2023 11th International Winter Conference on Brain-Computer Interface (BCI) | 978-1-6654-6444-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/BCI57258.2023.10078480

Reference Bank Multi-Feature Extraction for EEG-Based Concentration Discrimination

Jin Woo Choi[1,*], Jaehoon Choi[2,*], Sungho Jo[2,3]
[1]Information & Electronics Research Institute, KAIST, Republic of Korea
[2]School of Computing, KAIST, Republic of Korea
[3]shjo@kaist.ac.kr
[*]These authors contributed equally to this work.

***Abstract*—Discriminating concentration of a user is one of the few tasks that non-invasive BCIs can be applied in real-life situations. To have EEG-based BCIs more accessible to users, attempts have been made in terms of both hardware, where EEG acquisition devices have been redesigned to be more affordable and comfortable to wear, and software, where better algorithms have been introduced to improve the interface's performance. For concentration discrimination, a task highly relevant to EEG signals from the frontal lobe, using only electrodes in the forehead has previously been proposed to further simplify the setup required for EEG measurement. However, this requires careful selection of ground and reference electrodes; having ground and reference electrodes located on the forehead close to other electrodes results in less discriminant signals, while placing them on mastoids or other EEG neutral locations makes the interface bulky to wear and more susceptible to various sources of artifacts, such as ocular and facial muscle movements. Thus, in this paper, we propose a reference bank multi-feature extraction approach that aims to improve previous existing deep learning-based models with multiple forms of re-referenced data. We conducted an experiment using dry electrodes placed only on the forehead to collect brain signals related to concentration and resting state to evaluate our approach. Our method was applied to three pre-existing CNN-based models, exhibiting an average increase of 3.19% in their classification performance.**

***Keywords*—brain-computer interface (BCI), electroencephalogram (EEG), concentration discrimination, deep learning**

I. Introduction

Brain-Computer interface (BCI) provides direct ways of exchanging information from the brain to the computer, allowing users to control and communicate without any explicit actions [1], [2]. This makes BCIs suitable for monitoring tasks such as rehabilitation, sleep staging, or concentration detection, where users may not be able to provide self-feedback while carrying out experimental tasks [3]–[5]. These tasks are not only useful for research purposes, but may also be used in real-life for healthcare and self-monitoring purposes.

The design of brain-signal acquisition device is critical when used for monitoring tasks in real-world settings [6]. The acquisition device should be discrete and not obstruct the view of the user. It should also be easy to wear alone and remain comfortable over a long period of time. Amongst various methods for measuring brain activities, electroencephalogram (EEG) can satisfy these conditions. In addition to being non-invasive and cost-effective, EEG signals are capable of providing high temporal resolution signals that can be collected using dry electrodes. Previous works have studied collecting EEG signals in different manners to make BCIs more accessible; in-ear-EEG and around-ear-EEG have been developed to acquire different brain patterns from in and around the ear using earphone or headphone shaped devices [7], [8], while using only electrode channels from the forehead have been studied for sleep staging, detecting concentration levels and seizures [9]–[11].

Convenient and useful as these methods are, there are still several issues that require further examination. EEG collected from both the forehead and the ear is prone to artifacts from eye and other facial muscle movements [12]. Effective means of denoising are required to enhance the performance of BCIs using such configurations. A proper reference channel can prevent these external artifacts [13]. However, electrode channels, including both ground and reference, tend to be close together in these layouts. While using reference channels in this way may improve signal quality to some extent, it may also lead to the loss of important neural activity signals.

Thus, in this paper, we propose a reference bank approach to overcome this problem. By applying various re-referencing methods to the EEG signals and combining the output signals, we aim to construct an augmented EEG signal that removes noise while avoiding loss of information. We conducted a simple experiment involving mental arithmetic using our EEG headband to test the efficiency of our proposed method for detecting concentration using dry electrodes arranged on the forehead. We analyzed the classification performance before and after applying our methods to three commonly used deep learning models in BCIs.

II. Methods

A. Participants

Nine participants aged between 23 and 31, with no previous neurological concerns, volunteered for our experiment. All participants were informed of the detailed procedures prior to the experiment. This study was approved by the Korea Advanced Institute of Science and Technology Institutional Review Board.

978-1-6654-6444-4/23/$31.00 ©2023 IEEE

Authorized licensed use limited to: Korea Advanced Inst of Science & Tech - KAIST. Downloaded on April 11,2023 at 05:55:16 UTC from IEEE Xplore. Restrictions apply.

