Online Adaptive CNN: a Session-to-session Transfer Learning Approach for Non-stationary EEG

Shuailei Zhang
School of Instrumentation and Optoelectronic Engineering,
Beihang University, Beijing, China
Institute for Infocomm Research,
Agency for Science, Technology and Research, Singapore
School of Computer Science and Engineering,
Nanyang Technological University, Singapore
zhangshuailei@buaa.edu.cn

Dezhi Zheng
School of Instrumentation and Optoelectronic Engineering,
Research Institute for Frontier Science,
Beihang University, Beijing, China
Key Laboratory of Precision Opto-mechatronics Technology,
Ministry of Education, China
zhengdezhi@buaa.edu.cn

Ning Tang
Division of Rehabilitation Medicine,
Department of Medicine, National University Hospital,
Singapore
ning_tang@nuhs.edu.sg

Effie Chew
Division of Rehabilitation Medicine,
Department of Medicine, National University Hospital, Singapore
Yong Loo Lin School of Medicine,
National University of Singapore, Singapore
effie_chew@nuhs.edu.sg

Rosary Yuting Lim
Institute for Infocomm Research,
Agency for Science, Technology and Research, Singapore
lim_yuting_rosary@i2r.a-star.edu.sg

Kai Keng Ang
Institute for Infocomm Research,
Agency for Science, Technology and Research, Singapore
School of Computer Science and Engineering
Nanyang Technological University, Singapore
kkang@i2r.a-star.edu.sg

Cuntai Guan
School of Computer Science and Engineering,
Nanyang Technological University, Singapore
Singapore
ctguan@ntu.edu.sg

***Abstract*—The convolutional neural network (CNN) automatically learns EEG representations in higher and nonlinear space via backpropagation and outputs the predictions in an end-to-end manner. Owing to these advantages, CNN has been used to decode electroencephalogram (EEG) and drive brain computer interface (BCI). However, its applications in BCI-assisted post-stroke neurorehabilitation remain limited for it is unable to address the inherent session-to-session non-stationarity in the EEG between the initial calibration session and subsequent online sessions. In this paper, we present a simple but effective online adaptive CNN (aCNN) to address the non-stationarity in multi-session EEG by progressively updating the subject-specific model. The performance of the proposed aCNN is evaluated on two neurorehabilitation datasets with a large population of post-stroke patients (33 patients with a total of 358 EEG sessions). Results indicate that, our proposed aCNN reaches at least as good a performance as the widely used online adaptive Filter Bank Common Spatial Patterns (aFBCSP) and with significantly higher accuracies than that for DeepConv and offline FBCSP algorithms. Our results support, for the first time, the use of a CNN-based adaptive learning method to decode non-stationary EEG signals for BCI-assisted post-stroke rehabilitation.**

***Index Terms*—online adaptive CNN, brain computer interface, non-stationarity, neurorehabilitation**

This research was funded by National Natural Science Foundation of China (Grant No. 61873021; 62088101), the China Scholarship Council (Grant No. 202006020219), the special fund for basic scientific research in central colleges and universities-Youth talent support program of Beihang University and the Key Laboratory of Precision Opto-mechatronics Technology (Beihang University), Ministry of Education, China. This work is part of project (No.: EC-2020-040), "Next-Generation Brain-Computer-Brain Platform – A Holistic Solution for the Restoration and Enhancement of Brain Functions (NOURISH)" and is supported by the A*STAR RIE2020 AME Programmatic Fund, Singapore (No. A20G8b0102). The two stroke rehabilitation datasets used in this work are acknowledged as: 1. DSRB Ref A/06/286 – "Brain Computer Interface (BCI) Based Robotic Rehabilitation for Stroke", and 2. DSRB Ref D/10/072 – "Combined transcranial direct current stimulation and motor imagery-based robotic arm training for stroke rehabilitation – a feasibility study".

I. Introduction

Stroke is ranked as the second leading cause of death worldwide - with up to 50% of survivors left chronically disabled [1], [2]. Recent developments in brain–computer interfaces (BCI) provide a promising approach for post-stroke neurorehabilitation. A BCI setup provides a platform which connects the brain to external computers, enabling the transmission of information directly to the computer [3], [4]. Many BCI systems leverage EEG signals to study brain function due to the high temporal resolution of the signal. In addition, the hardware used to record those signals are relatively more portable, of lower costs, non-invasive and easy to use [5]. Motor imagery is a mental process in which an individual rehearses or simulates a given action in their mind without actually performing it. It is a widely-used approach in neurorehabilitation. When performing MI tasks, a decrease or increase of power in specific frequency bands in the patients' motor cortex can be observed. These phenomena are referred to as event-related desynchronization (ERD) and event-related synchronization (ERS) respectively [6]. Although patients usually lose partial control of their body after stroke, the ERD and/or ERS components can still be detected in their EEG readouts during MI. When undergoing BCI-assisted neurorehabilitation involving MI, the patients are asked to perform a specific MI task while the associated BCI system decodes their output EEG signal. The decoded output EEG subsequently serves as commands to control an external device to move the corresponding limb. Although motor imagery-based BCI (MI-BCI) has been repeatedly proven to have significant potential for post-stroke rehabilitation [6], this technology is still hampered by its low decoding accuracy in multi-session EEG studies.

