Advances in Computer, Signals and Systems (2024)
Clausius Scientific Press, Canada
DOI: 10.23977/acss.2024.080519
ISSN 2371-8838 Vol. 8 Num. 5

WPD Combined with One-on-one CSP for Motor Imagery EEG Signal Classification

Hongzhen Ruan*

Department of Biomedical Engineering, Shantou University, Shantou, Guangdong, China
22hzruan@stu.edu.cn
**Corresponding author*

Keywords: EEG Signal Classification, Brain-computer Interface, Motor Imagery, Wavelet Packet Decomposition, Common Spatial Pattern

Abstract: Regarding the EEG (electroencephalogram) signals of motor imagery, existing signal decomposition methods similar to EMD (Empirical Mode Decomposition) are often affected by mode aliasing and mode oscillation, and classifiers are prone to overfitting in high-dimensional data. This article combined WPD (Wavelet Packet Decomposition) and one-to-one CSP (Common Spatial Pattern) to study the classification of motor imagery EEG signals, aiming to provide better time-frequency resolution and improve classification performance. Using the publicly available dataset BCI (Brain-computer Interface) Competition IV 2a as the object: firstly, WPD was used to perform multi-level decomposition on four types of motor imagery EEG signals from nine subjects; next, the covariance matrix of each category of EEG signals in CSP was calculated to extract feature vectors, and the features that best distinguish different categories were selected to reduce dimensionality and avoid overfitting; finally, in the 10-fold cross-validation process, the number of features was optimized to improve the performance of the Random Forest (RF) classifier. The results showed that the method proposed in this article had a mean Maximum Mutual Information (MMI) of 0.67 bits and a maximum classification accuracy of 87.5% for the BCI Competition IV 2a dataset, which was approximately 2.1% higher than the Attention-based Temporal Convolutional Network (ATCNet) model.

1. Introduction

With the rapid development of BCI (Brain-computer Interface) technology, motor imagery EEG (electroencephalogram) signal classification has become a research hotspot at the intersection of neuroscience and artificial intelligence. Sports imagination can reflect an individual’s brain electrical activity without actual exercise, and has wide applications in rehabilitation training, neural engineering, and other fields [1]. However, EEG signals have nonlinear and non-stationary characteristics, and are susceptible to noise and artifact interference, making accurate classification of these signals a major challenge [2]. In previous signal processing methods, insufficient time-frequency resolution and overfitting of classifiers severely constrain the improvement of classification performance of EEG signals in motor imagery [3]. How to efficiently extract fine-grained features of EEG signals while improving classification accuracy is a hot research problem that urgently needs to be solved.

This article enhances the accuracy of motor imagery EEG signal classification and reduces overfitting by combining wavelet packet decomposition (WPD) and one-to-one common spatial pattern (CSP). After 10-fold cross-validation optimization, this method shows significant performance improvement on the BCI Competition IV 2a dataset. The main contributions are:

A method combining wavelet packet decomposition (WPD) and one-to-one common spatial pattern (CSP) is proposed, which effectively improves the time-frequency resolution of motor imagery EEG signals and extracts more discriminative features from them.

By performing 10-fold cross-validation optimization on the number of features and adjusting the key parameters of the random forest classifier, the overfitting problem in high-dimensional data is solved, and the performance of the classifier is improved.

On the BCI Competition IV 2a dataset, this method achieves a maximum classification accuracy of 87.5%, an improvement of approximately 2.1% compared to other advanced models such as ATCNet, and demonstrates better classification stability.

Chapter 2 summarizes the related work; Chapter 3 conducts WPD and CSP-based feature extraction; Chapter 4 conducts model training and experimental verification; Chapter 5 summarizes the entire content.