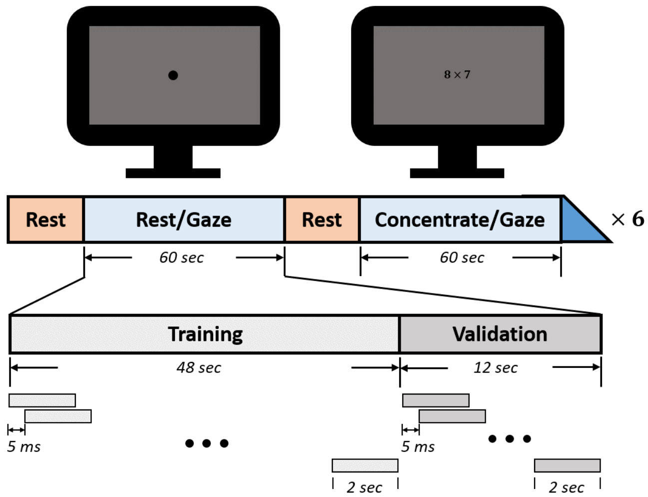

Fig. 1: The timeline of a single EEG signal acquisition trial consisted of a resting and concentration state. The retrieved signals were divided into training, validation, and testing sets.

B. Data Acquisition

The experiment was conducted in a soundproof room to minimize any unintended distractions. Participants were instructed to wear an EEG headband with a total of eight electrodes arranged around the forehead, two of which were the initial ground and reference electrodes, placed on the middle of the forehead. The dry electrodes used in this study were fabricated with silver conductive epoxy and the OpenBCI Cyton board was used to measure EEG signals at a sampling rate of 250 Hz. The data retrieved from the board resulted in EEG signals from six total electrodes.

Two distinct tasks were performed by the participants, with the purpose of measuring brain activity while they were in either a concentrated or resting state, as shown in Figure 1. The experiment consisted of six trials, with each trial including a 60-second resting period followed by a 60-second concentration period. During the resting period, participants were instructed to gaze at a monitor placed in front of them and asked to relax with minimal movements, including eye blinks. During the concentration period, participants were instructed to solve single-digit multiplication problems displayed on the monitor. One multiplication problem was presented each second and displayed in such a way that participants could see the problem by fixing their gaze at a specific position on the monitor, reducing unnecessary eye or head movements. To minimize user fatigue, participants were provided time to rest in between the periods, during which slight movements were permitted.

To consider brain signals related to concentration, we pre-processed the acquired EEG data by applying a band-pass filter with a frequency range between 0.1 and 45 Hz.

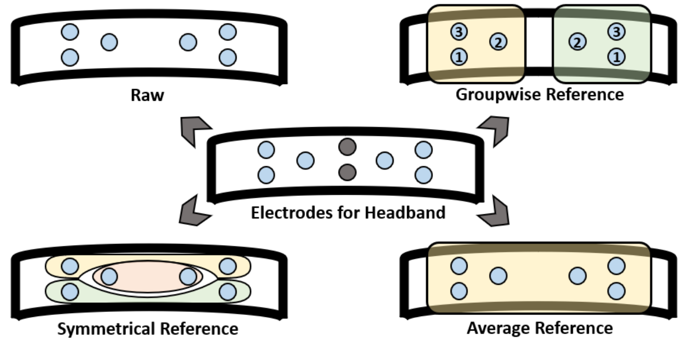

Fig. 2: Re-referencing methods used for reference bank multi-feature extraction. The numbers written on the electrodes for group-wise reference indicate the order of electrodes selected as a new reference per group, resulting in three additional distinct banks.

C. Methods for Reference Bank Construction

Our reference bank was constructed using three different re-referencing methods designed to consider bilateral and latitudinal differences in the positions of the electrodes, as shown in Figure 2. In addition to the original pre-processed signal, our method extracted and combined features from each re-referenced signal bank for classification.

In order to investigate the effect of each electrode on referencing, we first applied group-wise referencing. Here, electrodes were separated into two groups, left and right hemispheric groups, to reflect different ways in which concentration can affect brain patterns of the participants [14], [15]. The electrodes were re-referenced three times in total, where the two groups were separately re-referenced from each electrode of one group and its counterpart, respectively. A total of three reference banks resulted when this method was applied to the data from our experiment.

To examine EEG signals collected from different regions of the forehead, we further constructed another instance of reference bank. Here, the electrodes were split into three groups based on location: upper, middle and lower forehead. Each electrode was re-referenced using the average of its corresponding group, and the resulting data from the groups was combined to construct a single bank.

Lastly, we used Common Average Referencing (CAR), where re-referencing was performed with the averaged EEG signal from all six positions. The averaged signal was subtracted from each electrode.