Common spatial pattern (CSP) is a typical feature extraction method for MI decoding [7] and has demonstrated impressive performance. This method separates an EEG signal into additive subcomponents with maximum differences in the variance between two different frequency bands to select components with specific frequency patterns. Filter bank common spatial pattern (FBCSP) is a modification of CSP and was first introduced by our group [8]. In this study, MI signals were first bandpass-filtered by a filter bank. Then, the CSP filters were optimized for each band. Subsequently, different feature selection algorithms, such as the mutual information-based best individual feature algorithm, would select the most relevant features and feed them to the classifiers. FBCSP has been the winning method in many EEG-decoding competitions [9], [10] and has been regarded as the de facto standard for motor decoding from EEG recordings [11].

Recently, several studies have shown that deep learning methods have a promising future in BCI. Owing to their end-to-end strategies and highly nonlinear structures, these methods can learn and discriminate rich features automatically. In a representative study, Schirrmeister et al. [11] boosted MI signal classification accuracy by proposing a convolutional neural network (CNN)-based method. Sakhavi et al. [12] developed an MI data classification framework by introducing a new temporal data representation and utilizing the CNN architecture for classification. The network performance was investigated using the BCI competition IV dataset 2a. Wang et al. [13] proposed a long short-term memory (LSTM) network-based classification framework. Kumar et al. [14] proposed a new predictor, OPTICAL, that combined CSP and LSTM networks to improve MI EEG signal classifications. Instead of directly utilizing LSTM for classification, they used the regression-based output from LSTM network as one of the classification features.

Although the above-mentioned algorithms have their individual advantages, their common limitation is they have yet to address the non-stationarity inherent in EEG between the initial calibration session and subsequent online rehabilitation sessions. EEG non-stationarity can be caused by: 1) Variability of subjects' mental state over different sessions; 2) Instrumental artifacts such as fluctuations of electrodes impedance; 3) Physiological artifacts such as electrooculogram or electromyogram. Non-stationary EEG signal causes the initial model, which is trained on calibration data, to be no longer optimal for follow-up neurorehabilitation analyses and operations.

Therefore, in this paper, we proposed an online adaptive CNN (aCNN) to address the inherent problem of non-stationarity in EEG. This method continuously updates a subject-specific model by retraining the model using data from previous evaluation sessions. The proposed aCNN is evaluated on two datasets acquired from a large population of post-stroke patients with a total of 358 sessions.

II. Method

A. Data Preparation

The objective of data preparation is to exclude noise and bad trials from acquired EEG signals and perform normalization. The recorded EEG signal can be extremely weak and contains noise that may bias the analysis to result in skewed conclusions [15], [16]. Hence, preprocessing is utilized to filter noise and normalize signals. First, a zero-phase Chebyshev Type II filter with passband of 4 to 30 Hz is employed to remove unwanted frequency noise. Then we normalize the signal via electrode-wise exponential moving average method [11].

B. Learning Temporal-spatial Representations

The main objective of the temporal-spectral feature learning is to learn discriminative features and decode them in an end-to-end manner. In this phase, CNN is employed as it is well-suited to extract features from two-dimensional signals. Our CNN is designed with several layers as described below.

Input layer: The input is an EEG trial with size of $D \times T$, with D denoting the number of EEG channels and T denoting the number of discrete time points in a selected time window within this trial.

Temporal convolutional layer: This layer aims to learn temporal representations from EEG. It consists of 25 convolution kernels with size of 1×5. The activation function is selected as the rectified linear unit (ReLU), which is defined as:

$$ReLU(x) = (x)^{+} = max(0, x) \quad (1)$$

The main reason of using the ReLU function is that it bypasses the vanishing gradient problem and thereby allows a deep

