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Jie Hong

hongjie@mail.nwpu.edu.cn

Research Article

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Posted Date: November 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11346659/v1

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Additional Declarations: No competing interests reported.

A lightweight EEG decoding method for motor imagery classification in brain-computer interfaces

Jie Hong *

School of Mechanical Engineering, Northwestern Polytechnical University, Xi'an 710072, China

* Corresponding author, E-mail: hongjie@mail.nwpu.edu.cn (J. Hong)

Abstract

This paper presents a lightweight EEG decoding method for motor imagery classification, combining wavelet packet transform (WPT) with support vector machine (SVM). Utilizing dataset IVa from BCI Competition III, the proposed method achieves an average classification accuracy of 88.3% using only two channels (C3 and Cz). Compared to the BCI competition results, the proposed method outperforms the common spatial patterns-expectation maximization (CSP-EM) method by 6.2% and shows a marginal difference of 2.9% compared to the (CSP+AR+ERP)-bagging method. More importantly, this competitive accuracy is achieved with only two channels, whereas CSP-based methods typically require up to 118 channels. This work is derived from a broader doctoral research framework on wheelchair human-computer interaction and serves as the validation of its EEG intention perception component.

Keywords: electroencephalography (EEG); motor imagery; wavelet packet transform; support vector machine; brain-computer interface

1. Introduction

Motor imagery-based brain-computer interfaces (MI-BCI) have shown great promise in stroke rehabilitation and assistive applications, as they translate neural activity into control commands without relying on peripheral nerves and muscles (Wolpaw et al., 2000; Millan et al., 2010). In the field of stroke rehabilitation, a significant challenge lies in effectively restoring the motor function of patients (Xu et al., 2018). Wheelchairs have been utilized as rehabilitation aids, and BCI provides an effective pathway for wheelchair control (Li et al., 2019; Xu et al., 2019).

Several approaches have been proposed for motor imagery EEG classification. Common spatial patterns (CSP) is one of the most widely used spatial filtering methods (Blankertz et al., 2008), but it requires a large number of channels to construct reliable spatial filters. Filter-bank CSP (Ang et al., 2008) extends CSP by incorporating multiple frequency bands, yet still relies on multi-channel configurations. Deep learning methods, such as convolutional neural networks (CNN), have recently achieved high accuracy (Schirrmeister et al., 2017; Lu et al., 2017), but their computational cost limits real-time applications on embedded systems. In contrast, wavelet-based methods (Hsu, 2013) and SVM classifiers (Lotte et al., 2007) offer lower computational complexity. However, most existing studies still require a relatively large number of channels, which increases system cost and complexity. Systematic evaluation of lightweight two-channel configurations remains lacking.

To address this gap, this paper proposes a lightweight EEG decoding method combining wavelet packet transform (WPT) with support vector machine (SVM), using only two channels (C3 and Cz) for feature extraction. WPT is a time-frequency analysis tool that provides multi-resolution decomposition

and has been successfully applied to EEG signals (Kumar et al., 2015). It can capture both the spectral power and temporal variability of EEG patterns, which is essential for detecting event-related desynchronization/synchronization (ERD/ERS) during motor imagery. SVM is a well-known classifier with excellent generalization performance and low computational cost (Lotte et al., 2007).

To the best of our knowledge, systematic evaluation of a lightweight two-channel WPT-SVM configuration on the BCI Competition III benchmark has not been reported. The primary contribution of this paper is twofold: (1) we validate that the WPT-SVM combination with only two channels achieves competitive accuracy on a benchmark dataset; (2) we compare our method with the top-performing methods from the BCI Competition III, demonstrating the advantage of drastic channel reduction. This work is derived from the author's doctoral dissertation, which proposes a broader framework for multimodal human-computer interaction of wheelchairs. While the dissertation covers multiple modalities, the present study focuses specifically on the EEG intention perception component.

