EEGG: An analytic brain-computer interface algorithm

This paper was downloaded from TechRxiv (<https://www.techrxiv.org>).

LICENSE

CC BY 4.0

SUBMISSION DATE / POSTED DATE

04-01-2021 / 07-01-2021

CITATION

Liu, Gang; Wang, Jing (2021): EEGG: An analytic brain-computer interface algorithm. TechRxiv. Preprint.
<https://doi.org/10.36227/techrxiv.13516145.v1>

DOI

[10.36227/techrxiv.13516145.v1](https://doi.org/10.36227/techrxiv.13516145.v1)

EEGG: An analytic brain-computer interface algorithm

Gang liu¹, Jing Wang¹

¹ Institute of Robotics and Intelligent Systems, Xi'an Jiaotong University, Xi'an, China

Abstract

Objective. A black box called brain-computer interface (BCI) model is used to identify another black box, the brain. However, one black box cannot explain another black box. This paper presents the first analytic "white box" brain-computer interface algorithm named EEGG.

Approach. Independent and interactive effects of neurons or brain regions can fully describe the brain. This paper constructed a relationship model that extracted the independent and interactive features of EEG for intention recognition and analysis using ResDD, a novel dendrite module of Gang neuron. A total of 4,906 EEG data about motor imagery (MI) of left-hand movements and right-hand movements from 26 subjects were obtained from GigaDB. Firstly, we explored EEGG's generalization ability according to cross-subject accuracy. Secondly, we transformed the EEGG model into a relationship spectrum expressing independent and interactive effects of brain regions. Then, the relationship spectrum was verified through the known ERD/ERS phenomenon. Finally, we explored the previously unreachable further analysis based on a BCI model.

Main results. (1) EEGG was more robust than typical "CSP+" algorithms for the poor quality EEG data [$AUC: 0.825 \pm 0.074(EEGG) > 0.745 \pm 0.094(CSP+LDA)/0.591 \pm 0.104(CSP+Bayes)/0.750 \pm 0.091(CSP+SVM)$, $p < 0.001$]. (2) The transformed EEGG model showed the known ERD/ERS phenomenon. (3) Interestingly, EEGG showed that the interactive effects of brain regions put a brake on ERD/ERS effects for classification ($p < 0.001$). This means that generating fine hand intention needs more centralized activation of the brain.

Significance. EEGG implies that, henceforth, not only can BCI be used for recognition but also analysis.

Keywords: Brain-computer interface, Gang neuron, white box, EEG, analysis

1. Introduction

Brain-computer interface is a technology translating a user's brain activity into control commands [1-3]. BCI consists of paradigms, signals, and decoding algorithms. Paradigms aim to guide the user's brain to generate identifiable or generalized features. Signals refer to the recorded data reflecting on brain activity. There are many types of signals, and researchers prefer electroencephalography (EEG) because of its non-invasive, high temporal resolution, and low-cost characteristics [4, 5]. Decoding algorithms are methods that extract identifiable features from signals and divide these into commands. This paper focuses on decoding algorithms. *We enable the BCI*

algorithm not only to classify brain activity but also to tell us why this brain activity falls into this category.

BCI algorithms have been quickly developed over the past 20 years [3, 4]. These algorithms can be summarized into a typical framework: filters, feature extraction, and classifiers. Filters generally contain a band-pass filter and spatial filter. The spatial filter is typified by common spatial patterns (CSP) [6]. The representative EEG features are frequency band power and connectivity features [7, 8]. There are many classifiers used in EEG, such as linear discriminant analysis (LDA) [9], Support Vector Machines (SVM) [10, 11], Bayes classifier [12], and k-nearest-neighbor (kNN) [13]. Additionally, deep learning approaches (e.g., convolutional neural networks and restricted Boltzmann machines) have

Figure 1. EEGG. NC : the number of channels. NL : the number of data points for each channel. NG : the dimensions of inputs of ResDD. g : the number of ResDD. O : the dimensions of outputs.

been implemented into BCI [3, 14]. However, the above BCI algorithms only generate a black-box model.

One of the most significant challenges of science today is to unlock the brain's mysteries [15]. Nevertheless, the current BCI algorithms based on machine learning (ML) are inherently a black-box. It is difficult to utilize one black box to explain another black box, the human brain. Therefore, we have to recalculate independent measurement indexes (e.g., ERD/ERS phenomenon on time- and frequency-domain and correlation analysis) [16, 17]. However, this simple analysis lost the information from classification.