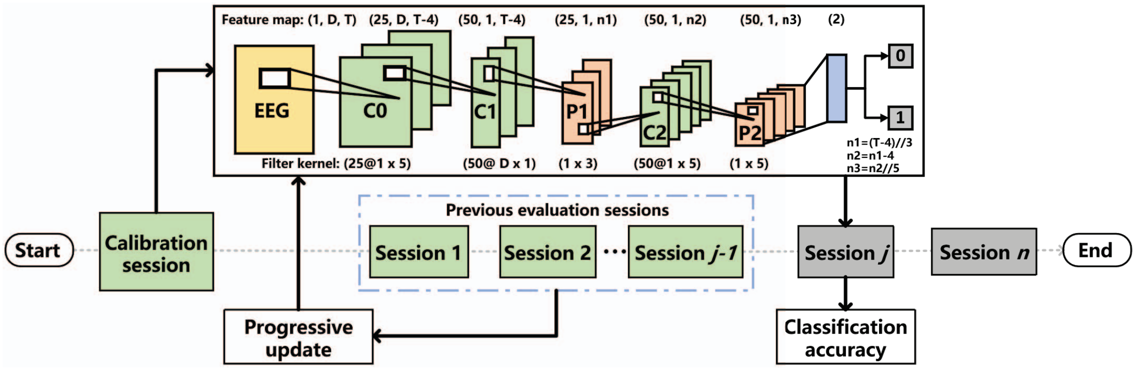

Fig. 1. A schematic diagram of the proposed aCNN framework. This framework includes three main phases: data preparation, temporal-spectral feature learning and online adaptive training. In the first phase, the multi-channel EEG signal is preprocessed to exclude noise. In the second phase, the convolutional structure learns temporal-spectral representations from EEG. In the final phase, an online adaptive training strategy is employed to address non-stationarity in EEG

neural network. Meanwhile, ReLU is easy to optimize and is computationally efficient.

Spatial convolutional layer: This layer aims to increase the local perception of spatial representations. It consists of 50 convolution kernels the size of $D \times 1$. ReLU is selected as the activation function.

The max-pooling layer: This layer aims to reduce the number of parameters and enhance the generalization capability of the proposed model. We used a max-pooling filter the size of 1×3.

Batch normalization layer: This layer aims to standardize the inputs and ensure high learning rates of the model; thereby increasing the training speed and reducing the initial weight sensitivity.

Dropout layer: This layer randomly ignores or "drops out" some parameters of a certain proportion. Here we set the dropout proportion as 0.5.

The following layers include one convolutional layer, one max-pooling layer, one batch normalization layer and one dropout layer. These structures allow network search representations in the higher dimension.

Flatten layer: a flatten layer reshapes the feature into one dimension.

Dense layer: Dense layer with a softmax classifier was used to predict the label by probability distribution of the two classes. The softmax classifier is defined as:

$$\sigma(\mathbf{z}_i) = \frac{e^{z_i}}{\sum_{c=1}^{C} e^{z_c}} \tag{2}$$

where $i = 1, \ldots, C$, C is the number of classes, which is 2 in our work. $\mathbf{z} = (z_1, \ldots, z_C) \in \mathbb{R}^C$, is the output feature from the fully connected layer.

C. Online Adaptive Training

The objective of online adaptive training is to address the session-to-session non-stationarity in the EEG. In this phase, we first compute a subject-specific model using EEG data collected from the calibration session and subsequently update the model using EEG data collected from the following sessions. Since merely increasing the amount of training data may also improve the algorithm performance, we designed the adaptive strategy using a fixed data size. When data from the previous sessions was added into the training set for the next iteration, an equal number of EEG trials from the first session will be removed from the training set. In this way, we are able to investigate if a changing subject-specific model will boost the decoding of non-stationary EEG.

Let $\mathbf{D}_i$ denote the data used for decoding the EEG from the i-th evaluation session. Considering that the label of EEG data collected from the previous $(i-1)$ sessions are already available, these supervised EEG data can be used to retrain a new model. The online adaptive training strategy can be formulated as:

$$\mathbf{V}_i = \begin{cases} \overline{\mathbf{V}} & \text{if } i = 1 \\ \left(\overline{\mathbf{V}} \cup \bigcup_{j=1}^{i-1} \mathbf{X}_j\right)_{[-k:0]} & \text{if } i > 1 \end{cases} \tag{3}$$

where $\overline{\mathbf{V}}$ is the data from the calibration session, $\mathbf{X}_j$ is the EEG data from the j-th evaluation session, and $\bigcup$ denotes the union operator. $[-k:0]$ means taking the last k EEG trials, where $k = n(\overline{\mathbf{V}})$ is the number of EEG trials in the calibration session. For example, in the upper limb dataset, the calibration session comprised of 160 trials of EEG data, and each evaluation session consisted of 40 trials. When performing online adaptive training on the first evaluation session, only data from the calibration session were used. In the i-th session, $160 + 40(i-1)$ trials of data were available. We will remove the first $40(i-1)$ EEG trials and ensure that a constant set of 160 EEG trials remain in the training set to train a new model.