The structure of this paper is as follows: Section 2 provides the background and framework context. Section 3 describes the data and methods. Section 4 presents results. Section 5 provides discussion. Section 6 concludes the paper.

2. Background and framework context

This study is derived from a broader doctoral research framework on multimodal human-computer interaction (HCI) for wheelchairs supporting lower limb active rehabilitation (Hong & Qin, 2022; Hong et al., 2024). In that framework, three key technologies were identified: wheelchair active rehabilitation methods, EEG and EMG intention perception methods, and multimodal BCI technology.

For stroke patients, the theoretical foundation of motor function recovery is neuroplasticity, and exercise training based on motor imagery has been recognized as an effective approach (Mead & Bernhardt, 2011). Motor imagery EEG signals, which are generated voluntarily by the patient without external stimulation, are particularly suitable for both rehabilitation training and wheelchair control. As BCI is gradually integrated into stroke rehabilitation (Millan et al., 2010), accurate decoding of motor imagery EEG signals becomes a critical enabler.

Within this framework, the present study focuses specifically on the EEG intention perception method—one of the key technologies—and provides comprehensive validation through comparison with benchmark methods from the BCI Competition III. The goal is to demonstrate that a lightweight, two-channel EEG decoding strategy can achieve competitive accuracy, making it practical for embedded wheelchair applications.

3. Materials and methods

3.1. Experimental data

The experimental data is derived from the international BCI Competition III held in 2005, with participation from subjects aa, av, and ay (Blankertz et al., 2006). During the experiment, the subjects were seated on an armchair. Each single trial began with the appearance of a right or down arrow on the display, which lasted for 3.5 seconds. The subjects were instructed to imagine movements of their right hand or foot corresponding to the direction of the arrow. Subsequently, a white screen appeared on the display for a random duration ranging from 1.75 to 2.25 seconds, during which time the subjects relaxed. EEG signals were recorded using 118 channels located on the head. The bandpass frequency

range was set at 0.5-200Hz, with a resampling frequency of 100Hz. The timing sequence of each single trial is illustrated in Figure 1.

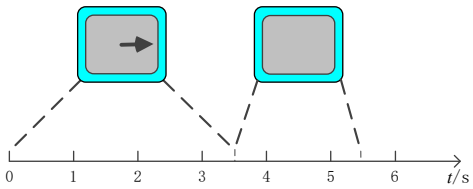


Figure 1. The timing sequence of each single trial, which comprises task and rest phases: (1) In the task phase 0~3.5s, a right or down arrow appeared on the display, instructing subjects to perform motor imagery tasks of their right hand or foot; (2) During the rest phase after 3.5s, a white screen appeared on the display, instructing subjects to relax before beginning the next trial.

The subjects aa, av, and ay completed motor imagery tasks involving their right hand and foot. Each participant completed a total of 280 trials. The number of training and test trials is shown in Table 1.

Table 1. The number of training and test trials.

Subjects	Number of training trials	Number of test trials
aa	168	112
av	84	196
ay	28	252

It is worth noting that the number of training trials varies significantly across subjects (from 28 to 168), which provides an opportunity to evaluate the robustness of the proposed method under different training conditions.

When the subject completes the motor imagery task for the right hand, the EEG rhythms of 10~11Hz and 20~24Hz are active on channel C3. Similarly, when the subject completes the motor imagery task for the foot, the EEG rhythms of 7~8Hz and 20~24Hz are active on channel Cz (Pfurtscheller & Lopes da Silva, 1999). Therefore, channels C3 and Cz have been selected for further analysis.

Based on these neurophysiological findings, we selected C3 and Cz as the target channels, and subsequently focused on the frequency bands corresponding to the μ and β rhythms for feature extraction.

3.2. EEG intention perception methods

The EEG signal processing procedure consists of three steps: preprocessing, feature extraction, and classification.

