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A Study of Spatial Feature Conservation in Reduced Channels of EEG-fNIRS Based BCI Using Deep Learning †

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Abstract: The state of art Hybrid Brain Computer Interface (BCI) have shown improved classification of mental states either by combining different modalities or by choosing a combination of BCI activation tasks. Among these, the classification of motor imagery/executions tasks of contralateral and ipsilateral data of upper arm is found challenging due to its spatial adjacency and retention of these spatial features. The proposed work uses a Hybrid BCI dataset acquired using EEG and fNIRS for upper limb movement (Right hand/Left Hand, Right Arm/Left Arm). The electrode positioning is along the motor cortex and previous deep learning studies have shown that a good accuracy can be obtained without any channel selection. Hence the current study is to apply a combination of deep learning methods to the data which was halved into two without using channel selection algorithms. The model was evaluated for both set of channels using F1-score, Precision and Recall with an accuracy of 89%. This investigation shows that all the channels of the studied dataset contained inter-related spatial information. Also, the problem of long-term EEG/fNIRS recording can be addressed using this study, if the total number of channels can be used in two halves by switching the channels after the minimum efficient time of recording.

Keywords: EEG-fNIRS; multi-class; hybrid CNN; ipsilateral; contralateral

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1. Introduction

Brain-Computer Interface (BCI) uses a single modality to acquire brain signals, performed during a task, and convert them into signals that can be actuated on other devices. However, this method has become old with the current research on Hybrid–BCI which can overcome the limitations of traditional BCI by combining 2 acquisition modalities. Non-invasive methods like electroencephalogram gram (EEG), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI) were more prominently combined for signal acquisition. EEG acquires the electrical activity of the cortex, while fNIRS and fMRI capture the changes in the Blood Oxygen Level Dependant (BOLD) signal due to changes in the hemodynamic activity of the cortex during a mental activation task. Although fMRI is proven to provide better information, fNIRS attracts better attention than fMRI due to its portability and cost-efficiency [1]. EEG-fNIRS is a common form of Hybrid BCI since the former has a good temporal resolution while the latter has a good spatial resolution.

Motor tasks are among the common BCI activation signals, which can either be motor imagery signals or motor execution signals. A μ wave (8–13 Hz) is generated in the motor cortex of the brain during imagined or executed motor tasks [2]. These signals are primarily used to improve or supplement BCI applications. Hence, the choice of the task for obtaining motor imagery/execution signals is carefully chosen. Researchers have given a study on both two-class and multi-class classification of these signals. The common choice for two-class classification was Right/Left hand while for multi-class (besides right/left hand), the other choices were either foot/tongue or others like mental arithmetic [3,4]. From these, we can conclude that spatial activation of the brain signal is important for classification, besides the temporal characteristics, thereby only contralateral mental tasks were initially chosen. Nevertheless, some works have been carried out with both contralateral and ipsilateral activations, like right/left hand and right/left arm [5]. The accuracy attained by these works is low, proving the spatial co-occurrence of features. Another author has suggested a channel selection method for obtaining improved spatial features [6]. However, this may lead to loss of spatial features preserved in the rejected channels.

This calls for the utilization of deep learning models to obtain a complex feature extraction and classification method which can overlook the spatial co-occurrence of the features. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are found to have improved memory, sequential information and spatio-temporal information encoding [7]. In our previous work, we have shown the use of CNN to attain a good classification accuracy without omitting any channel [8]. This also shows that every channel has a spatial information that cannot be omitted. In addition to this, the current work investigates the use of a hybrid CNN which is a combination of CNN and Bidirectional long short-term memory (Bi-LSTM), on the performance of half the total number of channels to understand if the acquisition system can be operated on a switched mode.