III. Experiments

A. Benchmark Dataset

Upper limb rehabilitation dataset [17]: 19 post-stroke patients were recruited in this experiment. In the calibration session, a total of 160 trials of EEG randomly comprising of 80 MI conditions of the stroke-affected upper limb and 80 idle conditions were collected. Subsequently, the patients underwent 10 rehabilitation sessions with real-time robotic feedback rehabilitation for 2 weeks, 5 times a week. Each rehabilitation session consisted of 20 minutes of stimulation with Transcranial Direct Current Stimulation (tDCS) or sham tDCS. After that, an 8-minute evaluation session with 20 upper-limb MI tasks and 20 idle conditions was performed followed by one hour of therapy using EEG-based MI-BCI with robotic feedback.

Lower-limb rehabilitation dataset [18]: 14 post-stroke patients underwent BCI-assisted rehabilitation. Similar screening and calibration sessions were arranged, followed by 12 rehabilitation sessions at a frequency of thrice a week. Each MI-BCI session includes 160 MI trials with a resting interval for every 40 trials. An 8-minute evaluation session with 10 lower-limb MI tasks and 10 idle conditions was performed after each rehabilitation.

In **Figure 2**, we present the experiment arrangement for (a) calibration session and (b) evaluation and therapy sessions in the two neurorehabilitation datasets. **Figure 2 (c)** shows a post-stroke patient undergoing upper limb rehabilitation via EEG-based MI-BCI with real-time robotic feedback. **Figure 2 (d)** shows the visual feedback when MI is successfully detected in the lower limb rehabilitation experiment. Both feedback strategies aim to facilitate patients in achieving self-regulation and enhancing the rehabilitation efficiency.

B. Implementation Details

1) *Baseline:* In this paper, FBCSP with online adaptive learning (denoted aFBCSP), FBCSP with offline adaptive learning (denoted oFBCSP) and DeepConv are reproduced as the baseline. For oFBCSP, we reproduced this method following the steps in [8]. For aFBCSP, it shares the same structure as oFBCSP, but has an additional operation of online adaptive training [9]. DeepConv is a relatively new approach for EEG decoding and is reported to reach the state-of-art performance [11]. we adopted the model structure from [11], trained it with data from the calibration session and then used this model to test the data in all evaluation sessions without adaptation.
2) *Parameter Setting:* All hyperparameters in this work (e.g., the learning rate, dropout rate, and batch normalization coefficient) were empirically chosen during all experiments and were not tuned to the task. To ensure a fair comparison, 80% of data in the calibration session was used for model training, leaving 20% of the data for model validation. Data in the evaluation sessions were used for model testing. When training aCNN, each batch consisted of 16 EEG trials and was trained with a learning rate of 0.001 for 200 iterations. To get stable results, we trained our proposed method and baselines for five times before recording the average classification accuracies as final results. The Wilcoxon signed-rank test was employed to test if there were significant differences in the performance of algorithms.

IV. Results

The performance of aCNN is evaluated and compared with that of three state-of-arts using the upper-limb and lower-limb rehabilitation datasets.

A. Upper-limb rehabilitation dataset

In the first experiment, **Table I** reports the mean classification accuracies averaged across evaluation sessions. The proposed aCNN algorithm yielded a mean accuracy of 69.3%, whereas DeepConv, aFBCSP and oFBCSP yielded mean accuracies of 61.0%, 68.9% and 60.7% respectively. For tests of significance, We divided the session into two groups using an accuracy of 70% as the threshold for ”good” or ”poor” performance. Together with test results on all sessions, results are reported in **Table III**. The aCNN algorithm performed significantly better than DeepConv and oFBCSP ($p < 0.001$) based on results of all sessions at the 5% level. At first pass, our proposed method did not seem to perform well when compared against aFBCSP ($p = 0.37$). However, a closer investigation revealed that our proposed method has a huge advantage over aFBCSP for sessions with accuracy lower than 70% ($p < 0.001$). But for those with accuracies higher than 70%, aFBCSP yielded significant higher classification accuracies than that from our proposed aCNN ($p < 0.001$).

B. Lower-limb rehabilitation dataset

Table II shows the classification results of the proposed aCNN as well as the baseline algorithms on the lower-limb rehabilitation dataset. It shows that the proposed aCNN achieved an average classification accuracy of 64.0%, which is higher than that for DeepConv (57.5%) and oFBCSP (57.3%). The Wilcoxon test in **Table III** shows that these advantages of aCNN are statistically significant ($p < 0.001$) on all sessions. Our proposed aCNN showed slightly higher but insignificant mean accuracy than aFBCSP ($p = 0.83$) in this group. However, in the group with accuracies lower than 70%, our proposed aCNN showed significantly higher accuracy than that of aFBCSP (61.5%>56.9%, $p < 0.001$). Therefore, our proposed method is significantly advantageous for sessions with poor performance.