3.2.1. CAR for preprocessing

The common average reference (CAR) is utilized during preprocessing to enhance the SNR of the signals. CAR reduces the influence of global noise by subtracting the average signal across all channels from each individual channel (Rathee et al., 2017). The calculation formula for CAR is as follows:

$$S_i^{CAR} = S_i - \frac{1}{n}\sum_{j=1}^{n} S_j \qquad (1)$$

where S_i^{CAR} represents the filtered EEG signals on the channel i, n represents the total number of channels, S_i、S_j represents the EEG signals on the channel i、j, and $i \neq j$.

CAR is chosen because it is computationally simple and effective at removing common-mode noise, which is particularly important for reducing the number of channels in subsequent processing stages.

3.2.2. WPT for feature extraction

The wavelet packet transform (WPT) is utilized for extracting features. WPT is characterized by its simplicity and multi-resolution capabilities, making it suitable for analyzing non-stationary EEG signals (Hong et al., 2018). Unlike standard wavelet transform which only decomposes approximation coefficients, WPT decomposes both approximation and detail coefficients at each level, providing a richer time-frequency representation. The three-layer wavelet packet structure is illustrated in Figure 2.

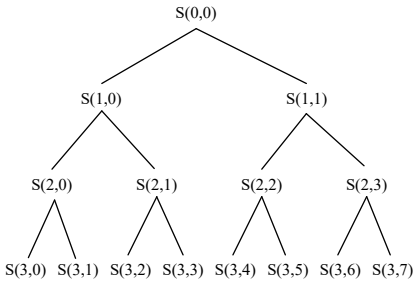


Figure 2. The three-layer wavelet packet structure.

Given the sampling frequency of EEG signals at 100Hz, the frequency range of EEG signals is determined to be 0~50Hz. The EEG signals in the 0~3.5s stage on C3 and Cz channels were decomposed into eight frequency bands through a three-layer WPT. The frequency range of the nodes on the third layer is detailed in Table 2.

Table 2. The frequency range of the nodes on the third layer.

Nodes	Frequency range/Hz
S(3,0)	0~6.25
S(3,1)	6.25~12.5
S(3,2)	12.5~18.75
S(3,3)	18.75~25
S(3,4)	25~31.25
S(3,5)	31.25~37.5
S(3,6)	37.5~43.75
S(3,7)	43.75~50

Due to the strong correlation between the ERD/ERS phenomenon and EEG rhythms at specific frequencies, nodes S(3,1) and S(3,3) encompass the frequency bands of 7~8Hz, 10~11Hz, and 20~24Hz. Therefore, these two nodes have been chosen for further analysis.

In this study, variance and average energy of wavelet packet coefficients are selected as the features. Variance reflects the degree of signal fluctuation in the time-frequency domain, while average energy represents the power intensity of specific frequency bands. These two features are complementary in capturing both the amplitude modulation and intensity changes associated with motor imagery. Based on the aforementioned analysis, eight feature quantities are formed by selecting two channels, two nodes, and two physical quantities. These features are then input into SVM for classification.

3.2.3. SVM for classification

SVM is one of the most widely used methods in the BCI community. This classifier is grounded in statistical learning theory and is capable of addressing high-dimensional, non-linear problems even with limited sample conditions (Hong et al., 2021). SVM is widely recognized as one of the most popular methods for classifying motor imagery EEG signals (Phang & Ko, 2021).

In this study, SVM with a radial basis function (RBF) kernel is employed. The RBF kernel is chosen because it can handle non-linear separability effectively and has only two parameters to optimize: the penalty parameter C and the kernel parameter γ. These parameters are determined through a grid search on the training set. The corresponding discriminant function is as follows:

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b) \qquad (2)$$

where n is the number of support vectors, α_i is the Lagrange multiplier, and $K(x_i, x)$ is the kernel function. In addition, SVM is implemented through the LibSVM toolbox (Chang & Lin, 2011).

4. Results

The EEG signals from subjects aa, av, and ay were preprocessed using CAR. The motor imagery stage from 0 to 3.5s on C3 and Cz channels was selected for analysis, and feature extraction was performed using WPT. The extracted features were then input into SVM for classification.