D. Reference Bank-Based Multi-Feature Extraction

Based on previous state-of-the-art CNN-based models, which employ temporal and spatial filters to extract spectral and spatial features, our reference bank-based approach utilizes multiple spatial extractors after the temporal convolutional layer. Similar to how multiple features from different frequency bands are merged in the filter bank common spatial pattern (FBCSP) algorithm, our model architecture concatenates the features extracted from each reference bank, as

Authorized licensed use limited to: Korea Advanced Inst of Science & Tech - KAIST. Downloaded on April 11,2023 at 05:55:16 UTC from IEEE Xplore. Restrictions apply.

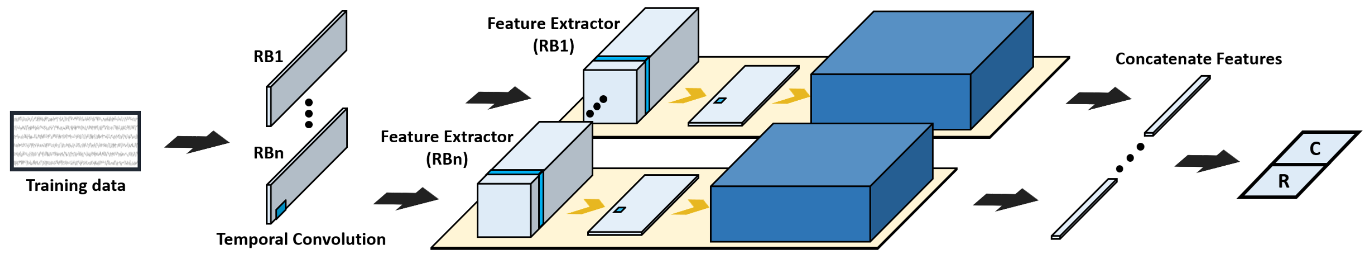

Fig. 3: The architecture of the model used for our reference bank-based multi-feature extraction method. Features were extracted separately for each bank after a temporal filter. The last blocks for reference bank (RB) feature extractors, indicated in blue, represent the remaining feature extractions after the spatial convolutional layer of each model used in this paper.

shown in Figure 3. By designing the architecture in this way, our model tends to learn important information from a wider range of extracted features.

To evaluate our reference bank-based multi-spatial feature extraction approach, we applied our method to three different CNN-based models that contain sequences of spectral and spatial feature extractions. The models used in this paper are Shallow ConvNet, EEGNet, and Deep ConvNet [16], [17], which extract features with the following characteristics:

- Shallow ConvNet. Utilizes squaring nonlinearity and logarithmic activations to behave similarly to the log-variance measure of the FBCSP model.
- EEGNet. Uses depthwise and pointwise separable convolutional layers to reduce the number of trainable parameters, resulting in a more compact model.
- Deep ConvNet. Contains multiple blocks to increase the depth of the model, aiming to learn a wide range of features inspired by the field of computer vision.

The effect of our approach was analyzed by comparing the accuracy of the models before and after applying our method.

E. Setups for Model Training and Evaluation

To measure the classification accuracy for each participant, we used a six-fold cross-validation, where a single fold consisted of the EEG data from a single trial. Of the five trial data used for constructing the model, the last 12 seconds of data, which corresponds to 20% of the recorded trial in terms of time, was used for validation. Data augmentation was further carried out to increase the number of data by segmenting the training, validation, and testing sets with a window-size of 2 seconds and step-size of 500 miliseconds. Model training was performed with a batch size of 32, and the adaptive moment algorithm with weight decay (AdamW) optimizer was used with an initial learning rate set to 0.001. We also applied early stopping to our model training, where the model stopped learning after no improvement in validation accuracy was seen for over 100 epochs. The training was limited to 1000 epochs, and the model with the greatest validation accuracy was chosen for evaluating the test set for each fold.

III. Results and Discussion

To analyze the performance of concentration classification using CNN-based deep learning models, we compared the accuracy of a total of six models: three different previous state-of-the-art CNN models with and without our reference bank method. To further investigate how our reference bank approach affected the performances of previous CNN models, we conducted subject-wise accuracy comparisons when using the three state-of-the-art models with and without our method.

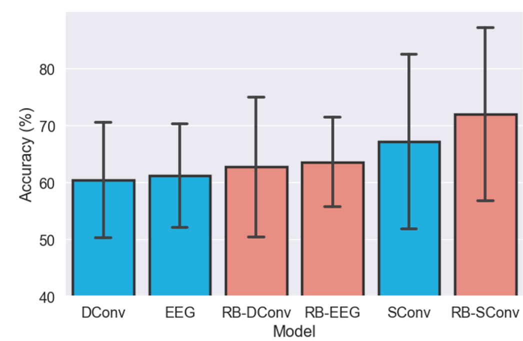

Fig. 4: The classification performance of the models evaluated with average cross-validated accuracy from all participants. The bars colored in red and blue represent models with and without our method applied, respectively. The error bars indicate the standard deviation.