2. Related Works

To address the challenges of processing EEG signals in motor imagery, many researchers have proposed different methods. EMD (Empirical Mode Decomposition) is widely used for decomposing non-stationary signals to capture signal characteristics in different frequency bands [4-5]. Based on the multivariate fast adaptive empirical mode decomposition method, Dash Shaswati [6] et al. successfully achieved automatic recognition of imaginative commands in EEG signals, with average accuracies of 60.72%, 59.73%, and 58.78% based on left and right, top and bottom, and front and back, respectively. Asghar Muhammad Adeel [7] et al. innovatively proposed an efficient spatial feature extraction and selection method with low computational cost through multiple empirical mode decomposition and Complex Continuous Wavelet Transform (CCWT). However, this method was often affected by mode aliasing and mode oscillation when processing complex EEG signals, resulting in unstable decomposition results. Some studies used time-frequency analysis and traditional linear classifiers to process high-dimensional features [8-9], but these methods often performed poorly in the face of individual differences and noise, which can lead to overfitting problems [10]. Although some methods have achieved certain results under specific conditions, how to overcome modal aliasing, reduce classifier overfitting, and improve model robustness are still key issues in existing research.

In recent years, various methods combining time-frequency analysis and spatial filtering have been proposed to address EEG decomposition problems. WPD, as an effective time-frequency decomposition method, can finely decompose EEG signals at multiple scales and provide higher time-frequency resolution [11]. Previous studies have shown that WPD can effectively improve the classification performance of motor imagery EEG signals, achieving significant results in reducing dimensionality and suppressing noise, and is commonly used in the diagnosis of epilepsy and other diseases. Sairamya Nanjappan Jothiraj [12] et al. used both Discrete Wavelet Transform (DWT) and WPD to automatically diagnose epileptic seizures and their types by identifying the optimal wavelet function and the required decomposition level for analyzing EEG signals from seven commonly used wavelet series. Dash Deba Prasad [13] et al. used dynamic mode decomposition power features, wavelet packet decomposition coefficients to evaluate power spectral density, variance, and Katz fractal dimension features for detection, achieving a classification accuracy of 95.5% for pre-seizure EEG segments. However, existing research often overlooks the issue of selecting high-dimensional features [14], leading to the continued existence of overfitting. CSP is a spatial filtering method that can effectively extract differentiated features between different motor imagery tasks [15]. This article further optimized the feature extraction and classification process through a one-to-one CSP strategy to address the challenges of dimensionality redundancy and insufficient classification accuracy in existing methods.

3. WPD and CSP-based Feature Extraction

3.1. Data Sources

This study uses the BCI Competition IV 2a dataset, which includes EEG data from 9 participants. The experiment includes four types of motor imagery tasks, with 288 trials per experiment. The signal is recorded through 22 electrodes. Figure 1 shows the EEG signal recordings of a single subject.

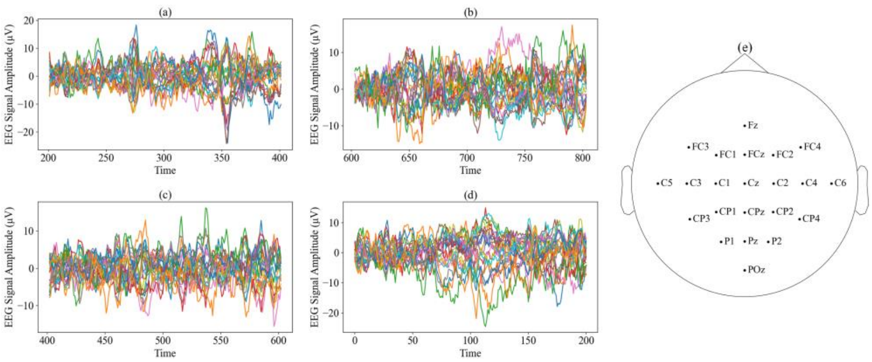

Figure 1: EEG and EEG channels for four types of motor imagery tasks

(Figure 1 (a): Motor imagery of both feet; Figure 1 (b): Motor imagery of left hand; Figure 1 (c): Motor imagery of right hand; Figure 1 (d): Motor imagery of tongue; Figure 1 (e): 22 EEG channel locations)

The subject sits on a chair, facing the computer screen. At the beginning of the experiment, a prompt appears, and the subjects follow the prompt to complete the task. After 6 seconds, the screen turns black and the experiment ends. The signal is sampled at 250Hz, bandpass filtered at 0.5-100Hz, and the amplifier sensitivity is 100 μV.