This paper presents EEGG, a novel analytic brain-computer interface algorithm integrating classification and analysis. According to Taylor series, independent and interactive effects of inputs can fully describe the general system's output. In other words, the state of the brain can be fully described by the independent and interactive effects of neurons or brain regions. Therefore, this paper intends to design a "white box" ML algorithm that can integrate intention recognition and analysis of independent and interactive effects of brain regions. Overall, EEGG has two uses. (1) Like other BCI algorithms, EEGG is used for intention recognition. (2) EEGG model can be transformed into the relationship spectrum representing brain regions for analysis directly.

This paper is organized as follows. Section 2 introduces EEGG and experiments. Section 3 presents the results. Section 4 discusses the results. Conclusions and outlook are given in Section 5.

2. Methods

2.1 EEGG

The architecture of EEGG is shown in Fig. 1. The independent and interactive effects of brain regions were stored in weights W . Weights were optimized by minimizing loss function using backpropagation. The mean-square error (MSE) is the loss function used in this paper. In the rest of this section, we will introduce each step in detail.

2.1.1 Spatial filter. The inputs $E^{Input} \in \mathbb{R}^{NC \times NL}$ of EEGG are the normalized EEG data after bandpass-filtering. The spatial filter is defined as follows.

$$E^{Spatial\ filtering} = (E^{Input})^T W_1 \quad (1)$$

Where $E^{Spatial\ filtering} \in \mathbb{R}^{NL \times NC}$ is the data after spatial filtering, $W_1 \in \mathbb{R}^{NC \times NC}$ is the weight matrix of the spatial filter.

In traditional methods, the spatial filter often be solved in two ways: first, an EEG-data-driven and unsupervised manner (e.g., PCA and ICA) [18], and second, a simple data-driven and supervised manner (e.g., CSP) [5]. However, the traditional spatial filter is a static filter that was not associated with later ML algorithms. Our spatial filter is a dynamic filter based on feature extraction and nonlinear classification.

2.1.2 Power calculation. After spatial filtering, we calculate the power of each channel of $E^{Spatial\ filtering}$. Unlike the previous method, the unsigned characteristic of EEG signals in the record is taken into account. EEGG uses the variance or standard error instead of the magnitude squared to remove the direct current (DC) component. Specific formulas are as follows.

Figure 2. Schematic diagram of analysis. (a) The transform of EEGG model. The step aims to transform EEGG model into simple expression about inputs and each output. (b) The relationship spectrum form of EEGG model. (c) The relationship spectrum removing the items with odd inputs. C_i : the i -th electrode. NC : the number of electrodes. NG : the dimensions of inputs of ResDD. g : the number of ResDD. O_j : the j -th output.

$$P_i = \frac{(D_{ij} - \bar{D}_i)^2}{NL} \text{ or } \sqrt{\frac{(D_{ij} - \bar{D}_i)^2}{NL}} \quad (2)$$

Where $P_i \in \mathbb{R}$ is the power of the i -th dimension, $D_i \in \mathbb{R}$ expresses the data of the i -th dimension.

2.1.3 ResDD. A traditional artificial neuron was expressed as $f(wx+b)$ or $f(WX)$ where w , b , x , W , and X expressed the weight, bias, inputs, weight matrix, and inputs with element 1, respectively, and f was activation function. However, this architecture lost the dendrites' information processing capacity. In 2020, Gang neuron was presented [19]. ResDD is one of the dendrite modules in Gang neurons. ResDD has the controllable nonlinear capability. Additionally, ResDD can be simplified after weight optimization because there is no nonlinear function in it. EEGG uses a dimensionality reduction module, appropriate ResDD, and one linear module whose dimensions O are determined by the number of categories. The number of ResDD can adjust the number of interaction terms. Specific formulas are as follows.