2. Methodology

The dataset was obtained from CORE datasets, consisting of EEG and fNIRS data for the Right/Left arm and right/left hand from 15 healthy, male subjects within the age group of 23–50 years. fNIRS was obtained in two wavelengths, W1 = 760 nm (red) and W2 = 850 nm (infrared). The EEG consists of 21 electrodes of the 10–20 electrode system, namely F3, Fz, F4, Fc5, Fc1, Fc2, Fc6, T3, C3, C1, Cz, C2, C4, T4, Cp5, Cp1, Cp2, Cp6, P3, Pz and P4. The electrode position shows that the electrodes are distributed in the frontal (F) and parietal (P) parallel such that the signal acquisition is restricted to the motor cortex. The fNIRS was so paired that the same source can be used for multiple detectors. The list of 34 fNIRS channels are, Fc3A, Fc1A, Fc3, Fc3M, Fc1M, C3A, C1A, C3L, C3M, C1M, Cp3A, Cp1A, Cp3L, Cp3M, Cp1M, Cp3P, Cp1P, Fc2A, Fc4A, Fc2M, Fc4M, Fc4L, C2A, C4A, C2M, C4M, C4L, Cp2A, Cp4A, Cp2M, Cp4M, Cp4L, Cp2P, Cp4P–(A = Anterior, P = Posterior, M = Medial, L = Lateral).

The data was randomly split into two sets, maintaining a similar count on each hemisphere. Table 1 shows the list of channels for set 1 and set 2 data. The pre-processing and augmentation of data were done separately and simultaneously for both sets. The overall methodology is seen in Figure 1.

Table 1. The electrode channels chosen for splitting the dataset.

	EEG	fNIRS
SET 1	‘F3’ ‘F4’ ‘Fc1’ ‘Fc6’ ‘C3’ ‘Cz’ ‘T4’ ‘Cp1’ ‘Cp2’ ‘Pz’	‘Fc3A’ ‘Fc1A’ ‘Fc3M’ ‘C1A’ ‘C3L’ ‘Cp1A’ ‘Cp3M’ ‘Cp1P’ ‘Fc4A’ ‘Fc4M’ ‘C2A’ ‘C2M’ ‘C4L’ ‘Cp2A’ ‘Cp4A’ ‘Cp4M’ ‘Cp2P’
SET 2	‘Fz’ ‘Fc5’ ‘Fc2’ ‘T3’ ‘C1’ ‘C2’ ‘C4’ ‘Cp5’ ‘Cp6’ ‘P3’ ‘P4’	‘Fc3L’ ‘Fc1M’ ‘C3A’ ‘C3M’ ‘C1M’ ‘Cp3A’ ‘Cp3L’ ‘Cp1M’ ‘Cp3P’ ‘Fc2A’ ‘Fc2M’ ‘Fc4L’ ‘C4A’ ‘C4M’ ‘Cp2M’ ‘Cp4L’ ‘Cp4P’

