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Decoding EEG for Spinal Cord Injury Rehabilitation: Integrating Source Localization with Residual CNN

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Abstract— **In this paper, we present a novel approach to classify motor tasks using electroencephalogram (EEG) data from participants with cervical spinal cord injury (SCI). Our method integrates advanced source localization techniques, including Minimum Norm Estimation (MNE), dipole fitting, and beamforming, with a customized Residual Convolutional Neural Network (ResNet-CNN) architecture. By leveraging these techniques, we enhance the spatial resolution and accuracy of EEG signal classification, which is crucial for developing assistive devices and neurorehabilitation strategies for individuals with SCI. We focus on six specific hand movements: pronation, supination, palmar grasp, lateral grasp, hand open, and a rest condition. The proposed approach achieved classification accuracies of 81.35% with Dipole fitting, 83.34% with MNE, and 83.36% with Beamforming, outperforming state-of-the-art methods in the sensor domain which reported accuracies ranging from 80.11% to 80.75%. Our ResNet-CNN model with source localization demonstrated F1-scores between 75.16% and 84.72%, highlighting the importance of accurate spatial mapping in EEG analysis. The findings of this study underscore the potential of integrating source localization with deep learning to improve brain-computer interface (BCI) applications for individuals with SCI. This approach offers a promising direction for enhancing rehabilitation and daily assistance technologies.**

I. Introduction

Electroencephalographic (EEG) signals are essential for brain-computer interfaces (BCIs), providing communication for individuals with neuromuscular disorders such as spinal cord injury (SCI) [1]. The complexity and noise of EEG signals necessitate advanced classifiers for single-trial classification [2], [3]. Convolutional neural networks (CNNs) have shown promise in classifying movement-related cortical potentials with high accuracy and minimal preprocessing [4]. Vision-based intention detection and soft-robotic gloves have enhanced activities of daily living (ADL) for stroke survivors by predicting hand postures [5]. Hybrid neuroprostheses combining functional electrical stimulation (FES) with motor imagery-based BCIs have restored upper extremity function in high SCI patients [6]. Riemannian geometry has improved decoding of multiclass Motor Imagery (MI) tasks for robotic arms and neural prosthetics [7]. Motor imagery-based BCIs controlling FES devices have proven effective for upper limb motor recovery [8]. BCIs using MRCP source features have successfully decoded complex grasping actions [9]. Recent studies have achieved online decoding of hand movements with average accuracies of 48% [10]. New models like TSCR-Net and TSCIR-Net have reached accuracies of up to 71.11% and 67.87% in classifying EEG signals from SCI patients[11].

In this study, we propose an innovative method for classifying motor tasks using EEG data from participants with cervical SCI, focusing on six specific hand movements: pronation, supination, palmar grasp, lateral grasp, hand open, and rest. Advancements in source localization techniques, such as MNE, dipole fitting, and beamforming, enhance our ability to pinpoint neural activity, aiding the development of targeted neurotherapies [12]. Therefore, we integrate advanced source localization techniques—MNE, dipole fitting, and beam-forming—with a CNN architecture to enhance classification accuracy by providing better spatial resolution and cortical activity representation. Our approach achieves classification accuracies of 81.35% (dipole fitting), 83.34% (MNE), and 83.36% (beamforming), surpassing state-of-the-art sensor domain methods (80.11% to 80.75%).

The main contributions of this paper include:

- **Integration of Advanced Techniques:** Utilizing advanced source localization methods (MNE, dipole fitting, beamforming) within a deep learning framework to significantly improve EEG signal classification accuracy. This work demonstrates the application of advanced EEG classification methods in health point care technology, particularly in developing assistive devices and neurorehabilitation strategies for SCI patients.
- **Comprehensive Evaluation and Performance:** A detailed evaluation showing that combining these techniques with deep learning enhances motor task classification, outperforming existing sensor domain methods, crucial for clinical applications in cervical SCI rehabilitation.

The paper is structured as follows: Section II details the Methodology, including system description, data acquisition, source localization techniques, and CNN architecture. Section III presents the Results, comparing classification performance with and without source localization. Section IV concludes with key findings and future research directions.

II. Methodology

A. System Description

Our system is designed to classify motor tasks using EEG data from participants with cervical SCI illustrated in Fig. 1.