3.2. Application of Wavelet Packet Decomposition

WPD is used to perform multi-level decomposition on motor imagery EEG signals to improve their time-frequency resolution. For each subject's EEG signal $\mathbf{X}(t)$, Daubechies wavelet (db4) is used for wavelet packet decomposition. The wavelet packet coefficients for a given signal are obtained through the following recursive filtering and downsampling operations:

$$\begin{cases} \mathbf{W}_{j,k}(n) = \sum_{m=-\infty}^{\infty} h(m-2n)\mathbf{W}_{j-1,k}(m) \\ \mathbf{V}_{j,k}(n) = \sum_{m=-\infty}^{\infty} g(m-2n)\mathbf{W}_{j-1,k}(m) \end{cases} \tag{1}$$

Among them, $\mathbf{W}_{j,k}(n)$ and $\mathbf{V}_{j,k}(n)$ are the approximate coefficients and detail coefficients of the j-th layer, respectively, and $h(m)$ and $g(m)$ are the orthogonal mirror filters. The initial condition is $\mathbf{W}_{0,k}(n) = \mathbf{X}(n)$. By repeatedly applying the above operation, the signal is recursively decomposed into multiple sub bands. In this study, the signal is decomposed into the third level, that is, the original signal $\mathbf{X}(t)$ is decomposed into 8 different frequency bands $\mathbf{X}_i(t)$, each band representing the energy distribution of the signal in different frequency ranges:

$$\mathbf{X}(t) = \sum_{i=1}^{8} \mathbf{X}_i(t) \tag{2}$$

After signal decomposition, the coefficients of each frequency band level are processed to eliminate noise and irrelevant signal interference. For each decomposed signal $\mathbf{X}_i(t)$, the soft thresholding is performed based on the energy threshold λ_i:

$$\mathbf{X}_{i,\text{thresholded}}(t) = \text{sign}(\mathbf{X}_i(t)) \cdot max(|\mathbf{X}_i(t)| - \lambda_i, 0) \tag{3}$$

Here, λ_i is adaptively selected based on the energy distribution of frequency band $\mathbf{X}_i(t)$, with the aim of removing low-energy noise components while preserving the main characteristic signals. The processed frequency band signal is reconstructed to form multiple decomposed EEG signal subsets $\mathbf{X}_{i,\text{thresholded}}(t)$, as shown in Figure 2, which represent the characteristics $\mathbf{X}_{\text{reconstructed}}(t) = \sum_{i=1}^{8} \mathbf{X}_{i,\text{thresholded}}(t)$ of the original signal in different frequency ranges.

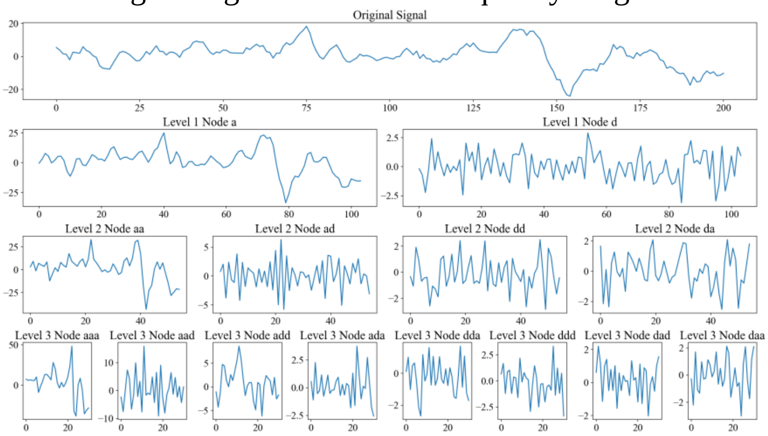

Figure 2: WPD of EEG signals for motor imagery of both feet in a single conversation

Figure 2 shows the decomposition process of WPD on motor imagery EEG signals, dividing the signals into approximate (low-pass) and detail (high pass) signals. Compared to EMD, which directly decomposes the original signal multiple times, WPD uses multiple high-pass and low-pass filters for hierarchical decomposition, with a structure similar to a binary tree and a hierarchical relationship. By decomposing EEG signals into more detailed frequency bands, WPD can capture subtle changes in signals at different time scales, overcoming the shortcomings of traditional EMD like methods in processing non-stationary signals.

