2024 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT)
September 19-20, 2024. Tucson, Arizona USA

Integrating EEG Source Localization and ResNet CNN for Advanced Stroke Rehabilitation

Sina Makhdoomi Kaviri and Ramana Kumar Vinjamuri[1]

Abstract— **Upper limb motor impairments resulting from stroke greatly limit daily activities and diminish quality of life, making effective rehabilitation essential. This study addresses this issue by classifying motor tasks using EEG data from acute stroke patients, focusing on left-hand motor imagery, right-hand motor imagery, and rest states. By using advanced source localization techniques combined with customized ResNetCNN architecture, we achieve superior spatial pattern recognition in EEG data. Our methodology results in classification accuracies of 91.03%, 89.07%, and 87.17%, compared to 55.57% to 72.21% achieved by traditional sensor domain methods. These findings demonstrate the potential of our approach to enhance brain-computer interfaces (BCIs) for more effective and personalized neurorehabilitation, ultimately improving recovery outcomes and quality of life for stroke patients. The results underscore the importance of advanced EEG classification techniques in providing clinicians with precise tools for developing individualized therapy plans, potentially leading to significant improvements in motor function recovery and patient outcomes.**

I. Introduction

Stroke is a leading cause of death and disability globally, causing significant morbidity despite advancements in therapies [1]. Most stroke patients experience upper limb motor impairment, limiting activities and burdening families [2]. Soft-robotic gloves aid rehabilitation by facilitating finger movements using biosignals [3]. Robot-based therapy has improved hand motor function and brain reorganization, emphasizing the need for neurophysiological studies for effective rehabilitation [4]. BMIs link brain circuitry to assistive devices like prostheses and wheelchairs [5]. EEG, MEG, fMRI, and NIRS are used for BCIs, with EEG being preferred for its non-invasive nature and cost [6]. EEG signals enable communication for individuals with severe neuromuscular disorders. Advances in brain function understanding have propelled BCI research, but signal complexity poses challenges, necessitating optimized classifiers [7], [8].

In recent years, classification algorithms for BCIs, including linear classifiers, neural networks, Bayesian classifiers, nearest neighbor classifiers, and combinations, have been reviewed to guide the design of BCI systems, with SVMs being particularly efficient for synchronous BCIs [9]. BMIs have shown promise in facilitating neuroplasticity and motor recovery in paralyzed stroke patients using noninvasive technologies like EEG, though further improvements are needed [10]. BCI-based therapy has shown promising results for post-stroke motor rehabilitation and holds potential for addressing non-motor deficits such as cognitive and emotional impairments, emphasizing a holistic approach to post-stroke rehabilitation [11]. Despite previous studies emphasizing deep learning methods for EEG signal analysis, advanced source localization techniques such as electrophysiological source imaging (ESI) have significantly improved the accuracy of brain source imaging in clinical applications by providing high spatial resolution using noninvasive scalp measurements [12]. For instance, EEG recordings can decode hand motion preparation by solving the inverse problem through beamforming. A custom deep CNN trained on these EEG source epochs achieved accuracy rates up to 89.65% for hand close versus rest and 90.50% for hand open versus rest. This method identified key cortical areas involved in hand movement preparation, such as the central region and the right temporal zone of the premotor and primary motor cortex [13].

In this paper, we introduce a novel approach for classifying motor tasks using EEG data from acute stroke patients, focusing on three specific movements: left-hand motor imagery, right-hand motor imagery, and rest [14]. By applying advanced source localization techniques such as MNE, dipole fitting, and beamforming, we enhanced our ability to accurately identify cortical activity, which is crucial for developing targeted neurotherapies. Our methodology integrates these advanced techniques with a specially designed Residual Convolutional Neural Network (ResNet) architecture to capture spatial patterns in EEG data, significantly improving classification accuracy. Transforming EEG data from the sensor domain to the source domain allowed us to achieve more precise cortical activity representation, resulting in classification accuracies of 91.03% (dipole fitting), 89.07% (MNE), and 87.17% (beamforming). These results surpass state-of-the-art methods in the sensor domain, which typically achieve accuracies ranging from 55.57% to 72.21%. The main contributions of this paper include:

- **Enhanced Classification Accuracy**: Demonstrating substantial improvements in classification accuracy by applying source localization techniques before CNN analysis, highlighting the potential for more precise and reliable BCIs in clinical applications.
- **Advanced Health Technology:** Presenting a comprehensive framework that combines advanced preprocessing, source localization, and deep learning techniques offering a robust solution for improved EE signal analysis in neurorehabilitation, thereby facilitating more effective and personalized therapies for stroke patients.