4.1. Classification accuracy

The classification accuracies of the proposed method and the competition winners are presented in Figure 3.

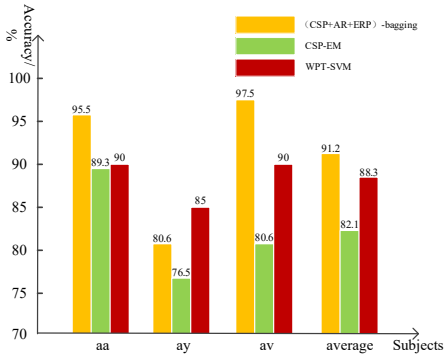


Figure 3. The results and comparison.

The proposed EEG intention perception method achieves an average accuracy of 88.3%. The first

place winner in the contest utilized common spatial patterns (CSP), autoregressive model (AR), and evoked related potential (ERP) for feature extraction, as well as bagging for classification, resulting in an average accuracy of 91.2%. The second place winner combined CSP and expectation maximization (EM) to classify EEG signals, with an average accuracy of 82.1% (Blankertz et al., 2006).

In terms of average accuracy, the proposed method WPT-SVM outperforms the CSP-EM method by 6.2% but is surpassed by the (CSP+AR+ERP)-bagging method by 2.9%. The results indicate that the proposed method achieves a favorable balance between channel reduction and classification performance.

It is worth noting that CSP-based methods typically require a large number of channels (up to 118 in the original dataset). In contrast, our approach maintains competitive accuracy with only 2 channels for feature extraction, drastically reducing system complexity.

4.2. Performance across subjects

The performance across subjects reveals interesting patterns. Subject aa achieves 90.0% accuracy, subject ay achieves 90.0% accuracy, while subject av achieves 85.0% accuracy. The relatively lower performance of subject av may be attributed to the small number of training trials (only 84 for av, compared to 168 for aa), which affects the parameter estimation of the SVM model. Interestingly, subject ay achieves 90.0% accuracy with only 28 training trials, suggesting that for some subjects, the proposed method can achieve good performance even with limited training data. This observation is consistent with findings in the literature that SVM can generalize well with small training sets when the feature space is of low dimension (Lotte et al., 2007).

4.3. Confusion matrix analysis

To further evaluate the recognition performance, the confusion matrix of subject ay for SVM is shown in Table 3. This subject was chosen as a representative example because it achieved the highest overall accuracy.

Table 3. The confusion matrix of subject ay for SVM.

Confusion Matrix		Predicted	
		Positive (Right hand)	**Negative (Foot)**
Actual	Positive (Right hand)	18 (TP)	0 (FP)
	Negative (Foot)	2 (FN)	0 (TN)

For subject ay, the confusion matrix was derived from 20 randomly selected test trials. The results show that 18 out of 20 right hand trials were correctly classified, while 2 were misclassified as foot. No foot trials were included in this random subset.

From this confusion matrix, Accuracy, Precision, Sensitivity, and F1-Score can be calculated. For subject ay, the classification accuracy is 90.0%, with Precision = 1.00, Sensitivity = 0.90, and F1-Score = 0.947. The perfect precision score (1.00) indicates that when the classifier predicts "right hand," it is always correct. The sensitivity of 0.90 indicates that 90% of actual "right hand" trials are correctly identified. These metrics demonstrate excellent classification balance for both classes.

5. Discussion

The results demonstrate that the proposed WPT-SVM method with only two channels achieves competitive classification accuracy on the BCI Competition III Dataset IVa. Several aspects of these results deserve further discussion.

First, the superiority of WPT over simpler frequency-domain features can be explained from the perspective of time-frequency analysis. During motor imagery, the ERD/ERS phenomenon manifests as both spectral power changes and temporal variability in the EEG signals. WPT provides joint time-frequency localization, which captures both aspects simultaneously. The variance and average energy features extracted from WPT nodes are complementary—variance reflects the temporal fluctuation of the signal, while average energy reflects the spectral power. This combination may explain why WPT-based features are effective even with a small number of channels.