$$P^{G1} = (PW_2)^T \quad (3)$$

$$P^{Gi+1} = W_{Gi} P^{Gi} \circ P^{Gi} + W_{Gi} P^{Gi}, i \in [1, g], i \in \mathbb{N}^+ \quad (4)$$

$$C^{EEGGoutputs} = (P^{Gg+1})^T W_3 \quad (5)$$

Where $P \in \mathbb{R}^{1 \times NC}$, $P^{G1} \in \mathbb{R}^{NG \times 1}$ expresses the inputs and outputs of the dimensionality reduction module, respectively. $P^{Gi} \in \mathbb{R}^{NG \times 1}$, $P^{Gi+1} \in \mathbb{R}^{NG \times 1}$ expresses the inputs and outputs of ResDD, respectively. $P^{Gg+1} \in \mathbb{R}^{NG \times 1}$ is the outputs of the last ResDD. $C^{EEGGoutputs} \in \mathbb{R}^{1 \times O}$ is the outputs of EEGG. $W_2 \in \mathbb{R}^{NC \times NG}$, $W_{Gi} \in \mathbb{R}^{NG \times NG}$, and $W_3 \in \mathbb{R}^{NG \times O}$ are the weight matrixes. $\circ$ expresses Hadamard product.

2.2 Gang transform of EEGG

The transform of EEGG model is in Fig. 2a. In Gang transform, the EEG is regarded as the ideal state without the DC component. The power of EEG is calculated by the magnitude squared. Therefore, there were only the Matrix product and Hadamard product in EEGG and no nonlinear function. Further, we can set the variables $C = [C_1, C_2, \dots, C_{NC}]$ and get the relationship spectrum through formula simplification in software (e.g., MATLAB or Python). The formulae are described below.

$$\begin{cases}
P^{G1} = ((CW_1)^2 W_2)^T \\
P^{G2} = W_{G1} P^{G1} \circ P^{G1} + W_{G1} P^{Gi} \\
\vdots \\
P^{Gi+1} = W_{Gi} P^{Gi} \circ P^{Gi} + W_{Gi} P^{Gi} \\
\vdots \\
C^{EEGG_{outputs}}_j = (W_{Gg} P^{Gg} \circ P^{Gg} + W_{Gg} P^{Gg})^T W_{3j}
\end{cases} \quad (6)$$

Fig. 2b shows the relationship spectrum form of EEGG model. The horizontal axis on the relationship spectrum shows the independent and interactive EEG items, and the vertical axis shows the value of items. Because of the unsigned characteristic of EEG signals in the record, the effects of odd items are random. Thus, odd items are removed, and the new relationship spectrum is shown in Fig.2c.

2.3 Experiments

2.3.1 Subjects. It is also well known that there is event-related desynchronization/synchronization (ERD/ERS) in the motor imagery paradigm [16, 17, 20]. Therefore, this paper used ERD/ERS in MI paradigm to confirm EEGG's analysis capacity. Additionally, there are many open MI datasets [16]. However, based on our knowledge of the MI paradigm, not all MI datasets notices essential details, such as BCI-inefficient subjects [21], inefficient MI [22], and mode of imagery [23]. Therefore, we selected the dataset from GigaDB as we consider that this dataset took into account the above necessary details [16, 24]. This dataset contains EEG data for MI of the left and right hands with 52 subjects. As shown in Fig. 9, a 64-channel montage based on the international 10-10 system was used to record the EEG signals with 512 Hz sampling rates [16]. Data with the noise electrodes and inefficient MI trials were marked. The most important detail was that subjects of this dataset were explicitly asked to imagine the kinesthetic experience rather than imagining the visual experience [16, 23]. Besides, an algorithm with high accuracy for a subject could perform terribly for other subjects, which is called cross-subject problem [25]. Thus, this paper tested cross-subject accuracy. 1/2 of the dataset (26 subjects) were randomly selected, and each subject was tested in turns. The testing subject's data were testing data, and other subjects' data were used to train models.

2.3.2 Data processing. Firstly, we removed the trial data with noise and intercepted the data from 0.5s after the MI cue to 3s. Secondly, the obtained data were filtered with a band-pass filter from 8 to 30 Hz. Finally, the obtained data were normalized between -1 and 1 in each trial. In addition, this problem was a two-class problem essentially, and thus we

Figure 3. Comparison between EEGG and other algorithms using all testing results. (a) Comparison in AUC. (b) Comparison in variance of the AUC. * $p < 0.05$. *** $p < 0.001$.

labeled the right-hand class as -1 and labeled the left-hand class as 1 [3].