C. Online adaptive training strategy

Non-stationarity in EEG can be attributed to fluctuations in mental states of the subject (fatigue, disengagement,etc.) or technical factors (placement or impedance of the EEG electrodes). These lead to differences in signal quality between the calibration and evaluation sessions, which in turn often result in failure of the classifier [19]. The online adaptation training strategy aims to address such session-to-session non-stationarity by continuously utilizing data from previous sessions into model training. We conducted session-to-session transfer experiments to compare classification results with and without online adaptive training. In experiments without

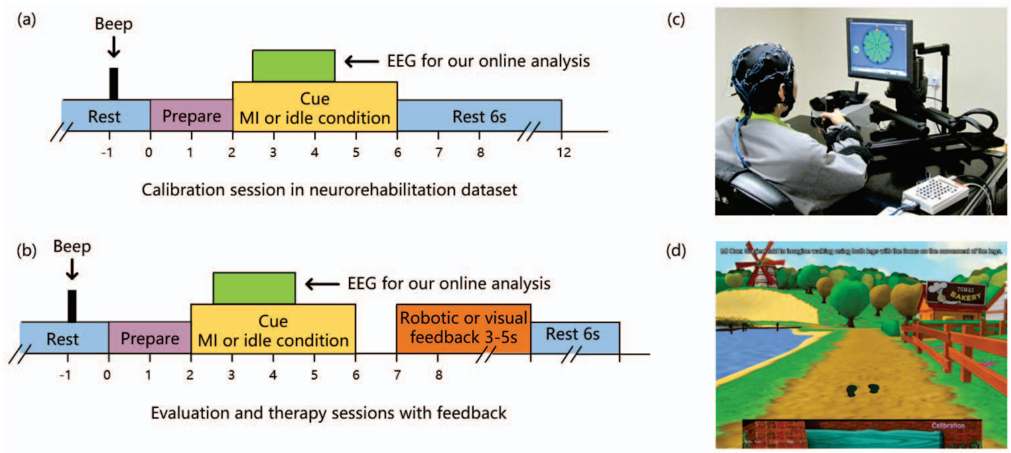

Fig. 2. The MI task protocol of the two neurorehabilitation datasets for (a) the calibration session before commencement of the therapy and (b) the evaluation sessions with robotic (upper limb dataset) or visual (lower limb dataset) feedback. (c) EEG-based MI-BCI with robotic feedback rehabilitation for stroke in upper limb dataset. (d) Visual feedback in lower limb rehabilitation experiment

TABLE I
CLASSIFICATION ACCURACIES ON THE UPPER-LIMB REHABILITATION DATASET. THE HIGHEST ACCURACIES ARE MARKED IN BOLDFACE.

Method	Avg±SD %	N001	N005	N006	N007	N009	N010	N011	N015	N018
aCNN	**69.3±11.2**	**88.7**	61.5	78.7	54.7	**78.1**	53.7	**70.8**	**91.7**	**62.9**
DeepConv	61.0±7.0	66.7	60.5	78.2	55.8	58.5	54.4	57.3	79.6	57.3
aFBCSP	68.9±9.8	85.3	**64.3**	**78.8**	**62.8**	71.5	**65.8**	70.5	82.8	54.3
oFBCSP	60.7±9.3	53.1	61.6	67.4	53.6	63.9	49.4	57.4	84.4	52.9
Method	N019	N021	N025	N027	N029	N030	N031	N032	N035	N037
aCNN	56.1	**67.1**	**73.4**	75.1	**67.5**	**68.8**	67.2	**58.3**	**85.0**	56.8
DeepConv	**56.7**	60.6	67.0	57.1	58.0	60.3	59.6	55.8	60.9	54.2
aFBCSP	56.3	61.8	71.3	**80.8**	58.0	65.5	**73.3**	52.8	83.5	**70.8**
oFBCSP	55.4	65.4	53.4	59.1	51.6	63.1	62.4	51.1	79.9	69.1

TABLE II
CLASSIFICATION ACCURACIES ON THE LOWER-LIMB REHABILITATION DATASET.