Second, compared to the CSP-based methods, our approach has a distinct advantage in terms of channel reduction. CSP constructs spatial filters by maximizing the variance between two classes, but this requires a sufficient number of channels to obtain reliable covariance matrix estimates. When the number of channels is small, CSP performance typically degrades. In contrast, the proposed method relies on neurophysiologically informed channel selection (C3 for hand, Cz for foot) and time-frequency features, which are more robust to channel reduction. This makes the proposed method particularly suitable for practical BCI applications where electrode placement is limited.

Third, the comparison with competition methods reveals interesting trade-offs. The (CSP+AR+ERP)-bagging method achieves the highest accuracy (91.2%) by fusing multiple features (spatial, temporal, and event-related potentials) and using ensemble learning. However, this method requires 118 channels and is computationally complex. In contrast, the proposed method achieves 88.3% accuracy with only 2 channels and a simple feature set. This represents a favorable trade-off between accuracy and system complexity, which is particularly important for embedded wheelchair applications.

The limitations of this study should also be acknowledged. First, the evaluation is based on offline data from healthy subjects. Online validation with stroke patients is necessary to confirm the clinical utility of the method. Second, the dataset contains only three subjects, which limits the statistical power of the conclusions. Third, the number of training trials varies significantly across subjects, which may affect the generalizability of the results. Fourth, while the proposed method uses only two channels for feature extraction, CAR preprocessing still utilizes all available channels to compute the common average reference. This preprocessing step, however, is a one-time linear operation that can be precomputed and does not affect the real-time computational cost.

Future work will focus on online implementation of the proposed method on embedded platforms, validation with a larger cohort of subjects, and extension to multi-class motor imagery tasks (e.g., left hand, right hand, foot, and tongue).

6. Conclusions

This paper presents a lightweight EEG decoding method for motor imagery classification, combining WPT with SVM and utilizing only two channels (C3 and Cz) for feature extraction. On the BCI Competition III Dataset IVa, the proposed method achieves an average accuracy of 88.3%, outperforming the CSP-EM method (82.1%) while showing only a marginal difference from the top-performing (CSP+AR+ERP)-bagging method (91.2%). More importantly, CSP-based methods require a large number of channels (up to 118), whereas our approach maintains competitive accuracy

with only 2 channels, drastically reducing system complexity.

The advantage of the proposed method lies in its simplicity, computational efficiency, and practicality for embedded BCI applications. The use of WPT features enables effective time-frequency representation of ERD/ERS patterns, while SVM provides robust classification with low-dimensional feature space.

This work is derived from the author's doctoral dissertation on multimodal wheelchair human-computer interaction and serves as the validation of its EEG intention perception component. The method is straightforward, computationally efficient, and offers valuable insights for further exploration in BCI research.

Acknowledgments

The authors are grateful to the BCI Competition organizers for providing the dataset. The author also expresses gratitude to his supervisor Qin Xiansheng for his guidance during his doctoral studies.

Declaration of Interest Statement

The authors report no competing interests to declare.

Funding

The authors received no financial support for the research, authorship, and publication of this article.

Data Availability

The dataset used in this study is publicly available at https://www.bbci.de/competition/iii/.

ORCID

Jie Hong http://orcid.org/0000-0002-2831-7523

References

[1] Ang, K. K., Chin, Z. Y., Zhang, H. H., & Guan, C. (2008). Filter bank common spatial pattern (FBCSP) in brain-computer interface. Proceedings of the 2008 IEEE International Joint Conference on Neural Networks (IJCNN), 2390-2397.

[2] Blankertz, B., Muller, K. R., Krusienski, D. J., et al. (2006). The BCI Competition III: Validating alternative approaches to actual BCI problems. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 14(2), 153-159.