2.3.3 Classification Performance. This paper mainly emphasized EEGG's analysis capacity, and a systematic review of the literature showed that deep learning methods have not yet demonstrated convincing improvement [3]. Therefore, this paper selected three typical "CSP+" BCI algorithms as control: CSP and LDA (CSP+LDA), CSP and Bayes classifier (CSP+Bayes), and CSP and SVM (CSP+SVM). Besides, we selected EEGG with one ResDD. The receiver operating characteristic (ROC) curve and the area under the curve (AUC) were used for performance measures [3].

Figure 4. Partition based on whether EEGG outperformed others. (a) EEGG's advantaged group. (b) EEGG's disadvantaged group. These above figures were ROC curves.

This paper performed three statistical analyses. Firstly, we compared the AUC and variance of the AUC of EEGG with other algorithms using all subjects' results (see Fig.3). Secondly, the subjects were partitioned into the group(a) and

group(b) based on whether EEGG outperformed others (see Fig.4). We compared the AUC of EEGG with other algorithms within the group(a) and group(b) (see Fig.5). Thirdly, we compared the AUC of each algorithm between both groups (see Fig.6).

Figure 5. Comparison between EEGG and other algorithms within groups. (a) Comparison within group (a). (b) Comparison within group (b). ** $p < 0.01$. *** $p < 0.001$. ns > 0.05 .

2.3.4 Analysis of EEGG model. Firstly, EEGG models were transformed into the new relationship spectrum form. Then, we checked the number of items. Because we only used one ResDD, there were pairwise interaction items, independent powers, and the squared of independent powers ($C_{64}^2 + 64 + 64 = 2144$). Secondly, this paper computed the correlation matrix between the subjects' EEGG models (see Fig.7). Thirdly, each item's mean against zero was performed using single sample t-tests under $p < 0.01$ and $p < 0.001$ (see Fig.8), because randomized effect approaches zero. Further, this paper visualized the items that differed significantly from zero in Fig. 8. Finally, this paper visualized the EEGG model using the BrainNet Viewer ($p < 0.001$) (see Fig.9) [26].

3. Results

3.1 Classification Performance

The purpose of this part of the experiments was to explore classification performance. Fig. 3a showed that EEGG significantly outperformed CSP+LDA and CSP+Bayes and

Figure 6. Comparison between groups. ** $p < 0.01$. ns > 0.05 .

might outperform CSP+SVM using all subjects' results. [AUC, Paired-samples t-test: $0.834 \pm 0.079 > 0.800 \pm 0.111$, $p < 0.05$; $0.834 \pm 0.079 > 0.662 \pm 0.159$, $p < 0.001$; $0.834 \pm 0.079 > 0.806 \pm 0.109$, $p = 0.057$] What stands out in Fig. 3a was that EEGG's AUC appeared to be more concentrated. Therefore, we compared the variance of AUC among algorithms. This is a rather interesting outcome (see Fig.3b).

Figure 7. EEGG models. (a) EEGG models in the new relationship spectrum form. (b) Correlation matrix between subjects' EEGG models.

Figure 8. Results of statistical analysis of relationship items in EEGG models. (b) Mean of relationship items in EEGG models. (b) Results of statistical analysis under $p < 0.01$. (c) Results of statistical analysis under $p < 0.001$. "+": positive effect. "-": Negative effect. The upper triangular matrixes of above figures were not used.

The variance of AUC of EEGG is smaller than others, which means that EEGG may have better robustness.

Further, we divided the subjects into both groups based on whether EEGG outperformed others (see Fig.4). Further analysis of the data within the group revealed that EEGG significantly outperformed others in EEGG's advantaged group (a). CSP+Bayes did not significantly outperform EEGG in EEGG's disadvantaged group (b). [Group (a), AUC, Paired-samples t-test: $0.825 \pm 0.074 > 0.745 \pm 0.094$, $p < 0.001$; $0.825 \pm 0.074 > 0.591 \pm 0.104$, $p < 0.001$; $0.825 \pm 0.074 > 0.750 \pm 0.091$, $p < 0.001$. Group (b), AUC, Paired-samples t-test: $0.847 \pm 0.087 < 0.873 \pm 0.090$, $p < 0.01$; $0.847 \pm 0.087 > 0.760 \pm 0.173$, $p = 0.061$; $0.847 \pm 0.087 < 0.881 \pm 0.087$, $p < 0.01$.]