Research supported by National Science Foundation (NSF) CAREER Award HCC-2053498 and NSF IUCRC BRAIN CNS-2333292.

[1] Sina Makhdoomi Kaviri, and Ramana Vinjamuri are with Department of Computer Science and Engineering, UMBC, Baltimore, MD. rvinjam1@umbc.edu

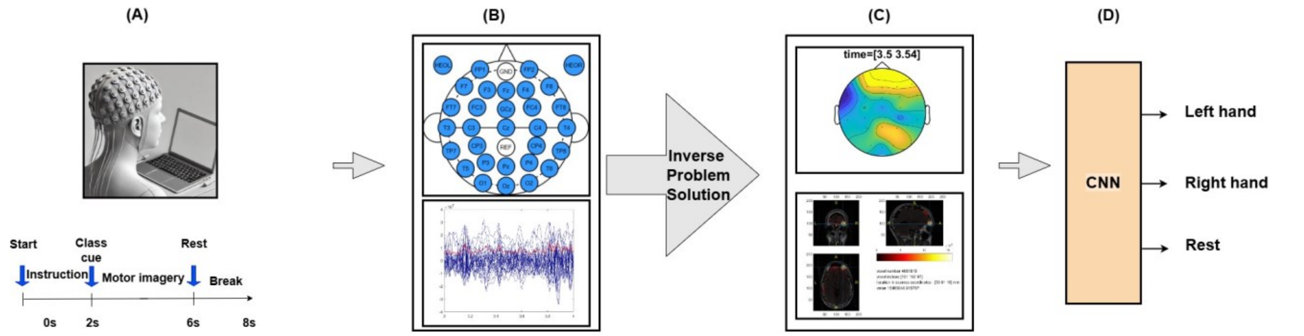

Fig. 1. Flowchart of the proposed framework. (A) Participant Setup: The trial timing includes subject preparation at 0s, a class cue at 2s, and a motor imagery phase until 6s, followed by a rest phase. The participant is equipped with a 32-channel EEG cap. (B) EEG Data Acquisition: Displays the 29 active electrode locations and 2 EOG electrodes according to the international 10-10 system, along with sample EEG signals recorded from these electrodes. The reference electrode is located at CPz and the grounding electrode at FPz. (C) Data Analysis: Topographical plots (topoplots) visualize the EEG data at defined time points. Source localization techniques such as MNE, dipole fitting, and beamforming identify cortical sources, with detailed source localization images highlighting the specific brain areas activated during the left-hand movement task. (D) Classification: The localized EEG data are fed into a ResNet-CNN for task classification, effectively distinguishing between left-hand movement, right-hand movement, and rest.

The rest of the paper is structured as follows: Section II outlines the Methodology, including system description, data acquisition, preprocessing, source localization techniques, and CNN architecture. Section III presents the Results, highlighting the classification performance achieved using source localization techniques compared to traditional sensor domain methods across various motor imagery tasks. Section IV provides the Conclusion, summarizing the key findings and discussing the potential impact on neurorehabilitation and future research directions.

II. Methods

A. System Description

This study investigates the neural correlates of motor imagery (MI) in acute stroke patients using EEG recordings from 50 patients at Xuanwu Hospital. Participants, seated 80 cm from a screen with an EEG cap, underwent three stages: instruction, motor imagery, and rest. Visual and audio cues guided them to imagine left- or right-hand movements. Figure 1 (B) shows the 29 EEG and 2 EOG electrodes used, with CPz as the reference and FPz as the ground. For analysis, one-second trials were selected to focus on motor imagery tasks, generating topographic plots of cortical activity. Figure 1 (C) presents topographic maps for the left-hand movement task, showing cortical activity and beta frequency (15-25 Hz). Advanced source localization techniques like Minimum Norm Estimation (MNE), dipole fitting, and beamforming were used. These methods provided accurate cortical localization, enhancing understanding of neural mechanisms during motor tasks. The topographic maps depict the distribution of neural activity, and the lower part of (C) shows detailed source localization images. These images highlight specific brain areas activated during the task, such as the premotor cortex and primary motor cortex, which are crucial for motor planning and execution. This precise localization offers a better understanding of the cortical dynamics involved in motor imagery. Figure 1 (D) illustrates the classification process using ResNet, which classified EEG data into left-hand movement, right-hand movement, and rest. This architecture achieves high classification accuracy, making it effective for EEG analysis and BCI applications.