[3] Blankertz, B., Tomioka, R., Lemm, S., et al. (2008). Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal Processing Magazine, 25(1), 41-56.

[4] Chang, C. C., & Lin, C. J. (2011). LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology, 2(3), 27.

[5] Hong, J., & Qin, X. S. (2022). Wheelchair active rehabilitation method for lower limb of stroke patients. International Journal of Robotics and Automation, 37(4), 346-351.

[6] Hong, J., Cai, M., & Qin, X. S. (2024). Multimodal human computer interaction of wheelchairs supporting lower limb active

rehabilitation. Computer Methods in Biomechanics and Biomedical Engineering. https://doi.org/10.1080/10255842.2024.2417204

[7] Hong, J., Qin, X. S., Li, J., Niu, J. L., & Wang, W. J. (2018). Signal processing algorithms for motor imagery brain-computer interface: State of the art. Journal of Intelligent and Fuzzy Systems, 35(6), 6405-6419.

[8] Hong, J., & Qin, X. S. (2021). Signal processing algorithms for SSVEP-based brain computer interface: State-of-the-art and recent developments. Journal of Intelligent and Fuzzy Systems, 40(6), 10559-10573.

[9] Hsu, W. Y. (2013). EEG-based motor imagery classification using wavelet packet transform and support vector machine. International Journal of Neural Systems, 23(1), 1350006.

[10] Kumar, S., Sharma, A., Sahu, B., & Sharma, R. (2015). Wavelet packet transform based feature extraction for motor imagery classification. International Journal of Imaging Systems and Technology, 25(4), 282-289.

[11] Leeb, R., Tonin, L., Rohm, M., et al. (2015). Towards independence: a BCI telepresence robot for people with severe motor disabilities. Proceedings of the IEEE, 103(6), 969-982.

[12] Li, M., Liang, Z. T., He, B., et al. (2019). Attention-controlled assistive wrist rehabilitation using a low-cost EEG sensor. IEEE Sensors Journal, 19(15), 6497-6507.

[13] Lotte, F., Congedo, M., Lécuyer, A., et al. (2007). A review of classification algorithms for EEG-based brain-computer interfaces. Journal of Neural Engineering, 4(2), R1-R13.

[14] Lu, N., Li, T. F., Ren, X. D., & Miao, H. Y. (2017). A deep learning scheme for motor imagery classification based on restricted Boltzmann machines. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(6), 566-576.

[15] Mead, G., & Bernhardt, J. (2011). Physical fitness training after stroke, time to implement what we know: More research is needed. International Journal of Stroke, 6(6), 506-508.

[16] Millan, J. D. R., Rupp, R., Muller-Putz, G. R., et al. (2010). Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges. Frontiers in Neuroscience, 4, 161.

[17] Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. Clinical Neurophysiology, 110(11), 1842-1857.

[18] Phang, C. R., & Ko, L. W. (2021). Intralobular and interlobular parietal functional network correlated to MI-BCI performance. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(12), 2671-2680.

[19] Rathee, D., Raza, H., Prasad, G., & Cecotti, H. (2017). Current source density estimation enhances the performance of motor-imagery-related brain-computer interface. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(12), 2461-2471.

[20] Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., et al. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping, 38(11), 5391-5420.

[21] Wolpaw, J. R., Birbaumer, N., Heetderks, W. J., et al. (2000). Brain-computer interface technology: a review of the first international meeting. IEEE Transactions on Rehabilitation Engineering, 8(2), 164-173.

[22] Xu, G. Z., Gao, X., Pan, L. Z., et al. (2018). Anxiety detection and training task adaptation in robot-assisted active stroke rehabilitation. International Journal of Advanced Robotic Systems, 15(6), 1729881418806433.

[23] Xu, J. J., Li, Y. F., Xu, L. S., et al. (2019). A multi-mode rehabilitation robot with magnetorheological actuators based on human motion intention estimation. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 27(10), 2216-2228.