If we now turn to Fig. 6, the subjects' data of group (b) were easier to classify correctly (see Fig. 6). This means group (b) data has more distinct features for classification and group (a) data contains more noise based on the same algorithm. There were significant differences in "CSP+" between group (a) and group (b). However, EEGG results showed no significant differences between groups. [AUC, Paired-samples t-test: CSP+LDA: $0.745 \pm 0.094 < 0.873 \pm 0.090$, $p < 0.01$; CSP+Bayes: $0.591 \pm 0.104 < 0.760 \pm 0.173$, $p < 0.01$; CSP+SVM: $0.750 \pm 0.091 < 0.881 \pm 0.087$, $p < 0.01$; EEGG: $0.825 \pm 0.074 < 0.847 \pm 0.087$, $p = 0.499$] Together, these above statistical analyses provided important insights that EEGG has better robustness for poor quality EEG data (see Fig.4, Fig.5, and Fig.6).

Figure 9. Visualization of the EEGG model under $p < 0.001$. (a) The EEGG model. "Ball" expresses the independent effects of brain regions, and "rod" expresses the interactive effects of brain regions. (b) Illustration of "red ball" in (a). (c) Illustration of "blue ball" in (a). (d) Illustration of "blue rod" in (a). (e) Illustration of "red rod" in (a). Please see the "3.2 Analysis of EEGG model" for detailed explanations.

3.2 Analysis of EEGG model

This section was divided into three major parts: (1) transformed EEGG models and verification of the correctness, (2) statistical analysis of relationship items in EEGG models, and (3) visualization of the EEGG model and analysis.

Fig. 7 showed the EEGG models in the new relationship spectrum form. To verify the correctness, we calculated the total number of pairwise interaction, independent powers, and the squared of independent powers items ($C_{64}^2 + 64 + 64 = 2144$) and calculated the correlation matrix between subjects' EEGG models (see Fig. 7b). The total number was equal to the number of items in the new relationship spectrum form.

Turning now to the statistical analysis of relationship items in EEGG models, we found some significant regularities, such as the symmetry of relationship items (see Fig. 8). In order to make the regularities more intuitional, we visualized the EEGG model using the BrainNet Viewer (see Fig. 8). "Ball" expresses the independent effects of brain regions, and "rod" expresses the interactive effects of brain regions. The effects of "red ball," "blue ball," "blue rod," and "red rod" in Fig. 8a can be expressed as follows, respectively.

$$\begin{cases} y^{\text{redball-effect}} = k_{\text{redball}} E_{\text{redball}} \\ y^{\text{blueball-effect}} = -k_{\text{blueball}} E_{\text{blueball}} \\ y^{\text{bluerod-effect}} = -k_{\text{bluerod}} E_{1\text{bluerod}} E_{2\text{bluerod}} \\ y^{\text{redrod-effect}} = k_{\text{redrod}} E_{1\text{redrod}} E_{2\text{redrod}} \end{cases} \quad (6)$$

Where $y^{\text{redball-effect}}$, $y^{\text{blueball-effect}}$, $y^{\text{bluerod-effect}}$, and $y^{\text{redrod-effect}}$ expresses the effects of "red ball," "blue ball," "blue rod," and "red rod," respectively. $k_{\text{redball}} \in \mathbb{R}^+$, $k_{\text{blueball}} \in \mathbb{R}^+$, $k_{\text{bluerod}} \in \mathbb{R}^+$, and $k_{\text{redrod}} \in \mathbb{R}^+$ are proportional coefficients. $E_{\text{redball}} \in [0,1]$, $E_{\text{blueball}} \in [0,1]$, $E_{1\text{bluerod}} \in [0,1]$, $E_{2\text{bluerod}} \in [0,1]$, $E_{1\text{redrod}} \in [0,1]$, and $E_{2\text{redrod}} \in [0,1]$ represents powers. To show the change of the above effects, we plotted the change when proportional coefficients were 1 (see Fig. 8b, Fig. 8c, Fig. 8d, and Fig. 8e). Next, we verified the known ERD/ERS phenomenon and showed new phenomenon [20].