A. Accuracy Comparison on the Used Models

Figure 4 shows the concentration classification accuracy results of Shallow ConvNet, EEGNet, and Deep ConvNet, along with their accuracy when our reference bank method was further applied. Amongst the three previous models without reference bank, Shallow ConvNet showed the greatest average accuracy of 67.12±15.32, followed by EEGNet with an accuracy of 61.19±9.04. Deep ConvNet showed the lowest accuracy with a value of 60.44±10.15.

Comparisons including the models using our reference bank method show that the reference bank Shallow ConvNet showed the highest average accuracy with a value of 72.02±15.18, higher than when the reference bank was not applied to the model. Improvements in average accuracy were also shown for EEGNet and Deep ConvNet when the reference bank was applied, with their accuracy being 63.56±7.86 and 62.73±12.27, respectively.

Authorized licensed use limited to: Korea Advanced Inst of Science & Tech - KAIST. Downloaded on April 11,2023 at 05:55:16 UTC from IEEE Xplore. Restrictions apply.

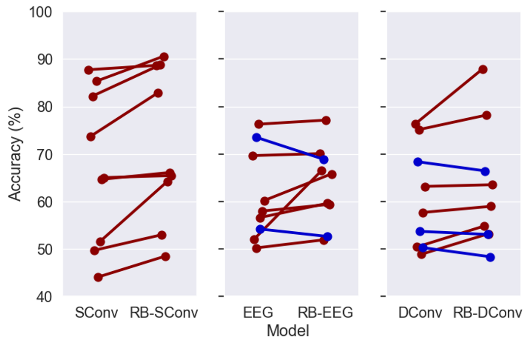

Fig. 5: The change in cross-validation accuracy for each participant. Lines colored in red and blue indicate whether the performance improved or degraded when reference bank was used, respectively.

Previous studies have claimed that concentration and resting state are known to be related to oscillatory brain signals from the frontal lobe [5], [15], [18]; this may explain why Shallow ConvNet and our RB-Shallow ConvNet showed the best performance overall in our experiment.

B. Subject-Wise Classification Accuracy Results

The changes in the classification accuracies for each participant with and without our proposed approach are shown in Figure 5. In the cross-validation results using Shallow ConvNet, all nine participants showed improvements in classification performance when the reference bank was applied. In the case of EEGNet, seven participants were able to elicit an enhancement of accuracy when the reference bank was used. Lastly, for Deep ConvNet, six out of nine participants showed improvements in accuracy.

A few participants performed poorly with low accuracy close to the random chance level. One possible explanation may simply be that the participants' brain signals displayed no discriminant characteristics, commonly denoted as being BCI illiterate. Another possible reason may be due to the electrode positions used in our experiment and the lack of variance between the measured brain activities in each channel in response to the same task. While previous studies commonly used mastoids for reference and ground channels, we used electrodes in the middle of the forehead instead, for reasons concerning aesthetics and wearability, to increase the accessibility of the device in real-life. The close proximity of the ground and reference electrodes to the EEG acquisition electrodes may result in a loss of relevant neural features for participants who show little variation between channels, leading to poor performance.

From our results, it is not yet known which re-referencing method was the most effective in increasing performance. Thus, further ablation studies will be carried out to examine the effects of each method. We will also apply our proposed method to BCI paradigms that have been shown to display clear spatial brain patterns or hemispheric lateralization, such as motor imagery and emotion.

IV. Conclusion

This study proposes a reference bank multi-feature extraction approach for CNN-based deep learning models that utilizes temporal and spatial convolutional layers. By applying our method to the EEG data from our experiment, where the concentration and resting state of users were measured using only electrodes located on the forehead, we have shown improvements in classification performance compared to using previous CNN-based models alone. The approach introduced in our paper may be used to improve detection of concentration in users, highlighting its potential as an effective approach to allow BCI systems to be more accessible for real-life usage.

Acknowledgment

This work was supported by the Institute of Information and Communications Technology Planning and Evaluation (IITP) grant funded by the Korea government (MSIT) (No. 2017-0-00432).

