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Transfer Learning with CNN Models for Brain-Machine Interfaces to command lower-limb exoskeletons: A Solution for Limited Data*

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***Abstract*—This study evaluates the performance of two convolutional neural networks (CNNs) in a brain-machine interface (BMI) based on motor imagery (MI) by using a small dataset collected from five participants wearing a lower-limb exoskeleton. To address the issue of limited data availability, transfer learning was employed by training models on EEG signals from other subjects and subsequently fine-tuning them to specific users. A combination of common spatial patterns (CSP) and linear discriminant analysis (LDA) was used as a benchmark for comparison. The study's primary aim is to examine the potential of CNNs and transfer learning in the development of an automatic neural classification system for a BMI based on MI to command a lower-limb exoskeleton that can be used by individuals without specialized training.**

***Clinical Relevance*— BMI can be used in rehabilitation for patients with motor impairment by using mental simulation of movement to activate robotic exoskeletons. This can promote neural plasticity and aid in recovery.**

I. Introduction

Electroencephalography (EEG) is a widely used neuroimaging technique for recording brain activity in brain-machine interfaces (BMI). Many EEG studies have employed analytical tools based on machine learning to uncover relevant information to classify different mental states [1]. These tools depend on data preprocessing and feature extraction that are typically designed by trained professionals with knowledge of neuroscience.

Data-driven approaches, specifically deep learning frameworks, have the potential to discover relevant features without the need for feature engineering. These methods have demonstrated promise in the development of automatic neural classification systems that can be used by individuals without specialized training [2]. Furthermore, deep learning networks have been successfully applied to transfer functions, enabling models to adapt from source domains to different target domains, this procedure is known as transfer learning [3].

BMI can serve as a rehabilitation tool for patients with motor impairment, such as by using the mental task of motor imagery (MI) - the imagination of a movement without physical execution - to trigger powered robotic exoskeletons. The receipt of motion-related feedback while performing MI can promote neural plasticity, potentially leading to recovery [4][11].

In terms of BMI based on MI, the state-of-the-art is divided between traditional machine learning approaches, which rely on spatial, temporal and/or spectral features, and deep learning frameworks. Traditional methods such as the combination of common spatial patterns (CSP) and linear discriminant analysis (LDA) or support vector machines (SVM) have shown the highest results [5]. In contrast, deep learning frameworks utilizing convolutional neural networks (CNNs) have been proven to be the most efficient. These frameworks typically use raw EEG or filtered and/or normalized signals as input data [2].

The primary aim of this study is to evaluate the performance of two convolutional neural networks (CNN) using a small dataset collected from five participants. The EEG data was obtained while the participants performed MI of gait wearing a lower-limb exoskeleton since the final goal is to control the device by using the BMI. To tackle the issue of limited data availability, transfer learning was employed [12]. This involved training models on EEG signals from other subjects, and subsequently fine-tuning them to specific users. In addition, a combination of CSP and LDA was used as a benchmark for comparison.

II. Material and methods

A. Subjects

In this study, five healthy subjects participated (mean age: 24.4±2.07). These subjects did no report movement

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impairments or known diseases and had no prior experience with BMI. All participants were informed about the experiments and provided written informed consent in accordance with the Helsinki Declaration. The study was approved by the Responsible Research Office of Miguel Hernández University of Elche (Spain).

B. Equipment

EEG signals were recorded using the Starstim R32 device (Neuroelectrics, Spain) at a sampling rate of 500 Hz. Ground and reference electrodes were placed on the right earlobe. 27 electrodes were positioned over a cap, following the 10-10 international system for electrode placement, including F3, FZ, F4, FC5, FC3, FC1, FCZ, FC2, FC4, FC6, C5, C3, C1, CZ, C2, C4, C6, CP5, CP3, CP1, CPZ, CP2, CP4, CP6, P3, PZ, and P4.

All participants wore the H3 exoskeleton (Technaid, Spain), a powered hip-knee-ankle exoskeleton designed to emulate human walking. They also used crutches for walking stability, and were assisted by a technician holding the exoskeleton from the back to prevent any risk of loss of balance. H3 was controlled with commands sent from the computer via Bluetooth. Fig. 1 shows the experimental setup.

Figure 1. Experimental setup. The subject is depicted standing still while wearing the H3 exoskeleton with crutches and a Starstim R32 cap that records the EEG signal.

C. Experimental protocol

Each subject participated in five experimental sessions. During each session, they wore the exoskeleton and performed 22 trials. Each trial consisted of a sequence of mental tasks, as illustrated in Fig. 2. The status of the exoskeleton was varied among trials by a researcher. During half of the trials the exoskeleton was walking, and during the other half it remained standing still. This design enabled subjects to train four different strategies that can be used to define the classes used in the classification models designed for closed-loop control: 1) Being relaxed while remaining stationary, which could be used to keep the exoskeleton stationary; 2) Performing MI while remaining stationary, which could be used to send a MOTION command to the exoskeleton; 3) Performing MI while walking, which could be used to maintain the gait of the exoskeleton; and 4) Being relaxed while walking, which could be used to send a STOP command.