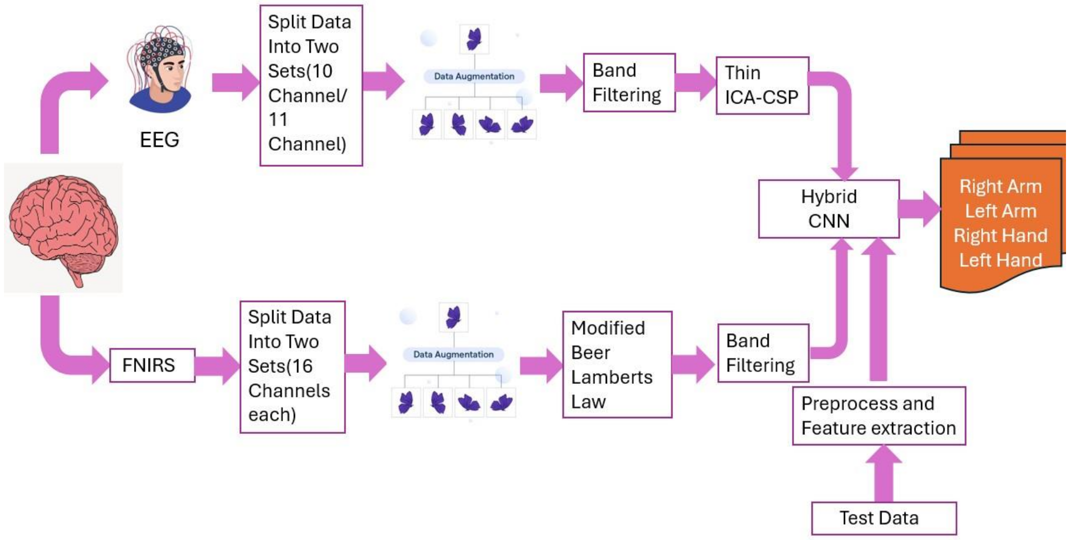

Figure 1. Block diagram of methodology.

The dataset needs to be augmented since deep learning models will require a large amount of data. The dataset consisted of 6 s rest and 6 s task for every trial and 25 such trials were performed for each class. The 6 s window of task performance, was augmented for a 3 s time window with an overlap of 1 s.

The EEG signals of both sets were band-filtered using an Infinite Impulse Response (IIR) filter with a frequency band of 8–30 Hz and were normalized. This frequency will contain both motor imagery (8–13 Hz) and motor execution (13–30 Hz) frequencies. This also omits the power line interference. The normalization was done by subtracting the data with its mean and dividing by the standard deviation. The fNIRS signals were also augmented similar to EEG signals. The wavelength information should be converted to changes in hemoglobin concentration, that is, oxygenated and deoxygenated hemoglobin (HbO and HbR). This is done by using Modified Beer-Lamberts Law (MBLL). Where, However, since these are slow varying signals, they are band filtered using an IIR filter, between, 0.01–0.1 Hz since this band is in-phase. Both EEG and fNIRS use a 5th order filter since this has a constant group delay.

The HbO and HbR data was considered as features for fNIRS signal [8]. However, the features for EEG data were obtained by combining Independent Component Analysis (ICA) and Common Spatial Pattern (CSP) using Thin–ICA CSP method [4]. CSP is known to give good results on two class problems [9]. Integrating this with ICA can improve spatial features which are better applicable for use in CNN. Since CSP is better on 2 class, the multi class problem is initially considered as a binary problem as Right/left and Arm/hand. The obtained filters are used as initialization matrix for ICA. The term Thin-ICA denotes that only second and higher order statistics are considered. Hence from thin-ICA two features for each class is extracted.

These features are combined and fed to the hybrid CNN model. In this study there are two ways in which the data is presented to the model. The first method was with a redundancy in the EEG data alone and the second method was without the redundancy. This was done to check if the amount of data was sufficient for producing a good classification accuracy. The combined features are first given to a three-layer CNN with 256, 128 and 64 filters. This was then presented to three layers of Bi-LSTM with two 128 and one 64 filters. Bi-LSTM was particularly chosen in this hybrid model due to its proven performance in EEG classification [10]. This is further given to 4 dense layers with 128 and 32 filters. Max pooling and elu activation was followed throughout the layers. Softmax activation was applied in the last dense layer. Adam optimiser was used along with 5-fold cross validation.

3. Results and Discussion

The dataset for the work was taken from https://figshare.com/search?q=EEG-fNIRS+hybrid+SMR+BCI+data. The data was split into two groups as seen in Table 1. EEG signals were band filtered and features were extracted using Thin-ICA algorithm. fNIRS on the other hand was also band filtered after converting the signals to optical densities. However, no other feature extractions methods were performed on HbO/HbR data, as they were considered as features itself. These were then combined using zero padding since the number of channels (column data) is less in EEG than that of fNIRS, i.e., 10 and 17 channels respectively. EEG data was zero-padded and masked before giving it to the model, so that the zeros would not affect the classification accuracy. The amount of training and validation was split at 60% and 40% initially which gave an accuracy of 73%. Hence 80% of the data was split for training and 20% of data was set for validation. A 5-fold cross validation was performed to ensure a good classification.