B. Data Description and Methodology

The dataset includes EEG data from 50 acute stroke patients, aged 31 to 77 years, collected through motor imagery (MI) tasks. Each patient performed 40 trials of MI tasks, with each trial lasting 8 seconds [14]. The EEG system used a wireless multichannel acquisition setup with 29 EEG recording electrodes and 2 electrooculography (EOG) electrodes placed according to the international 10-10 system, with the reference electrode at CPz and the grounding electrode at FPz. Preprocessing of the data, performed using the EEGLAB toolbox in MATLAB (R2019b), involved baseline removal, time-domain filtering from 0.5 to 40 Hz, and segmentation into ‘trials × channels × time-samples’ format. The preprocessed data were then ready for source localization and further analysis. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board in their respective institution.

C. Source Localization and Inverse Problem

To enhance the spatial resolution of EEG signals in our study, we employed advanced source localization techniques including MNE, dipole fitting, and beamforming. MNE provides a distributed source model by estimating the current density across the entire cortex. Dipole fitting estimates the location and orientation of equivalent current dipoles representing the brain's activity. Beamforming enhances spatial resolution by focusing on specific regions of interest while suppressing activity from other areas [15][16][17]. These methods aim to reconstruct the cortical sources of EEG signals by solving the inverse problem using the New York Head (NYH) forward model [18].

$$x(t) = L \times q_r(t) \tag{1}$$

In this equation, $x(t)$ denotes the vector of scalp potentials at time t, L represents the lead field matrix, and $q_r(t)$ indicates the vector of current dipoles at cortical location r.

EEG signals were recorded using a 29-electrode high-density cap, covering the frontal, central, parietal, and temporal areas. The forward model was applied to these preprocessed signals to project the contributions of cortical

TABLE I. COMPARISON OF AVERAGE CLASSIFICATION PERFORMANCE OF VARIOUS METHODS. THE FIRST FOUR METHODS, CSP + LDA, FBCSP + SVM, TSLDA + DGFMDRM, AND TWFB + DGFMDRM, REPRESENT STATE-OF-THE-ART TECHNIQUES FOR EEG-BASED MOTOR IMAGERY CLASSIFICATION AS CITED IN [14]. THE LAST THREE ROWS PRESENT OUR PROPOSED SOURCE LOCALIZATION METHODS, DIPOLE FITTING, MNE, AND BEAMFORMING, DEMONSTRATING SIGNIFICANT IMPROVEMENTS IN CLASSIFICATION ACCURACY, KAPPA, PRECISION, AND SENSITIVITY.

METHOD	AVERAGE ACCURACY (%)	KAPPA	PRECISION	SENSITIVITY
CSP + LDA [14]	55.57	0.1114	0.5619	0.5707
FBCSP + SVM [14]	57.57	0.1514	0.5690	0.5668
TSLDA + DGFMDRM [14]	61.20	0.2240	0.6160	0.6111
TWFB + DGFMDRM [14]	72.21	0.4442	0.7543	0.7845
DIPOLE FITTING	**91.03**	**0.8655**	**0.9106**	**0.9103**
MNE	**89.07**	**0.8360**	**0.8916**	**0.8907**
BEAMFORMING	**87.17**	**0.8075**	**0.8734**	**0.8717**

sources onto the scalp sensors. The inverse problem was then solved using MNE, dipole fitting, and beamforming techniques, allowing us to precisely localize the cortical activity associated with various hand movements. This approach provided a more accurate understanding of the neural mechanisms underlying the EEG signals recorded from the participants.

D. *Residual Convolutional Neural Network Architecture*

The localized signals were subsequently processed using a customized ResNet, designed to classify the EEG data into three distinct motor tasks: left-hand movement, right-hand movement, and rest. The proposed CNN model begins with an input layer for EEG signal data shaped into images, followed by convolutional layers for feature extraction. The first convolutional layer uses 32 filters to capture low-level features, stabilized by batch normalization and reduced in dimension by max-pooling and dropout layers to prevent overfitting.

A notable feature of the model is the incorporation of inception modules and residual blocks. Inception modules process input through multiple convolutional layers with different kernel sizes, capturing various feature levels. Residual blocks address the vanishing gradient problem, allowing the training of deeper networks with shortcut connections. Additionally, an attention mechanism enhances the model's focus on informative features. The final fully connected dense layers integrate the learned features and output the classification results, with dropout ensuring robust learning. This architecture, combining inception modules, residual blocks, and attention mechanisms, achieves high classification accuracy, making it effective for EEG signal analysis and BCI applications.

III. RESULTS & DISCUSSION

In this study, we focused on the classification of MI EEG data, specifically distinguishing between left-hand, right-hand, and rest states. Previous studies have employed various classification methods such as CSP + LDA and FBCSP + SVM, achieving moderate accuracy. Additionally, methods based on Riemannian geometry, including MDRM, TSLDA, Fisher discriminant geodesic filtering followed by MDRM classification (DGFMDRM), and a decision fusion method combining TSLDA and DGFMDRM, have shown promising results. However, our approach outperforms by applying advanced source localization techniques to enhance classification performance.