The positive output of EEGG model in this paper represented motor imagery of the left hand. In the subsequent analysis, the motor imagery of the left hand was shown as examples. We assume that subject imagines the left-hand movement, the power of the right hemisphere will decrease (ERD), and the power of the left hemisphere will increase (ERS) [20]. It happened that most "blue balls" distribute on the right hemisphere, and most "red balls" distribute on the

left hemisphere (see Fig. 8a). The output of EEGG model increases with decreasing power of "blue ball" (see yellow arrow in Fig. 8c), which is the ERD. Likewise, the output of EEGG model increases with increasing power of "red ball" (see yellow arrow in Fig. 8b), which is the ERS.

Additionally, it happened that most "red rods" distribute on the right hemisphere, and most "blue rods" distribute on the left hemisphere (see Fig. 8a). The effects of "rods" put a brake on the effects of "balls." The most gradient was on the diagonal line (see Fig. 8d and Fig. 8e). In Fig. 8e, we found the output of EEGG model decreases with decreasing power in both ends of "red rod" (see yellow arrow in Fig. 8e). In Fig. 8d, we found the output of EEGG model decreases with increasing power in both ends of "blue rod" (see yellow arrow in Fig. 8d). In order to slow the rate of decline, the power of both connected "balls" should not change at the same time as possible. This implies that the activation of the brain should be more centralized to be identified as the motor imagery of the left hand.

4. Discussion

The human brain is a complex interconnected dynamical system [27]. Since the first BCI has been proposed, efforts were then paid to decipher the human brain. We thought the deciphering might need to contain the recognition results and the recognition's reason. Therefore, this paper presents the analytic "white box" Brain-computer interface algorithm named EEGG for the first time. Of course, this statement ignores the simple ERD/ERS method and regards the ERD/ERS as a phenomenon.

The inquiry of EEGG consists of both aspects: classification performance and analysis of EEGG model. Of these, the EEGG model analysis contains the verification of known ERD/ERS phenomenon [20] and the inquiry of new phenomena.

4.1 EEGG was specially designed for the low signal-to-noise ratio EEG.

EEG is the most common brain signal that has been utilized in BCI applications because of its non-invasive nature and low cost [4, 5]. However, it is well known that EEG has a weak signal-to-noise ratio due to the acquisition points on the scalp [4-6]. Most ML algorithms aim to get more excellent expression ability [14]. Nevertheless, it is easy to cause over-fitting for the low signal-to-noise ratio EEG data using ML algorithms with too excellent expression ability. EEG-ML algorithms' expression ability should happen to meet the expression of a small amount of classified information and do not have the ability to express a large amount of other information. Dendrite Net presented by Gang Liu et al. in 2020 has controllable logical expression capacity, which happens to meet the low signal-to-noise ratio

character of EEG [28]. In this paper, we used the enhanced DD, ResDD of Gang neuron [19]. As expected, we found that EEGG had better robustness for poor quality EEG data because EEGG in this paper only used one ResDD and can only express the relationship less than two-degrees (see Fig. 3, Fig. 4, Fig. 5, and Fig. 6).

4.2 EEGG models were human-readable.

Inheriting ResDD of Gang neuron [19, 29], EEGG models were human-readable. We first verified the correctness of transformed EEGG models using the known ERD/ERS phenomenon (see Fig. 8). Further, because the EEGG model's results were obtained under t-test with $p < 0.001$, we draw the activation of the brain should be more centralized for fine hand intention from Fig. 8. In other words, fine motion corresponded to a centralized region. This finding was similar to the anatomy study [30].

There are also limitations to this paper. This paper did not contrast deep learning methods because it mainly emphasized EEGG's analysis capacity. A systematic review of the literature showed that deep learning methods have not yet shown convincing improvement [3]. Additionally, in order to verify the correctness of transformed EEGG models, this paper selected the MI paradigms with the known ERD/ERS phenomenon. Multiclass classification of EEGG will be explored in future research. Because the correctness of transformed EEGG models has been verified and Gang transform was the same for both and multiclass classification, the multiclass EEGG models can be analyzed in future research.