Two sets of input were passed through the model separately and the results of the same are shown in Figure 2, which shows an accuracy of 78%. The confusion matrix labels, 0,1,2,3 denotes the 4 classes, Right hand Left hand, Right arm and Left arm.

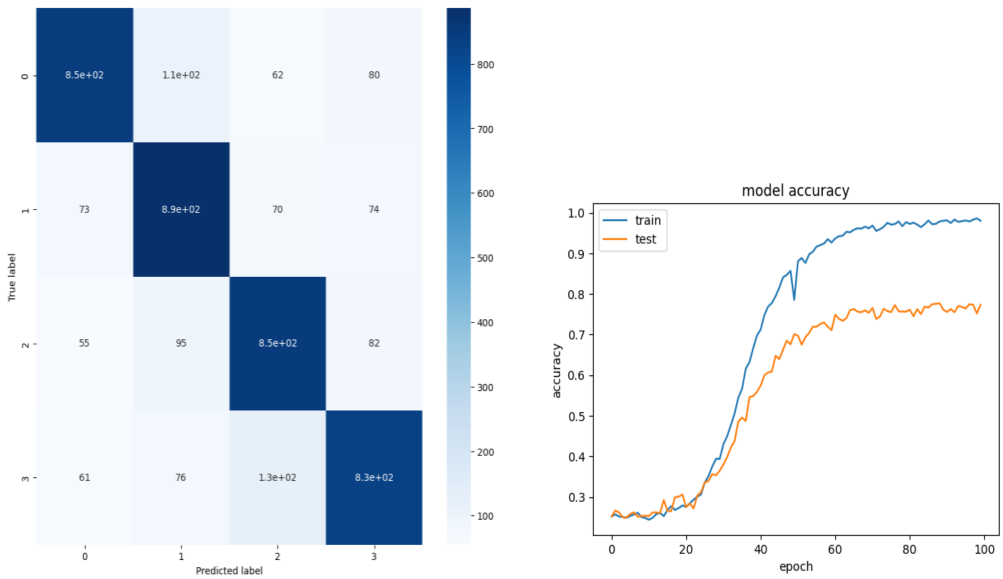

Figure 2. Confusion Matrix (0—Right hand, 1—Left hand, 2—Right arm, 3—Left arm) (**left**) and training curve (**right**) for set 1 data.

To improve accuracy, a redundancy was induced only in EEG data assuming data insufficiency. The classification results and their confusion matrix of redundant data of set 1 and 2 are shown in Figures 3 and 4 respectively. The performance metrices for both redundant and non-redundant data are shown in Table 2. It can be seen from Table 2, that a 10% increase in the performance was noted while redundancy was introduced. The previous studies that used the entire channel gave an accuracy of 99% [8]. However, the main aim of the study was to know if every channel contributes to the spatial features by halving the data to consist equal number of channels on left and right hemispheres.