3.3. One-on-one CSP Feature Extraction

The overall feature extraction process is shown in Figure 3. Firstly, based on WPD, four types of motor imagery EEG are decomposed, with each imagery task divided into eight sub segments: left hand A (A1, A2... A8), right hand B (B1, B2... B8), feet C (C1, C2... C8), and tongue D (D1, D2... D8). The comparison between each two categories is considered: A-B, A-C, A-D, B-C, B-D, C-D. One-on-one CSP-based feature extraction is performed on the sub segments decomposed by their respective WPDs (such as A-B being A1-B1, A2-B2... and so on).

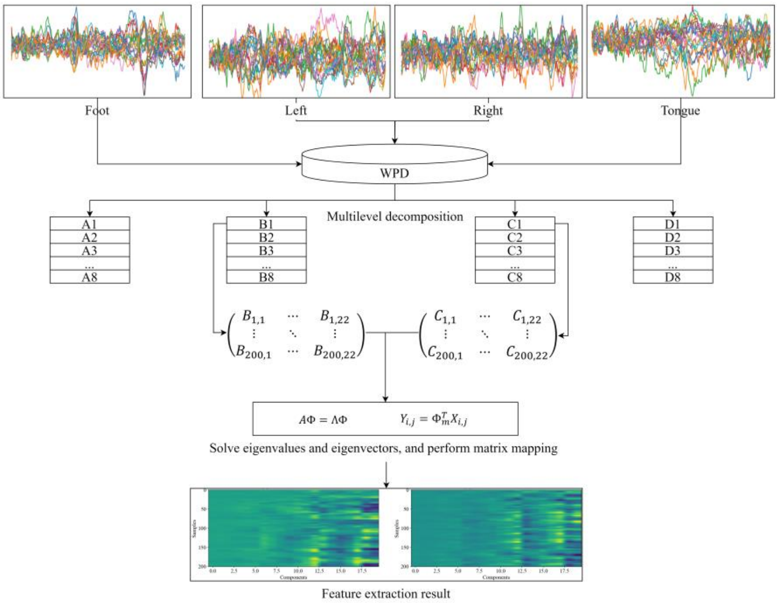

Figure 3: One-on-one CSP feature extraction process

At each level of WPD decomposition, the covariance matrix C_i for the i-th type of motor imagery task is calculated:

$$C_i = \frac{1}{N_i - 1} \sum_{j=1}^{N_i} \left(X_{i,j} - \bar{X}_i\right)\left(X_{i,j} - \bar{X}_i\right)^T \tag{4}$$

Among them, $\bar{X}_i$ is the mean vector of the i-th type signal. Similarly, for each pair of task categories (i, j), covariance matrices C_i and C_j are calculated, and the CSP algorithm is applied for feature extraction:

A feature matrix A is constructed for the category pair (i, j):

$$A = C_i^{-1} C_j \tag{5}$$

Here, C_i^{-1} is the inverse matrix of the covariance matrix of the i-th type signal. Performing eigenvalue decomposition on matrix A yields eigenvalues Λ and eigenvectors Φ:

$$A\Phi = \Lambda\Phi \tag{6}$$

Here, Φ is the eigenvector matrix, and Λ is the diagonalized eigenvalue matrix. The top m features Φ_m with the highest eigenvalues are selected to construct a feature space, and these feature vectors Φ_m can maximize the separation of class signals. The projected feature after selecting feature vectors is:

$$Y_{i,j} = \Phi_m^T X_{i,j} \tag{7}$$

Among them, $X_{i,j}$ is the raw data of the i-th and j-th class signals, and the projection result $Y_{i,j}$ is the representation in the new feature space. By calculating the power spectral density function $P_{Y_{i,j}}(f)$ of the projected features for each pair of tasks, the most discriminative feature for classification is selected with the aim of maximizing the power difference between categories:

$$D_i = \frac{\mathrm{Var}(Y_i) - \mathrm{Var}(Y_j)}{\mathrm{Var}(Y_i) + \mathrm{Var}(Y_j)} \tag{8}$$

Here, $\mathrm{Var}(Y_i)$ and $\mathrm{Var}(Y_j)$ are the variances of the i-th and j-th projection features, respectively.