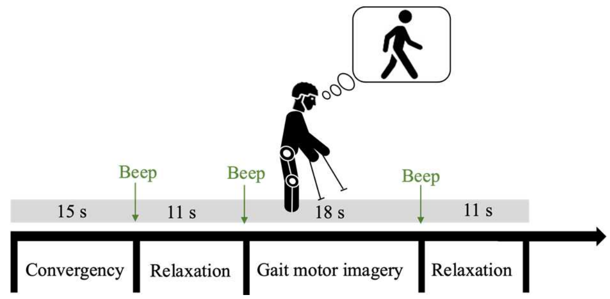

Figure 2. Sequence of tasks for each trial. Participants were not required to perform any mental task during the initial 15 seconds, as this time was allocated for the estimation of parameters for all preprocessing algorithms. Auditory cues in the form of beeps instructed participants when to commence each mental task, with the subsequent 4 seconds of signal being disregarded for subsequent analysis to prevent the presence in the classes of any related evoked potentials to the cues.

D. Preprocessing

Signals were first downsampled to a rate of 200 Hz. Then, a Notch filter was applied at 50 Hz to eliminate power line noise. Based on previous studies that have employed deep learning frameworks for identifying MI, three additional preprocessing steps were implemented [2]. These procedures were performed in real time, with signals split into 2-second segments (epochs) and with a 0.5-second overlap between each segment, allowing for individual analysis of each epoch. These steps included:

1. Common Average Reference (CAR), which involved averaging measures from all electrodes and subtracting this value from each electrode at each time point. This helped to reduce noise that is common to all electrodes, creating an electrically neutral reference [6].

2. Butterworth band-pass filters were applied at two different frequency bands: 8-40 Hz, which focused solely on the alpha and beta bands associated with MI; and 1-100 Hz, which broadened the spectrum. Filters were implemented by state variables to allow its use sample by sample, avoiding any over oscillation in the processing epochs.

3. Normalization of the signal using the maximum visual threshold method, which involved estimating the maximum amplitude of all electrodes at each epoch, averaging this value

with previous epochs, and using it to normalize the signals [7].

E. Neural network frameworks

This study utilized two CNNs that have been specifically designed to work with EEG data: EEGNet [8], and DeepConvNet [9]. Table I provides the number of parameters for each framework and how many need to be adjusted. The DeepConvNet and EEGNet architectures both utilize 1D convolutional filters to extract features in the spatial and temporal domains. By using pooling layers to downsample the data, a variety of frequency ranges are taken into account. However, the DeepConvNet is more intricate in design and requires a longer training period compared to the EEGNet.

To achieve the best results for our dataset, a variety of hyperparameters were explored as seen in Table II. When it came to batch size, only values that were a power of 2 were considered. Dropout and learning rate values were selected based on the recommendations of the developers of the frameworks. Finally, the number of epochs was not increased beyond 80 as overfitting was observed.

TABLE I. PARAMETERS OF THE NEURAL FRAMEWORKS

	Total parameters	Trainable parameters	Non-trainable parameters
EEGNet	2130	2050	80
DeepConvNet	236177	235427	750

TABLE II. CHOICE OF HYPERPARAMTERS

Batch size	[32, 64, 128, 256]
Dropout rate	[0.4, 0.5]
Learning rate	[0.0001, 0.001]
Number epochs	[20, 80]

F. Benchmark

The signals were preprocessed slightly differently for the benchmark approach compared to neural network models. To start, they were downsampled to a frequency of 200 Hz and a Notch filter was applied at 50 Hz, in line with the other methods. Then, four state variables based band-pass filters were applied at frequencies of 5-10 Hz, 10-15 Hz, 15-20 Hz, and 20-25 Hz, as previously established in our prior research [7]. The subsequent step entailed calculating CSP for each frequency band. The goal of CSP is to compute spatial filters that linearly transform the signals from each channel, in order to maximize the differences between two mental tasks, in this case, between motor imagery of gait and blank minded state. The signals from 27 electrodes were filtered, and only the 8 most discriminant were selected as features. The log-variance was computed for all of them, resulting in a vector of 32 features, (8 x 4 frequency bands). LDA was then trained with these features to distinguish between two classes: MI and blank minded state.

III. RESULTS

In training neural networks, three different approaches were assessed:

1. Subject-independent training, which involved training the model with data from all subjects except one, and then testing it with all trials of the remaining subject.

2. Subject-dependent training, which involved training the model with data from all subjects except one and then fine-tuning it with the remaining subject. This approach consisted of one independent leave-one-out cross-validation analysis per session of that subject, with the model pre-trained on data from other subjects and re-trained on each step of cross-validation.

3. Hybrid, which closely resembled the previous method, but with the distinction that when re-training the model with data from the subject, only the weights of the last three layers were updated, while the remainder of the model remained as it had been trained through subject-independent training.