References

[1] T. Milekovic, A. A. Sarma, D. Bacher, J. D. Simeral, J. Saab, C. Pandarinath, B. L. Sorice, C. Blabe, E. M. Oakley, K. R. Tringale, *et al.*, "Stable long-term bci-enabled communication in als and locked-in syndrome using lfp signals," *Journal of neurophysiology*, vol. 120, no. 7, pp. 343–360, 2018.

[2] J. W. Choi, S. Huh, and S. Jo, "Improving performance in motor imagery bci-based control applications via virtually embodied feedback," *Computers in Biology and Medicine*, vol. 127, p. 104079, 2020.

[3] R. Agarwal and J. Gotman, "Computer-assisted sleep staging," *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 12, pp. 1412–1423, 2001.

[4] J. W. Choi, B. H. Kim, S. Huh, and S. Jo, "Observing actions through immersive virtual reality enhances motor imagery training," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 7, pp. 1614–1622, 2020.

[5] I. A. Zaeni, U. Pujianto, A. R. Taufani, M. Jiono, and P. S. Muhammad, "Concentration level detection using eeg signal on reading practice application," in *2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*, vol. 6, pp. 354–357, IEEE, 2019.

[6] A. J. Casson, S. Smith, J. S. Duncan, and E. Rodriguez-Villegas, "Wearable eeg: what is it, why is it needed and what does it entail?," in *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 5867–5870, IEEE, 2008.

[7] K. B. Mikkelsen, S. L. Kappel, D. P. Mandic, and P. Kidmose, "Eeg recorded from the ear: characterizing the ear-eeg method," *Frontiers in neuroscience*, vol. 9, p. 438, 2015.

[8] N. Kaongoen, J. Choi, and S. Jo, "Speech-imagery-based brain–computer interface system using ear-eeg," *Journal of neural engineering*, vol. 18, no. 1, p. 016023, 2021.

[9] J. He, D. Liu, Z. Wan, and C. Hu, "A noninvasive real-time driving fatigue detection technology based on left prefrontal attention and meditation eeg," in *2014 International Conference on Multisensor Fusion and Information Integration for Intelligent Systems (MFI)*, pp. 1–6, IEEE, 2014.

[10] C.-S. Huang, C.-L. Lin, L.-W. Ko, S.-Y. Liu, T.-P. Sua, and C.-T. Lin, "A hierarchical classification system for sleep stage scoring via forehead eeg signals," in *2013 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB)*, pp. 1–5, IEEE, 2013.

[11] C. Wusthoff, R. Shellhaas, and R. Clancy, "Limitations of single-channel eeg on the forehead for neonatal seizure detection," *Journal of Perinatology*, vol. 29, no. 3, pp. 237–242, 2009.

[12] S. L. Kappel, D. Looney, D. P. Mandic, and P. Kidmose, "Physiological artifacts in scalp eeg and ear-eeg," *Biomedical engineering online*, vol. 16, no. 1, pp. 1–16, 2017.

[13] A. de Cheveigné and D. Arzounian, "Robust detrending, rereferencing, outlier detection, and inpainting for multichannel data," *NeuroImage*, vol. 172, pp. 903–912, 2018.

Authorized licensed use limited to: Korea Advanced Inst of Science & Tech - KAIST. Downloaded on April 11,2023 at 05:55:16 UTC from IEEE Xplore. Restrictions apply.

[14] D. A. Valentino and R. L. Dufresne, "Attention tasks and eeg power spectra," *International journal of psychophysiology*, vol. 11, no. 3, pp. 299–301, 1991.

[15] S. Basharpoor, F. Heidari, and P. Molavi, "Eeg coherence in theta, alpha, and beta bands in frontal regions and executive functions," *Applied Neuropsychology: Adult*, vol. 28, no. 3, pp. 310–317, 2021.

[16] R. T. Schirrmeister, J. T. Springenberg, L. D. J. Fiederer, M. Glasstetter, K. Eggensperger, M. Tangermann, F. Hutter, W. Burgard, and T. Ball, "Deep learning with convolutional neural networks for eeg decoding and visualization," *Human brain mapping*, vol. 38, no. 11, pp. 5391–5420, 2017.

[17] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces," *Journal of neural engineering*, vol. 15, no. 5, p. 056013, 2018.

[18] B. Hamadicharef, H. Zhang, C. Guan, C. Wang, K. S. Phua, K. P. Tee, and K. K. Ang, "Learning eeg-based spectral-spatial patterns for attention level measurement," in *2009 IEEE International Symposium on Circuits and Systems*, pp. 1465–1468, IEEE, 2009.

Authorized licensed use limited to: Korea Advanced Inst of Science & Tech - KAIST. Downloaded on April 11,2023 at 05:55:16 UTC from IEEE Xplore. Restrictions apply.