Table I presents the average classification accuracy, kappa, precision, and sensitivity for the cited methods. These results provide a benchmark for evaluating our source localization techniques. In our study, we employed dipole fitting, MNE, and beamforming to precisely localize cortical activity associated with MI tasks. This approach allowed us to achieve significantly higher classification performance compared to traditional sensor domain methods. As shown in Table I, dipole fitting achieved an average accuracy of 91.03%, kappa of 0.8655, precision of 0.9106, and sensitivity of 0.9103. MNE and beamforming also demonstrated high classification performance with average accuracies of 89.07% and 87.17%, respectively. These results highlight the potential of source localization methods for enhancing BCI applications by improving classification accuracy. Figure 2 illustrates the confusion matrices for dipole fitting, MNE, and beamforming methods. These matrices provide a visual representation of the classification performance, indicating the number of correct and incorrect predictions for each class (left hand, right hand, and rest). The high values along the diagonal of each matrix indicate a strong agreement between the predicted and actual classes, further demonstrating the effectiveness of source localization techniques in MI classification tasks.

The inclusion of the rest state in our classification task, along with the application of advanced source localization methods, has significantly enhanced the accuracy and reliability of our MI classification. This work has substantial implications for the development of BCIs and neurorehabilitation technologies. By moving beyond traditional sensor domain methods and incorporating source localization techniques, we can achieve more precise and robust detection of neural activity patterns associated with motor imagery.

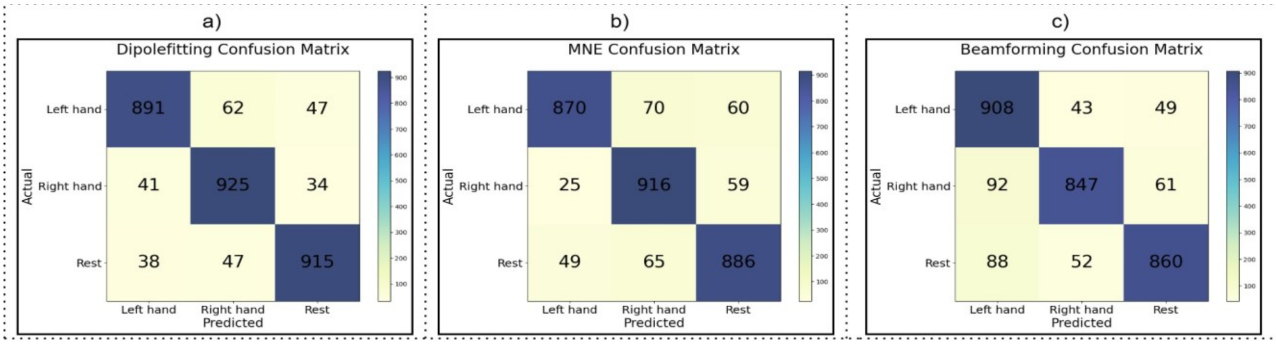

Fig. 2. Confusion matrices for (a) dipole fitting, (b) MNE, and (c) beamforming methods. The matrices show the number of correct and incorrect predictions for each class (left hand, right hand, and rest), highlighting the effectiveness of source localization techniques in improving classification accuracy for motor imagery tasks.

In the context of health technology, these findings can lead to improved BCI systems for stroke rehabilitation, facilitating more effective and personalized therapy by accurately interpreting patients' motor intentions. This can accelerate the recovery process by providing real-time feedback and adaptive training protocols based on the patients' neural activity. The enhanced classification accuracy also improves the reliability of assistive technologies, such as prosthetic control, allowing for more natural and intuitive interactions for users. Understanding the detailed neural mechanisms underlying MI through source localization can offer insights into brain function and plasticity, contributing to developing new treatments and interventions for various neurological conditions.

IV. Conclusion

In this study, we implemented advanced source localization techniques combined with a ResNet CNN architecture, significantly improving the classification of MI tasks in acute stroke patients. Our approach achieved classification accuracies of 91.03% with dipole fitting, 89.07% with MNE, and 87.17% with beamforming, outperforming traditional sensor domain methods, which range from 55.57% to 72.21%. These results highlight the advantage of transforming EEG data from the sensor domain to the source domain for more precise cortical activity representation. Our findings suggest a significant advancement in BCI technology for neurorehabilitation, offering precise detection of neural activity patterns related to motor imagery. This approach can lead to the development of personalized therapy plans, enhancing motor function recovery and quality of life for stroke patients. Future work should explore the practical integration of these techniques into BCI systems and assess their long-term effectiveness in rehabilitation.