Method	Avg±SD %	L008	L009	L011	L012	L013	L014	L015	L018	L020	L021	L022	L023	L024	L025
aCNN	**64.0±7.6**	**57.4**	**59.5**	**61.3**	85.9	59.2	**74.4**	62.9	58.5	**60.6**	**64.4**	**67.4**	**56.2**	65.6	62.4
DeepConv	57.5±6.3	56.0	54.4	55.8	77.8	53.7	65.3	55.0	54.2	57.9	55.4	56.6	**56.2**	53.6	53.1
aFBCSP	63.0±9.7	53.0	55.2	58.0	**88.0**	**74.3**	68.3	**67.8**	**62.4**	53.4	51.8	61.0	55.6	63.8	**69.4**
oFBCSP	57.3±8.6	54.4	51.0	51.3	81.5	66.5	57.3	55.0	52.3	52.3	50.4	50.2	52.7	**66.7**	61.0

adaptive training, the data from the calibration session is used to train an initial model before using it to decode testing data in all the evaluation sessions. **Figure 3** shows the comparison results. **Figure 3 (a)** shows results of session-to-session transfer on the upper limb dataset. In the first session, the adaptive methods show no significant difference with non-adaptive methods. However, as the session proceeds, a deteriorating trend over sessions is observed for DeepConv and oFBCSP. This indicates that session-to-session non-stationarity exists throughout the neurorehabilitation process. On the contrary, aCNN and aFBCSP showed no significant decline in classification accuracies. A similar phenomenon is observed for the lower limb dataset as shown in **Figure 3 (b)**.

D. *Impact of the length of EEG trial*

The length of an EEG trial has a significant impact on the model performance. An experiment was conducted to show how this parameter influences our network. **Figure 4** shows the results from patient N006 session 1 on the upper limb rehabilitation dataset. As the number of time points increases, the classification accuracy becomes higher. But when the number of time points is close to 2s, the increase of the classification accuracy becomes gradual. Considering training efficiency, EEG trials with a length of 2s are suitable for EEG decoding in our rehabilitation datasets.

V. DISCUSSION

In this article, we developed a aCNN framework to address non-stationarity in EEG trials. Results on two neuroreha-

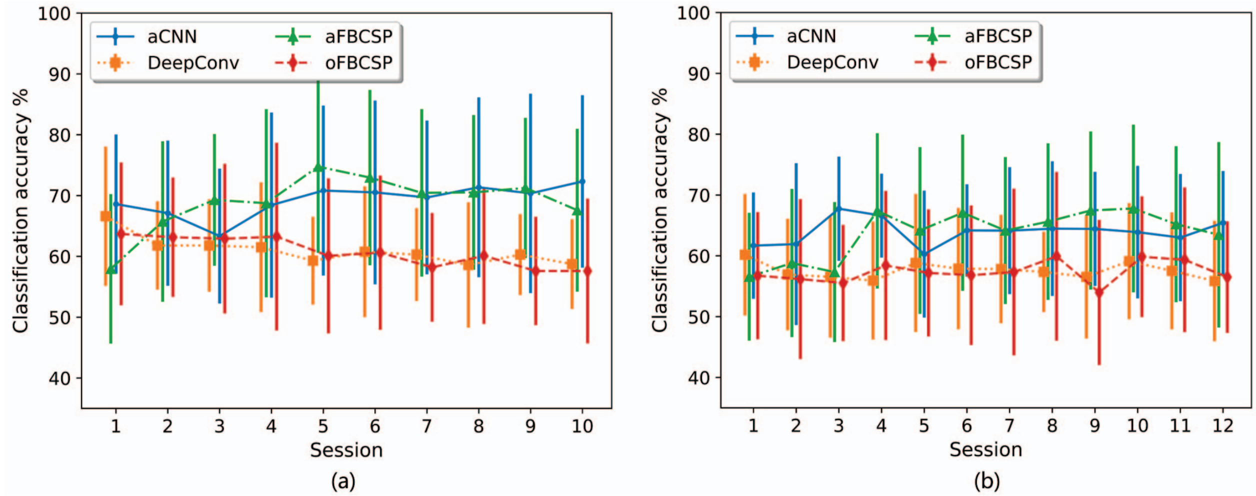

Fig. 3. Comparison between session-to-session transfer with and without online adaptive training on (a) upper limb rehabilitation dataset and (b) lower limb rehabilitation dataset. Horizontal axis represents the rehabilitation sessions which patients underwent. Vertical bar plots SDs across patients in each dataset.

TABLE III
OVERVIEW AND TESTS OF SIGNIFICANCE OF ALL THE RESULTS ON THE TWO NEUROREHABILITATION DATASETS. GROUPING WAS PERFORMED BASED ON THE ACCURACIES OF THREE BASELINES. "***" DENOTES $p < 0.001$ AND "*" DENOTES $p < 0.05$.