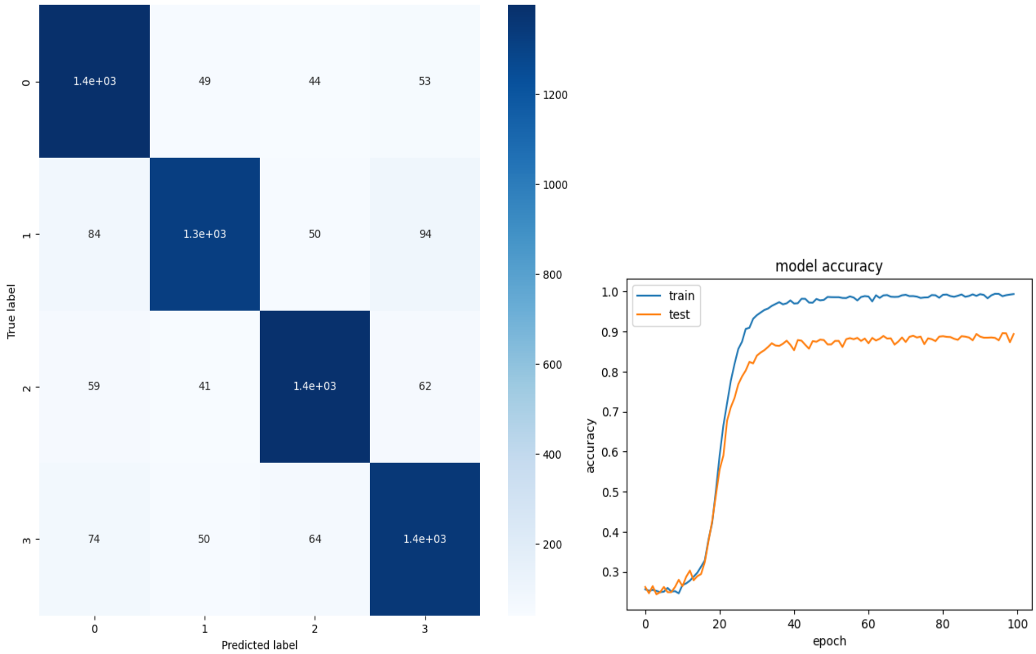

Figure 3. Confusion Matrix (0—Right hand, 1—Left hand, 2—Right arm, 3—Left arm) (**left**) and Accuracy (**right**) for redundant set 1 data.

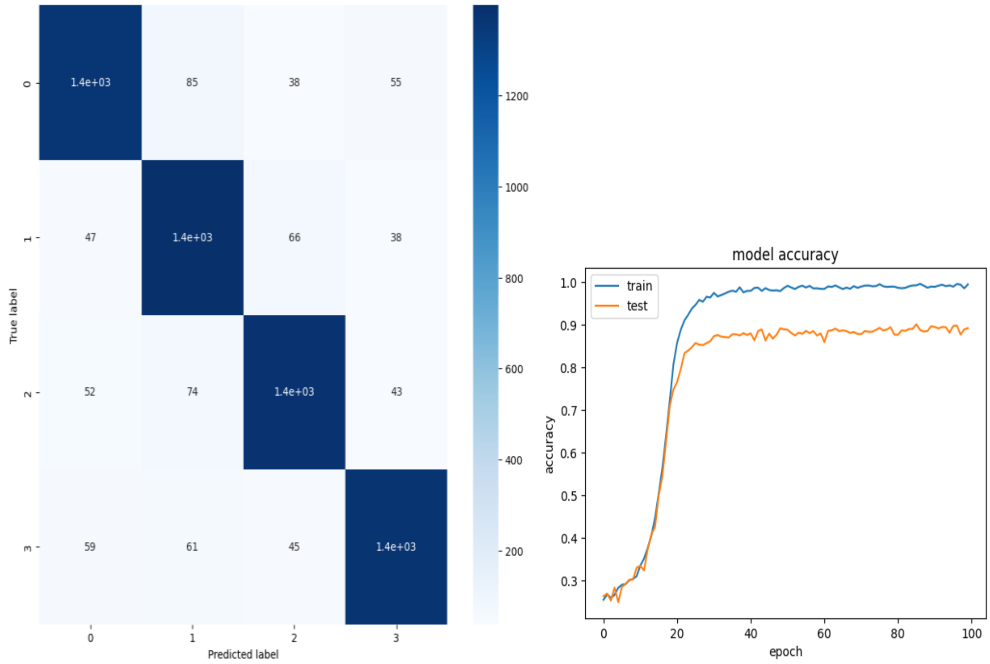

Figure 4. Confusion Matrix (0—Right hand, 1—Left hand, 2—Right arm, 3—Left arm) (**left**) and Accuracy (**right**) for redundant set 2 data.

Table 2. Performance metric for redundant and non-redundant data.

Metric	Non-redundant Data		Redundant Data	
	Set 1	Set 2	Set 1	Set 2
Accuracy	78	81	88	89
Precision	78	81	88	89
Recall	78	81	88	89
F1-Score	78	81	88	89

It is seen from Figures 4 and 5, that the model is underfitting which may be due to limited input data since in Thin–ICACSP algorithm the total number of independent components extracted were only 2 instead of 5 (due to reduced number of channels), so that singular value decomposition can be performed. The performance metrics although low compared to the whole dataset, however show an equal performance. This shows that each channel has contributed to the features and hence the acquisition system can be used in switched modes if needed with equal distribution of channels on the left and right hemispheres.