4. Results and Discussions

4.1. Model Parameter Optimization

This article uses 70% of EEG data for training and 30% for testing. The features are optimized through 10-fold cross-validation and random forest analysis. The verification accuracy is shown in Figure 4.

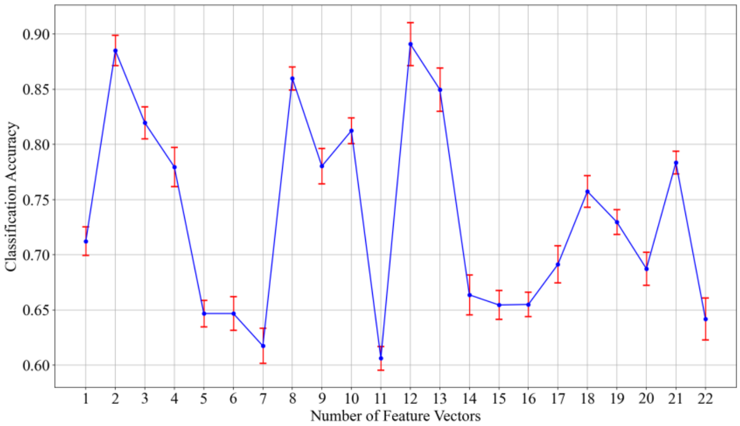

Figure 4: Process of selecting the number of feature vectors

Figure 4 shows that when using 12 feature vectors, the classification accuracy reaches 0.89 with a standard deviation of 0.019. When the number of feature vectors is between 1 and 22, the accuracy fluctuates. Although some feature vectors (such as 2, 8, 10, 13) also exhibit high accuracy, considering both accuracy and stability, selecting 12 feature vectors as the optimal solution can ensure high classification accuracy while maintaining low standard deviation. Therefore, 12 feature vectors are selected in subsequent experiments to optimize classification performance.

After feature selection, the parameters of the random forest are optimized (tree depth, minimum sample size for node splitting, and minimum sample size for leaf nodes). The parameter settings and results are shown in Table 1.

Table 1: Parameter setting combinations and corresponding classification results of random forest classifier

Configuration No.	Tree Depth	Min Samples Split	Min Samples Leaf	Classification Accuracy (%)
1	5	2	2	82.4
2	5	2	4	81.7
3	5	5	2	83.5
4	5	5	4	82.9
5	10	2	2	85.1
6	10	2	4	84.3
7	10	5	2	86.0
8	10	5	4	85.4
9	20	2	2	87.5
10	20	2	4	86.8
11	20	5	2	86.7
12	20	5	4	85.9

When the tree depth is 20, the highest accuracy reaches 87.5%. Setting the minimum sample size for node splitting and leaf nodes to 2 also achieves this accuracy. Therefore, a tree depth of 20 is used in the study, with a minimum sample size of 2 for node splitting and leaf nodes.

4.2. Classification Performance Evaluation

The optimized random forest classifier is evaluated based on accuracy, sensitivity (Sn), and specificity (Sp). This article compares the model with the ATCNet model proposed by Altaheri Hamdi [16] et al. in 2022 and the enhanced convolutional neural network based on temporal data proposed by Li Hongli [17] et al. in 2023. The result is shown in Figure 5.