— **Code availability** Custom code will be available on request to the corresponding author.

References

[1] AHA Statistical Update," heart disease and Stroke Statistics–2017 Update," Circulation, vol. 135, pp. e146-e603, 2017.

[2] E. Rho, H. Lee, Y. Lee, K.-D. Lee, J. Mun, M. Kim, D. Kim, H.-S. Park, and S. Jo," Multiple hand posture rehabilitation system using vision-based intention detection and soft-robotic glove," IEEE Transactions on Industrial Informatics, 2024.

[3] C. D. Takahashi, L. Der-Yeghiaian, V. Le, R. R. Motiwala, and S. C. Cramer," Robot-based hand motor therapy after stroke," Brain, vol. 131, no. 2, pp. 425–437, 2008.

[4] N. Takeuchi and S.-I. Izumi," Rehabilitation with poststroke motor recovery: a review with a focus on neural plasticity," Stroke Research and Treatment, vol. 2013, no. 1, p. 128641, 2013.

[5] M. Lebedev," Brain-machine interfaces: an overview," Translational Neuroscience, vol. 5, pp. 99–110, 2014.

[6] M. W. Slutzky," Brain-machine interfaces: powerful tools for clinical treatment and neuroscientific investigations," The Neuroscientist, vol. 25, no. 2, pp. 139–154, 2019.

[7] H. Zeng and A. Song," Optimizing single-trial EEG classification by stationary matrix logistic regression in brain–computer interface," IEEE Transactions on Neural Networks and Learning Systems, vol. 27, no. 11, pp. 2301-2313, 2015.

[8] A. Biasiucci, B. Franceschiello, and M. M. Murray," Electroencephalography," Curr Biol, vol. 29, no. 3, pp. R80–R85, Feb. 2019, doi: 10.1016/j.cub.2018.11.052.

[9] F. Lotte, M. Congedo, A. L´ecuyer, F. Lamarche, and B. Arnaldi," A review of classification algorithms for EEG-based brain–computer interfaces," Journal of Neural Engineering, vol. 4, no. 2, p. R1, 2007.

[10] E. L´opez-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday," Brain-machine interfaces for rehabilitation in stroke: a review," NeuroRehabilitation, vol. 43, no. 1, pp. 77–97, 2018.

[11] R. Mane, T. Chouhan, and C. Guan," BCI for stroke rehabilitation: motor and beyond," Journal of Neural Engineering, vol. 17, no. 4, p. 041001, 2020.

[12] A. Sohrabpour and B. He," Exploring the extent of source imaging: Recent advances in noninvasive electromagnetic brain imaging," Current Opinion in Biomedical Engineering, vol. 18, p. 100277, 2021.

[13] C. Ieracitano, N. Mammone, A. Hussain, and F. C. Morabito," A novel explainable machine learning approach for EEG-based brain- computer interface systems," Neural Computing and Applications, vol. 34, no. 14, pp. 11347–11360, 2022.

[14] H. Liu, P. Wei, H. Wang, X. Lv, W. Duan, M. Li, Y. Zhao, Q. Wang, X. Chen, G. Shi, et al.," An EEG motor imagery dataset for brain computer interface in acute stroke patients," Scientific Data, vol. 11, no. 1, p. 131, 2024.

[15] R. Grech, T. Cassar, J. Muscat, K. P. Camilleri, S. G. Fabri, M. Zervakis, P. Xanthopoulos, V. Sakkalis, and B. Vanrumste," Review on solving the inverse problem in EEG source analysis," Journal of Neuroengineering and Rehabilitation, vol. 5, pp. 1-33, 2008.

[16] S. Asadzadeh, T. Y. Rezaii, S. Beheshti, A. Delpak, and S. Meshgini " A systematic review of EEG source localization techniques and their applications on diagnosis of brain abnormalities," Journal of Neuroscience Methods, vol. 339, pp. 108740, 2020.

[17] M. Grosse-Wentrup, C. Liefhold, K. Gramann, and M. Buss," Beam-forming in noninvasive brain–computer interfaces," IEEE transactions on Biomedical Engineering, vol. 56, no. 4, pp. 1209-1219, 2009.

[18] S. Haufe, Y. Huang, and L. C. Parra," A highly detailed FEM volume conductor model based on the ICBM152 average head template for EEG source imaging and TCS targeting," in Conf. Proc. IEEE Eng. Med. Biol. Soc., vol. 2015, pp. 5744-5747, 2015.