Two tests were conducted, one for stationary trials (static data) and one for walking trials (motion data). The best results for EEGNet were found with a batch size of 128, a dropout rate of 0.5, a learning rate of 0.0001, and 80 epochs for static data; and a batch size of 32, a dropout rate of 0.4, a learning rate of 0.001, and 80 epochs for motion data. The optimal parameters for DeepConvNet were different, with a batch size of 256, a dropout rate of 0.4, a learning rate of 0.001, and 20 epochs for static data; and a batch size of 128, a dropout rate of 0.4, a learning rate of 0.0001, and 80 epochs for motion data.

Table III compares the accuracy of the two neural frameworks and the three training approaches to the benchmark model trained on a subject-dependent basis. The accuracy was measured as the percentage of correctly classified epochs, and it is presented as the average and standard deviation among sessions.

IV. DISCUSSION

In general, both EEGNet and DeepConvNet frameworks demonstrated higher accuracy when they were re-trained with data from individual subjects, resulting in an increase of accuracy between 9 and 12% compared to subject-independent training.

When analyzing static data, EEGNet and DeepConvNet performed better when all layers were fine-tuned for a specific subject, as opposed to only fine-tuning the last three layers. The performance of the model varied greatly among subjects, indicating that the model works better when adapted to a specific individual. EEGNet trained in a subject-dependent manner yielded the best results, followed by the benchmark model and closely by DeepConvnet trained in a subject-dependent manner too. Notably, for subject S3, who had the lowest results with the benchmark model at 59.48%, EEGNet trained in a subject-independent manner was able to achieve the same level of accuracy. This suggests that the model benefits from having information from other participants and it may be a potential solution for dealing with BMI illiteracy [10], allowing all users to effectively use a BMI.

As with static data, the trend for motion data was similar. The benchmark model exhibited a superior level of accuracy compared to both networks when they were trained in a subject-independent manner. However, when the networks were fine-tuned for each individual subject, regardless of whether all layers of the last three were fine-tuned, their effectiveness was comparable or even superior to the

TABLE III. ACCURACY OF THE DIFFERENT METHODOLOGIE AVERAGED BY SUBJECT (S1-S5)

STATIC DATA		S1	S2	S3	S4	S5	Avg.
Benchmark		68.9±4.96	82.92±10.56	59.48±2.7	83.99±7.34	80.45±3.35	75.15±10.62
EEGNet	**Subject-independent training**	56.95±3.59	65.49±7.26	59.84±1.48	65.91±8.55	45.94±12.86	58.82±8.14
	Subject-dependent training	75.68±6.98	86.75±10.24	64.61±3.23	88.25±2.94	82.66±3.87	79.59±9.69*
	Hybrid	63.34±3.94	76.82±5.98	59.25±1.98	78.34±7.04	71.46±6.25	69.84±8.34
DeepConvNet	**Subject-independent training**	52.66±2.61	58.08±4.59	51.1±1.25	63.08±10.88	47.86±7.52	54.56±6.03
	Subject-dependent training	71.07±3.4	86.04±8.97	52.11±1.98	86.04±4.67	79.19±4.08	74.89±14.15
	Hybrid	55.91±3.83	73.21±6.54	50.19±1.24	74.35±6.74	65.16±8.91	63.77±10.6

MOTION DATA		S1	S2	S3	S4	S5	Avg.
Benchmark		57.34±2.49	68.15±5.64	60.75±3.37	58.44±4.27	75.68±9.8	64.07±7.74
EEGNet	**Subject-independent training**	52.34±3.22	48.25±4.07	49.68±3.15	51.01±1.73	54.81±7.63	51.21±2.52
	Subject-dependent training	60.91±7.88	74.16±5.59	66.56±9.14	63.05±6.1	81.3±8.34	69.84±8.34*
	Hybrid	54.71±2.34	61.49±8.74	57.37±4.64	51.14±4.61	69.97±7.07	63.16±9.71
DeepConvNet	**Subject-independent training**	52.79±3.44	47.47±5.27	50.29±0.35	51.01±0.82	51.92±9.06	50.69±2.03
	Subject-dependent training	57.66±4.58	67.44±12.32	61.04±12.08	58.38±4.88	74.58±6.77	63.77±10.6
	Hybrid	51.82±3.72	60.36±9.18	53.41±2.11	51.49±2.69	62.31±5.75	69.66±9.12

[a]There is an asterisk next to the approach that reached the highest accuracy for static and motion data.

benchmark model. However, DeepConvNet showed higher results when only the last three layers were re-trained which means the data of an individual subject was not enough to adapt all layer weights. Lastly, CNN with transfer learning was found to outperform the state-of-the-art machine learning approach.

V. CONCLUSION

In conclusion, this study examined the application of transfer learning in the development of a brain-machine interfaces based on motor imagery that utilizes information from all participants. Two CNN frameworks were evaluated and compared against a conventional machine learning approach that involved the combination of CSP and LDA. The results demonstrated that the performance of all participants was enhanced with this new approach.

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