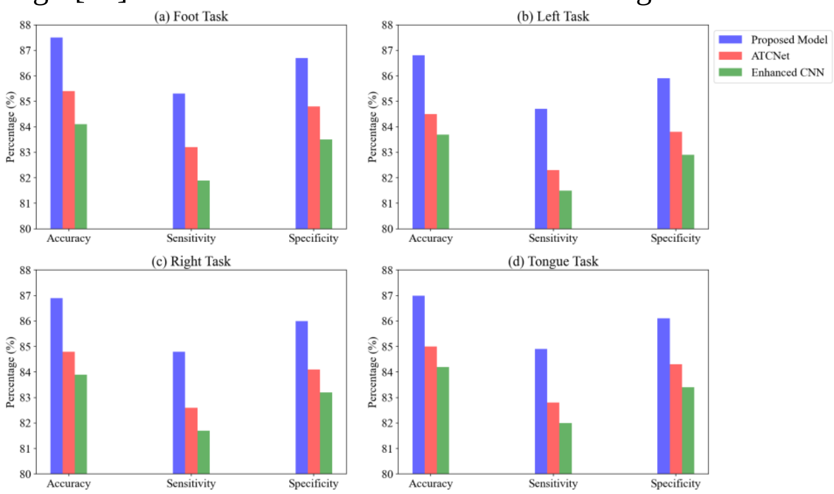

Figure 5: Classification performance evaluation

(Figure 5 (a): Motor imagery of both feet; Figure 5 (b): Motor imagery of left hand; Figure 5 (c): Motor imagery of right hand; Figure 5 (d): Motor imagery of tongue)

Figure 5 shows the performance of WPD and one-on-one CSP methods. In the motor imagery of both feet task, the model has an accuracy of 87.5%, a sensitivity of 85.3%, and a specificity of 86.7%, which is better than the ATCNet model and the enhanced CNN model. In the motor imagery of left hand, the accuracy rate is 86.8%; in the motor imagery of right hand, the accuracy rate is 86.9%; in motor imagery of tongue, the accuracy rate is 87.0%. Overall, the model performs excellently in all tasks, validating the effectiveness of the method.

4.3. Maximum Mutual Information Assessment

Table 2: MMI comparison of different models

Task Category	Proposed Model (WPD + One-vs-One CSP)	ATCNet (2022)	Enhanced CNN (2023)
Both Feet Motor Imagery	0.67	0.65	0.64
Left Hand Motor Imagery	0.66	0.64	0.63
Right Hand Motor Imagery	0.67	0.65	0.64
Tongue Motor Imagery	0.68	0.66	0.65
Average	0.67	0.65	0.64

MMI is calculated to reflect the maximum correlation between extracted features and category labels, measuring the discriminative ability of classification features. After discretizing the feature space, the mutual information between features and category labels is calculated using information entropy, and the maximum mutual information is selected as the evaluation criterion. The results are shown in Table 2.

In the four motor image tasks, the MMI value of this model ranges from 0.66 to 0.68 bits, higher than the 0.64 to 0.66 bits of ATCNet and the 0.63 to 0.65 bits of enhanced CNN. This model demonstrates higher effectiveness in feature extraction and classification.

5. Conclusions

This article improved the classification of motor imagery EEG signals by using WPD for time-frequency decomposition and CSP for feature extraction. By optimizing features through 10-fold cross-validation, the accuracy of the random forest classifier was improved to 87.5%, with an average MMI of 0.67 bits. Although the method proposed in this article has achieved significant improvements in classification performance, further research is needed to investigate its adaptability in larger datasets or multi-task environments. Future work can focus on optimizing the computational efficiency of algorithms and exploring their potential applications in real-time BCI systems.

References

[1] Altaheri, Hamdi, Muhammad, Ghulam, Alsulaiman, Mansour, Amin, Syed Umar, Altuwaijri, Ghadir Ali, Abdul, Wadood, et al. (2023). Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review. Neural Computing and Applications, 35 (20), 14681-14722.

[2] Duan, Lijuan, Lian, Zhaoyang, Qiao, Yuanhua, Chen, Juncheng, Miao, Jun, & Li, Mingai. (2024). A Novel Feature Fusion Approach for Classification of Motor Imagery EEG Based on Hierarchical Extreme Learning Machine. Cognitive Computation, 16 (2), 566-580.

[3] Tiwari, Virendra Kumar, & Singh, Priyanka. (2023). Classification of Motor Imaginary in EEG using feature Optimization and Machine Learning. International Journal of Advanced Networking and Applications (IJANA), India, 15 (02), 5887-5891.