	Upper limb dataset			Lower limb dataset		
Accuracy	0-70	>70	All	0-70	>70	All
aCNN mean	66.9	83.7	69.3	62.7	80.7	64.0
DeepConv mean	58.2	77.9	61.0	55.8	80.3	54.9
p (aCNN vs. DeepConv)	***	*	***	0.62	***	***
aCNN mean	63.7	76.6	69.3	61.5	69.8	62.0
aFBCSP mean	58.5	82.7	68.9	56.9	80.4	63.8
p (aCNN vs. aFBCSP)	***	***	0.47	***	***	0.83
aCNN mean	67.5	75.9	69.3	62.8	72.6	64.0
oFBCSP mean	55.5	80.4	60.7	54.0	81.8	57.3
p (aCNN vs. oFBCSP)	***	0.10	***	***	*	***

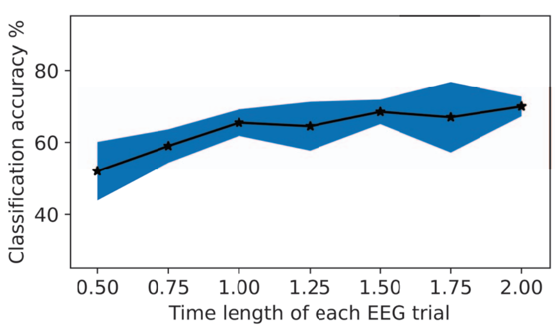

Fig. 4. Classification accuracy changes over the time length of each EEG trial. Results are calculated from patient N006 session 1 on upper limb rehabilitation dataset.

bilitation datasets proved that the proposed aCNN reaches significantly higher accuracies than DeepConv and aFBCSP ($p < 0.001$) and demonstrated at least as good a performance as aFBCSP ($p > 0.05$). Wilcoxon test further demonstrated that our proposed method is advantageous for sessions with decoding accuracies lower than 70%. Taken together, this implies that our method is more promising for patients with poor BCI performance. **Figure 3** provides evidence that non-stationarity exists in EEG, and that it can be successfully eliminated by online adaptive training. Notably, because our proposed aCNN requires the same number of training samples as non-adaptive methods, it will not lead to a more tedious calibration process than the baseline methods. This result strongly suggests that it is imperative to adopt the online adaptive training strategy for BCI-assisted post-stroke neurorehabilitation data.

DeepConv and oFBCSP, two state-of-arts in MI decoding, were reproduced as the benchmarking baselines in our work. Before serving as our baselines, both of them were reproduced and compared against the same ones as reproduced in other publications. We used oFBCSP to decode BCI competition III dataset IVa, and showed that our reproduced oFBCSP revealed slightly lower but statistically insignificant accuracies than in [8] (mean accuracy: 90.0% <90.2%). On the other hand, validation of the reproduced DeepConv on the high gamma dataset [20] achieved slightly higher accuracies (median accuracy: 86.5% >84.7%). Since these differences are not significant, our baselines can guarantee a fair comparison against our proposed aCNN.

In the two neurorehabilitation datasets, our proposed aCNN attained significantly higher performance accuracies as compared to that of oFBCSP and DeepConv. However, its mean accuracies were not significantly higher than the recommended accuracy of 70% for BCI control. Such results are still acceptable because BCI for neurorehabilitation is mainly utilized to provide feedback but not for device control which requires high degrees of accuracy.

Compared to aFBCSP, our proposed method showed a slightly higher but statistically insignificant classification accuracy. On the other hand, our proposed aCNN holds another advantage over aFBCSP - its end-to-end training strategy frees us from priors and parameter optimization, which is a time consuming and tedious process for aFBCSP.

VI. Conclusion

In this paper, we proposed a CNN-based adaptive learning method to decode multi-session EEG for BCI-assisted post-stroke neurorehabilitation. Owing to its end-to-end structure, this network can learn representations and make predictions automatically. The proposed method is evaluated on two large post-stroke clinical datasets with a total of 358 sessions. Results proved that the proposed method reaches significantly better classification accuracies compared to baselines without adaptation, and is especially successful in sessions with decoding accuracies lower than 70%. Therefore, our proposed method has demonstrated to be a promising tool in decoding multi-session EEG. Future works can be focused on applying the proposed algorithm onto other real-world BCI systems, such as EEG-based real-time robotic control.

References

[1] Valery L Feigin, Benjamin A Stark, Catherine Owens Johnson, Gregory A Roth, Catherine Bisignano, Gdiom Gebreheat Abady, Mitra Abbasifard, Mohsen Abbasi-Kangevari, Foad Abd-Allah, Vida Abedi, et al. Global, regional, and national burden of stroke and its risk factors, 1990–2019: A systematic analysis for the global burden of disease study 2019. *The Lancet Neurology*, 20(10):795–820, 2021.

[2] Eric S Donkor. Stroke in the century: a snapshot of the burden, epidemiology, and quality of life. *Stroke research and treatment*, 2018, 2018.

[3] Fabien Lotte, Laurent Bougrain, Andrzej Cichocki, Maureen Clerc, Marco Congedo, Alain Rakotomamonjy, and Florian Yger. A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. *Journal of neural engineering*, 15(3):031005, 2018.