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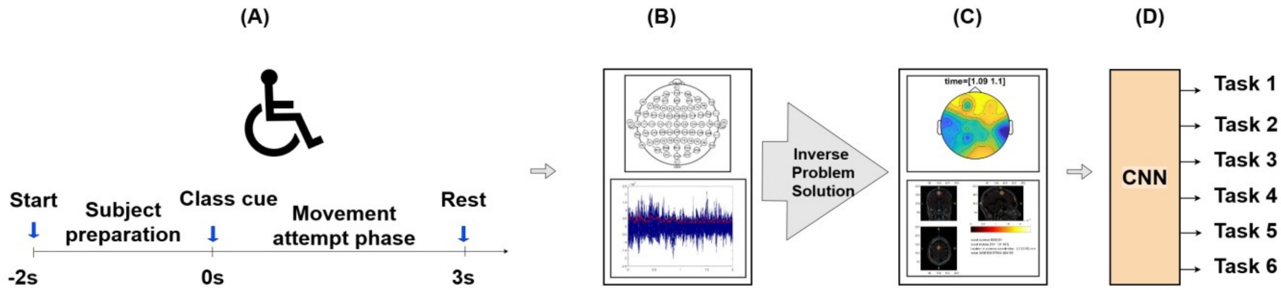

Fig. 1. Flowchart of the proposed framework. (A) Participant Setup: The trial includes preparation at -2s, a cue at 0s, and a movement phase until 3s. The participant with SCI wears a 61-channel EEG cap. (B) EEG Data Acquisition: Shows the 61 electrode locations and the recorded signals. (C) Data Analysis: Topographical plots visualize EEG data. Source localization techniques such as MNE, dipole fitting, and beamforming identify cortical sources. (D) Classification: Localized EEG data are fed into a Residual CNN for task classification, distinguishing six motor tasks.

Participants are equipped with a high-density 61-channel EEG cap to record brain activity. The trial includes subject preparation, a class cue, and a movement attempt phase. The recorded EEG signals undergo preprocessing, including the selection of relevant data and plotting topographical maps (topoplots) to visualize EEG activity at specific time points. Advanced source localization techniques such as MNE, dipole fitting, and beamforming are employed to accurately identify cortical sources of the EEG signals. These localized signals are then fed into a Residual CNN designed to classify the EEG data into six distinct motor tasks, demonstrating the system's capability to effectively differentiate between various motor activities.

B. Data Description and Methodology

The dataset includes EEG data from 10 participants with cervical SCI, aged 20 to 69 years, primarily male, collected through offline paradigms. Through this paradigm, ten participants (P01-P10) performed or attempted specific hand movements (pronation, supination, palmar grasp, lateral grasp, or hand open) while seated in front of a computer screen. In addition to the five movement classes, rest trials were considered as the “rest condition” for the sixth class. Each trial lasted 5 seconds, beginning with a fixation cross and beep, followed by a visual cue for the movement. Participants completed nine runs of 40 trials each, totaling 72 trials per class, plus additional runs for eye movement and rest conditions. EEG was recorded using 61 electrodes, supplemented by electrooculogram (EOG) measurements, with signals sampled at 256 Hz and filtered between 0.01 Hz and 100 Hz. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board in their respective institution [13].

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 [14][15][16]. These methods aim to reconstruct the cortical sources of EEG signals by solving the inverse problem using the New York Head (NYH) forward model [17].

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

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.

D. Convolutional Neural Network Architecture

The Customized ResNet-CNN model employed in this study features a combination of specialized layers to enhance the classification of EEG signals. The architecture begins with an initial convolutional layer that extracts low-level features using 32 filters, followed by a batch normalization layer, ReLU activation, and max pooling to reduce dimensionality. This is succeeded by Inception Modules, which apply multiple convolutional kernels of varying sizes to capture multi-scale features, and Residual Blocks, which include shortcut connections to mitigate the vanishing gradient problem.

Further into the architecture, the model incorporates an attention mechanism that includes a global average pooling layer and a convolutional layer, allowing the network to focus on salient features. This setup is followed by fully connected dense layers that culminate in the final classification layer. The model employs dropout layers to prevent overfitting and uses the Adam optimizer for training. The architecture is evaluated using stratified 5-fold cross-validation, ensuring a robust assessment of its classification performance across metrics such as accuracy, precision, recall, and F1-score. In our analysis, 5-fold cross-validation is separately performed for each subject to assess the model’s performance consistently across different data subsets for each individual. This approach allows us to account for within-subject variability and ensures robustness in model evaluation. The results reported in this study represent the best performance metrics obtained from the cross-validation process for each individual subject.