[4] Samal, Priyadarsini, & Hashmi, Mohammad Farukh. (2023). Ensemble median empirical mode decomposition for emotion recognition using EEG signal. IEEE Sensors Letters, 7 (5), 1-4.

[5] Zulfikar, Aslan, & Mehmet, Akin. (2022). Empirical mode decomposition and convolutional neural network-based approach for diagnosing psychotic disorders from eeg signals. Applied Intelligence, 52 (11), 12103-12115.

[6] Dash, Shaswati, Tripathy, Rajesh Kumar, Panda, Ganapati, & Pachori, Ram Bilas. (2022). Automated recognition of imagined commands from EEG signals using multivariate fast and adaptive empirical mode decomposition based method. IEEE Sensors Letters, 6 (2), 1-4.

[7] Asghar, Muhammad Adeel, Khan, Muhammad Jamil, Rizwan, Muhammad, Shorfuzzaman, Mohammad, & Mehmood, Raja Majid. (2022). AI inspired EEG-based spatial feature selection method using multivariate empirical mode decomposition for emotion classification. Multimedia Systems, 28 (4), 1275-1288.

[8] Meng, Ming, Dong, Zhichao, Gao, Yunyuan, & She, Qingshan. (2023). Optimal channel and frequency band-based feature selection for motor imagery electroencephalogram classification. International Journal of Imaging Systems and Technology, 33 (2), 670-679.

[9] Miao, Minmin, Hu, Wenjun, & Zhang, Wenbin. (2021). A spatial-frequency-temporal 3D convolutional neural network for motor imagery EEG signal classification. Signal, Image and Video Processing, 15 (8), 1797-1804.

[10] Thuwajit, Punnawish, Rangpong, Phurin, Sawangjai, Phattarapong, Autthasan, Phairot, Chaisaen, Rattanaphon, Banluesombatkul, Nannapas, et al. (2021). EEGWaveNet: Multiscale CNN-based spatiotemporal feature extraction for EEG seizure detection. IEEE Transactions on Industrial Informatics, 18 (8), 5547-5557.

[11] Fang, Hua, Jin, Jing, Daly, Ian, & Wang, Xingyu. (2022). Feature extraction method based on filter banks and Riemannian tangent space in motor-imagery BCI. IEEE journal of biomedical and health informatics, 26 (6), 2504-2514.

[12] Sairamya, Nanjappan Jothiraj, Premkumar, M Joel, George, S Thomas, & Subathra, MSP. (2021). Performance evaluation of discrete wavelet transform, and wavelet packet decomposition for automated focal and generalized

epileptic seizure detection. IETE journal of Research, 67 (6), 778-798.
[13] Dash, Deba Prasad, Kolekar, Maheshkumar H, & Jha, Kamlesh. (2022). Surface EEG based epileptic seizure detection using wavelet based features and dynamic mode decomposition power along with KNN classifier. Multimedia Tools and Applications, 81 (29), 42057-42077.
[14] Amiri, Youkabed, & Omranpour, Hesam. (2024). Efficient space learning based on kernel trick and dimension reduction technique for multichannel motor imagery EEG signals classification. Neural Computing and Applications, 36 (3), 1199-1214.
[15] Yin, Xu, Meng, Ming, She, Qingshan, Gao, Yunyuan, & Luo, Zhizeng. (2021). Optimal channel-based sparse time-frequency blocks common spatial pattern feature extraction method for motor imagery classification. Mathematical Biosciences and Engineering, 18 (4), 4247-4263.
[16] Altaheri Hamdi, Muhammad Ghulam, Alsulaiman Mansour. Physics-informed attention temporal convolutional network for EEG-based motor imagery classification. IEEE transactions on industrial informatics, 2022, 19 (2): 2249-2258.
[17] Li Hongli, Liu Haoyu, Chen Hongyu, Zhang Ronghua. Multi-scale feature extraction and classification of motor imagery electroencephalography based on time series data enhancement. Journal of biomedical engineering, 2023, 40 (3): 418-425.