synchronization, developing advanced fusion algorithms, and exploring the combination of tFUS with EEG-fNIRS systems to achieve a synergistic effect in comprehensive brain monitoring and control.

References

[1] Ibrahim Arafat. Brain–Computer Interface: Past, Present & Future. Trends in Neurosciences, 2006, 29 (9): 536 - 546.

[2] Yan Heng, Zhou Zhengkang, He Xinsheng, et al. Dynamic graph-temporal convolutional neural network for EEG-fNIRS multimodal motor imagery/execution decoding. Control Theory and Applications, 2024.

[3] Zhang Yunyan. Research on multimodal motion imagination classification method based on EEG and fNIRS. 2024.

[4] Zhao Xin, Wu Jianhang, Wang Kun, et al. Removing artifacts from EEG signals: A review. Journal of Signal Processing, 2025, 41 (6): 1015 - 1039.

[5] Liu Baogen, Zhou Tong, Li Feifei. A new method for brain function imaging: Functional near-infrared spectroscopy technology. Journal of Psychological Science, 2011, 34 (4): 943 - 949.

[6] Zhou Yijie, Song Xizi, He Feng, et al. Research progress of multimodal functional neural imaging technology based on EEG. Chinese Journal of Biomedical Engineering, 2020, 39 (5): 0258 - 8021.

[7] Feng Xianqi. EEG-fNIRS study on motor imagery based on MPDFN. 2025 - 06 - 03.

[8] Wang Wenming, Zhang Xueying, Chen Guijun, et al. EEG-fNIRS emotional recognition based on multi-feature fusion and graph convolutional neural network. Computer Engineering and Applications, 2025.

[9] Chen Chao, Wang Jintao, Jiao Xuejun, et al. Alertness grading and brain neural mechanisms under fNIRS and EEG. Journal of Tianjin University of Technology, 2025.

[10] Jin Yuzhang. Signal denoising and imaging system of magneto-acousto-electrical tomography. 2023 - 05 - 28.

[11] Li Xiaodun. Numerical simulation study of transcranial focused ultrasound based on pseudospectral method. 2024.

[12] Li Yingxuan, Lin Hua. Clinical research and application status of transcranial focused ultrasound stimulation. The Journal of Practical Medicine, 2018, 34 (24).

[13] Yan Heng, Zhou Zhengkang, He Xinsheng, et al. Dynamic graph-time convolutional neural network EEG-fNIRS multimodal motor imagery/execution decoding. Control Theory & Applications, 2024.