III. RESULTS & DISCUSSION

In this study, we evaluated the performance of a deep ResNet-CNN in classifying six distinct hand movement tasks (pronation, supination, palmar grasp, lateral grasp, hand open, and rest condition) for individuals with SCI. We utilized three different source localization methods: Dipole Fitting, MNE, and Beamforming, and compared their performance against state-of-the-art deep CNN models in the sensor domain as reported in reference [12].

1) **Classification with Dipole Fitting Source Localization:** Table I shows the performance metrics for the proposed deep CNN model using Dipole Fitting source localization. The results indicate that the accuracy ranges from 78.80% to 83.56%, with Subject 1 achieving the highest accuracy. Precision, recall, and F1-score metrics are also consistently high, demonstrating the reliability of the model in classifying the hand movement tasks using Dipole Fitting source localization.

TABLE I. PERFORMANCE OF THE PROPOSED DEEP CNN FOR DIPLOE FITTING SOURCE LOCALIZATION IN TERMS OF RECALL, PRECISION, F1-SCORE, AND ACCURACY FOR THE SCI REACH AND GRASP CLASSIFICATION TASKS.

SUBJECT	ACCURACY (%)	PRECISION (%)	RECALL (%)	F1-SCORE (%)
SUBJECT 1	83.56	83.86	83.56	83.58
SUBJECT 2	78.80	78.98	78.70	78.65
SUBJECT 3	82.85	83.32	82.85	82.91
SUBJECT 4	80.79	80.88	80.79	80.80
SUBJECT 5	82.87	83.03	82.87	82.88
SUBJECT 6	80.79	80.96	80.79	80.79
SUBJECT 7	79.40	79.53	79.40	79.40
SUBJECT 8	80.56	80.68	80.56	80.51
SUBJECT 9	83.33	83.50	83.33	83.36
SUBJECT 10	80.56	80.73	80.56	80.58

2) **Classification with MNE Source Localization:** Table II, presents the performance of the proposed deep CNN model using MNE source localization. The accuracy for this method ranges from 79.72% to 84.44%, with Subject 6 achieving the highest accuracy. The metrics indicate that MNE source localization provides a robust framework for classifying hand movements in SCI patients, with consistently high precision, recall, and F1-score values.

TABLE II. PERFORMANCE OF THE PROPOSED DEEP CNN FOR MNE SOURCE LOCALIZATION IN TERMS OF RECALL, PRECISION, F1-SCORE, AND ACCURACY FOR THE SCI REACH AND GRASP CLASSIFICATION TASKS.

SUBJECT	ACCURACY (%)	PRECISION (%)	RECALL (%)	F1-SCORE (%)
SUBJECT 1	79.72	81.78	79.72	79.86
SUBJECT 2	83.06	83.22	83.06	83.07
SUBJECT 3	83.89	84.64	83.89	84.02
SUBJECT 4	82.12	84.03	82.12	82.37
SUBJECT 5	84.28	85.50	85.28	85.27
SUBJECT 6	84.44	85.79	84.44	84.70
SUBJECT 7	84.00	85.19	84.00	85.01
SUBJECT 8	83.89	85.32	83.89	84.15
SUBJECT 9	84.43	84.47	84.43	84.45
SUBJECT 10	83.56	84.02	83.56	86.65

3) **Classification with Beamforming Source Localization:** The performance metrics for the proposed deep CNN model using Beamforming source localization summarized in Table III. The results show that the accuracy ranges from 81.25% to 84.72%, with Subject 10 achieving the highest accuracy. Precision, recall, and F1-score metrics are also high, indicating the effectiveness of Beamforming in accurately classifying the hand movement tasks.

TABLE III. PERFORMANCE OF THE PROPOSED DEEP CNN FOR BEAMFORMING SOURCE LOCALIZATION IN TERMS OF RECALL, PRECISION, F1-SCORE, AND ACCURACY FOR THE SCI REACH AND GRASP CLASSIFICATION TASKS.

SUBJECT	ACCURACY (%)	PRECISION (%)	RECALL (%)	F1-SCORE (%)
SUBJECT 1	83.56	84.15	83.56	83.66
SUBJECT 2	84.03	84.21	84.03	84.08
SUBJECT 3	81.25	81.67	81.25	81.34
SUBJECT 4	82.87	82.99	82.87	82.87
SUBJECT 5	82.18	82.24	82.18	82.18
SUBJECT 6	83.33	83.60	83.33	83.37
SUBJECT 7	84.26	84.48	84.26	84.31
SUBJECT 8	83.61	84.02	83.61	83.71
SUBJECT 9	83.80	84.20	83.80	83.85
SUBJECT 10	**84.72**	**84.83**	**84.72**	**84.72**

4) **Comparison and Discussion:** Table IV, compares the average classification accuracy obtained by the source localization methods with state-of-the-art recent methods. The proposed method using Beamforming source localization achieved the highest average accuracy of 83.36%, outperforming other methods such as Dipole Fitting (81.35%) and MNE (83.34%). In contrast, the state-of-the-art methods in the sensor domain, including the Modified EEGNet model, TSCR-Net, and TSCIR-Net, reported lower average accuracies ranging from 80.11% to 80.75%. Moreover, the confusion matrices for the SCI dataset (subject 10) using different source localization methods is shown in Figure 2.