[4] Ravikiran Mane, Tushar Chouhan, and Cuntai Guan. Bci for stroke rehabilitation: motor and beyond. *Journal of Neural Engineering*, 17(4):041001, 2020.

[5] Jing Jin, Ruocheng Xiao, Ian Daly, Yangyang Miao, Xingyu Wang, and Andrzej Cichocki. Internal feature selection method of csp based on l1-norm and dempster-shafer theory. *IEEE Transactions on Neural Networks and Learning Systems*, 2020.

[6] Nicholas Cheng, Kok Soon Phua, Hwa Sen Lai, Pui Kit Tam, Ka Yin Tang, Kai Kei Cheng, Raye Chen-Hua Yeow, Kai Keng Ang, Cuntai Guan, and Jeong Hoon Lim. Brain-computer interface-based soft robotic glove rehabilitation for stroke. *IEEE Transactions on Biomedical Engineering*, 67(12):3339–3351, 2020.

[7] Zoltan Joseph Koles. The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG. *Electroencephalography and clinical Neurophysiology*, 79(6):440–447, 1991.

[8] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan. Filter bank common spatial pattern (fbcsp) in brain-computer interface. In *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, pages 2390–2397. IEEE, 2008.

[9] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan. Filter bank common spatial pattern (fbcsp) algorithm using online adaptive and semi-supervised learning. In *The 2011 International Joint Conference on Neural Networks*, pages 392–396. IEEE, 2011.

[10] Michael Tangermann, Klaus-Robert Müller, Ad Aertsen, Niels Birbaumer, Christoph Braun, Clemens Brunner, Robert Leeb, Carsten Mehring, Kai J Miller, Gernot Mueller-Putz, et al. Review of the BCI competition iv. *Frontiers in neuroscience*, 6:55, 2012.

[11] Robin Tibor Schirrmeister, Jost Tobias Springenberg, Lukas Dominique Josef Fiederer, Martin Glasstetter, Katharina Eggensperger, Michael Tangermann, Frank Hutter, Wolfram Burgard, and Tonio Ball. Deep learning with convolutional neural networks for eeg decoding and visualization. *Human brain mapping*, 38(11):5391–5420, 2017.

[12] Siavash Sakhavi, Cuntai Guan, and Shuicheng Yan. Learning temporal information for brain-computer interface using convolutional neural networks. *IEEE transactions on neural networks and learning systems*, 29(11):5619–5629, 2018.

[13] Ping Wang, Aimin Jiang, Xiaofeng Liu, Jing Shang, and Li Zhang. Lstm-based EEG classification in motor imagery tasks. *IEEE transactions on neural systems and rehabilitation engineering*, 26(11):2086–2095, 2018.

[14] Shiu Kumar, Alok Sharma, and Tatsuhiko Tsunoda. Brain wave classification using long short-term memory network based optical predictor. *Scientific reports*, 9(1):1–13, 2019.

[15] Sabine Leske and Sarang S Dalal. Reducing power line noise in eeg and meg data via spectrum interpolation. *Neuroimage*, 189:763–776, 2019.

[16] Fatemeh Fahimi, Zhuo Zhang, Wooi Boon Goh, Tih-Shi Lee, Kai Keng Ang, and Cuntai Guan. Inter-subject transfer learning with an end-to-end deep convolutional neural network for eeg-based bci. *Journal of neural engineering*, 16(2):026007, 2019.

[17] Kai Keng Ang, Cuntai Guan, Kok Soon Phua, Chuanchu Wang, Ling Zhao, Wei Peng Teo, Changwu Chen, Yee Sien Ng, and Effie Chew. Facilitating effects of transcranial direct current stimulation on motor imagery brain-computer interface with robotic feedback for stroke rehabilitation. *Archives of physical medicine and rehabilitation*, 96(3):S79–S87, 2015.

[18] N Tang, C Guan, KK Ang, KS Phua, and E Chew. Motor imagery-assisted brain-computer interface for gait retraining in neurorehabilitation in chronic stroke. *Annals of Physical and Rehabilitation Medicine*, 61:e188, 2018.

[19] Joshua Giles, Kai Keng Ang, Kok Soon Phua, and Mahnaz Arvaneh. A transfer learning algorithm to reduce brain-computer interface calibration time for long-term users. *Frontiers in Neuroergonomics*, 3, 2022.

[20] Felix A Heilmeyer, Robin T Schirrmeister, Lukas DJ Fiederer, Martin Volker, Joos Behncke, and Tonio Ball. A large-scale evaluation framework for eeg deep learning architectures. In *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 1039–1045. IEEE, 2018.