4. Conclusions

The objective of the current study was to investigate the spatial conservation of features in each channel. The data for four classes upper limb movement, namely Right/Left hand clenching and Right/Left arm raising, acquired from EEG/FNIRS system was used in this study. The classification was done using a CNN+BiLSTM model. This data was halved with each set containing equal channels on left and right hemispheres. Results show that a redundancy in EEG data could improve the classification. Although this method has shown a lower performance than using the entire data for classification, the performance metrics show that the two sets of data show an equal performance explaining that, each of the channel preserves the features (since they are arranged along the motor cortex). The limitation can be overcome with increasing the input size by augmentation methods or using models that can handle a smaller dataset. This will be further explored in future works with other models or hyperparameter tuning.

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References

1. Cui, X.; Bray, S.; Bryant, D.M.; Glover, G.H.; Reiss, A.L. A quantitative comparison of NIRS and fMRI across multiple cognitive tasks. *Neuroimage* **2011**, *54*, 2808–2821. https://doi.org/10.1016/j.neuroimage.2010.10.069.
2. Pfurtscheller, G.; da Silva, F.H.L. Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clin. Neurophysiol.* **1999**, *110*, 1842–1857. https://doi.org/10.1016/S1388-2457(99)00141-8.
3. Fazli, S.; Mehnert, J.; Steinbrink, J.; Curio, G.; Villringer, A.; Müller, K.-R.; Blankertz, B. Enhanced performance by a hybrid NIRS–EEG brain computer interface. *Neuroimage* **2012**, *59*, 519–529. https://doi.org/10.1016/j.neuroimage.2011.07.084.
4. Thiyam, D.B.; Cruces, S.; Rajkumar, E.R. ThinICA-CSP algorithm for discrimination of multiclass motor imagery movements. In Proceedings of the IEEE Region 10 Conference (TENCON)—Proceedings of the International Conference, Singapore, 22–25 November 2016.
5. Buccino, A.P.; Keles, H.O.; Omurtag, A. Hybrid EEG-fNIRS asynchronous brain-computer interface for multiple motor tasks. *PLoS ONE* **2016**, *11*, e0146610. https://doi.org/10.1371/journal.pone.0146610.
6. Hasan, M.A.H.; Khan, M.U.; Mishra, D. A Computationally Efficient Method for Hybrid EEG-fNIRS BCI Based on the Pearson Correlation. *Biomed. Res. Int.* **2020**, *2020*, 1838140. https://doi.org/10.1155/2020/1838140.
7. Shin, J.; von Lühmann, A.; Kim, D.-W.; Mehnert, J.; Hwang, H.-J.; Müller, K.-R. Simultaneous acquisition of EEG and NIRS during cognitive tasks for an open access dataset. *Sci. Data* **2018**, *5*, 180003. https://doi.org/10.1038/sdata.2018.3.
8. Shelishiyah, R.; Thiyam, D.B. Performance Analysis of Hybrid–BCI Signals Using CNN for Motor Movement Classification. *Trait. Du Signal* **2024**, *41*, 2143–2152. https://doi.org/10.18280/ts.410442.
9. Thiyam, D.; Cruces, S.; Olias, J.; Cichocki, A. Optimization of Alpha-Beta Log-Det Divergences and their Application in the Spatial Filtering of Two Class Motor Imagery Movements. *Entropy* **2017**, *19*, 89. https://doi.org/10.3390/e19030089.

10. Margaret, M.J.; Banu, N.M.M. Performance analysis of EEG based emotion recognition using deep learning models. *Brain-Comput. Interfaces* **2023**, *10*, 79–98. https://doi.org/10.1080/2326263X.2023.2206292.