TABLE IV. COMPARISON OF AVERAGE CLASSIFICATION ACCURACY OBTAINED BY THE SOURCE LOCALIZATION METHODS AND STATE-OF-THE-ART RECENT METHODS.

METHOD	ACCURACY (%)
MODIFIED EEGNET MODEL [12]	80.28
TSCR-NET [12]	80.11
TSCIR-NET [12]	80.75
DIPOLE FITTING	**81.35**
MNE	**83.34**
BEAMFORMING	**83.36**

The results show that incorporating source localization significantly enhances the classification performance of the deep CNN model for SCI reach and grasp tasks. Among the methods, Beamforming achieved the highest average accuracy, demonstrating its superiority in capturing cortical activity.

- **Improved Spatial Resolution**: Techniques like Beamforming, MNE, and Dipole Fitting enhance the spatial resolution of EEG signals, leading to better capture of neural activity and higher classification accuracy.

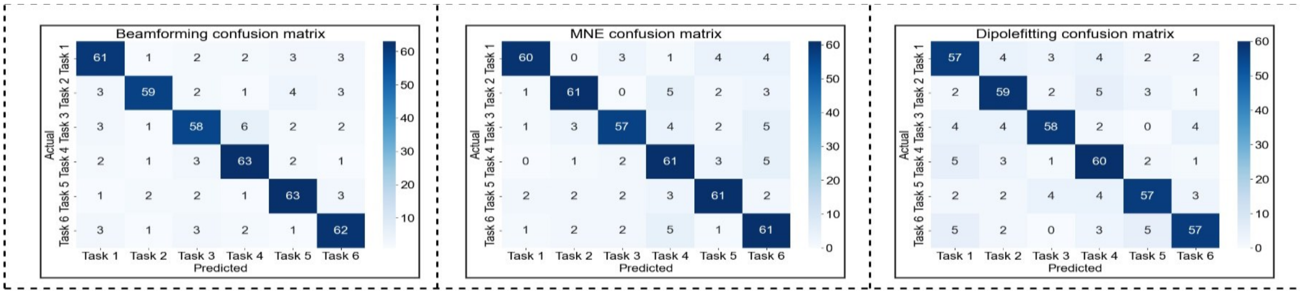

Fig. 2. Confusion matrices for the SCI dataset (subject 10) using different source localization methods. Confusion matrices for the SCI dataset using beamforming, MNE, and dipole fitting methods, displaying classification results for Task 1 (Pronation), Task 2 (Supination), Task 3 (Palmar Grasp), Task 4 (Lateral Grasp), Task 5 (Hand Open), and Task 6 (Rest). The matrices highlight the number of correctly and incorrectly classified instances for each task.

- **Enhanced Feature Representation:** Transforming data from the sensor to the source domain provides a precise representation of cortical activity, improving neural pattern capture.
- **Beamforming Superiority:** Beamforming achieved the highest average accuracy of 83.36%, outperforming methods in the sensor domain with average accuracies of 80.11% to 80.75%.

Overall, incorporating source localization techniques significantly enhances the CNN model's ability to classify hand movements in individuals with SCI, outperforming state-of-the-art methods. In EEG-based BCIs, even small accuracy improvements are crucial, especially in clinical applications where every percentage point can impact usability and effectiveness.

IV. Conclusion

This paper presents a novel framework for classifying motor tasks using EEG data from individuals with cervical SCI. By integrating advanced source localization techniques (MNE, dipole fitting, beamforming) with a customized Residual CNN, classification accuracy significantly improved. Beamforming achieved the highest accuracy at 83.36%, followed by MNE at 83.34%, and dipole fitting at 81.35%, surpassing state-of-the-art methods in the sensor domain (80.11%-80.75%). The CNN model with source localization attained F1-scores between 79.86% and 84.72%. This study highlights the potential of source localization and deep learning in enhancing BCI systems for SCI rehabilitation, suggesting future research to refine the CNN architecture and explore additional techniques for improved performance.

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