4. Conclusion

A "white box" brain-computer interface algorithm named EEGG that integrates intention recognition and analysis was proposed in the paper. Statistical analysis and principle of EEGG demonstrated that EEGG had better robustness for poor quality EEG data. The known ERD/ERS verified the correctness of transformed EEGG models for analysis. Besides, the transformed EEGG model in this paper found that the activation of the brain should be more centralized for fine hand intention.

Before closing, it is worth mentioning that, henceforth, the trained BCI models can be used for analysis.

Acknowledgements

Gang Liu presented EEGG (E-mail: gangliu.6677@gmail.com). Jing Wang provided advice (E-mail: wangpele@gmail.com). As previously shown, the example of Gang neuron could be found at <https://github.com/liugang1234567/Gang-neuron>.

References

- [1] M. A. L. Nicolelis, "Actions from thoughts," *Nature*, vol. 409, no. 6818, pp. 403-407, 2001/01/01, 2001.
- [2] L. F. Nicolas-Alonso, and J. Gomez-Gil, "Brain Computer Interfaces, a Review," *Sensors*, vol. 12, no. 2, pp. 1211-1279, Feb, 2012.
- [3] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, "A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update," *Journal of Neural Engineering*, vol. 15, no. 3, pp. 28, Jun, 2018.
- [4] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," *Journal of Neural Engineering*, vol. 4, no. 2, pp. R1-R13, Jun, 2007.
- [5] U. Chaudhary, N. Birbaumer, and A. Ramos-Murguialday, "Brain-computer interfaces for communication and rehabilitation," *Nature Reviews Neurology*, vol. 12, no. 9, pp. 513-525, Sep, 2016.
- [6] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Muller, "Optimizing spatial filters for robust EEG single-trial analysis," *Ieee Signal Processing Magazine*, vol. 25, no. 1, pp. 41-56, Jan, 2008.
- [7] P. Herman, G. Prasad, T. M. McGinnity, and D. Coyle, "Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification," *Ieee Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no. 4, pp. 317-326, Aug, 2008.
- [8] D. J. Krusienski, D. J. McFarland, and J. R. Wolpaw, "Value of amplitude, phase, and coherence features for a sensorimotor rhythm-based brain-computer interface," *Brain Research Bulletin*, vol. 87, no. 1, pp. 130-134, Jan 4, 2012.
- [9] A. Schlogl, F. Lee, H. Bischof, and G. Pfurtscheller, "Characterization of four-class motor imagery EEG data for the BCI-competition 2005," *Journal of Neural Engineering*, vol. 2, no. 4, pp. L14-L22, Dec, 2005.
- [10] R. Sitaram, H. H. Zhang, C. T. Guan, M. Thulasidas, Y. Hoshi, A. Ishikawa, K. Shimizu, and N. Birbaumer, "Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface," *Neuroimage*, vol. 34, no. 4, pp. 1416-1427, Feb, 2007.
- [11] Y. Jiao, T. Zhou, L. Yao, G. Zhou, X. Wang, and Y. Zhang, "Multi-view Multi-scale Optimization of Feature Representation for EEG Classification Improvement," *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, vol. PP, 2020-Nov-27, 2020.
- [12] C. Zhang, and A. Eskandarian, "A Computationally Efficient Multiclass Time-Frequency Common Spatial Pattern Analysis on EEG Motor Imagery,"

- Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, vol. 2020, pp. 514-518, 2020-07, 2020.
- [13] S. Chaudhary, S. Taran, V. Bajaj, and S. Siuly, "A flexible analytic wavelet transform based approach for motor-imagery tasks classification in BCI applications," *Computer Methods and Programs in Biomedicine*, vol. 187, pp. 8, Apr, 2020.
- [14] 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, Nov, 2017.
- [15] M. R. Joglekar, L. Chariker, R. Shapley, and L. S. Young, "A case study in the functional consequences of scaling the sizes of realistic cortical models," *Plos Computational Biology*, vol. 15, no. 7, pp. 25, Jul, 2019.
- [16] H. Cho, M. Ahn, S. Ahn, M. Kwon, and S. C. Jun, "EEG datasets for motor imagery brain-computer interface," *Gigascience*, vol. 6, no. 7, pp. 1-8, May, 2017.
- [17] K. Wang, M. P. Xu, Y. J. Wang, S. S. Zhang, L. Chen, and D. Ming, "Enhance decoding of pre-movement EEG patterns for brain-computer interfaces," *Journal of Neural Engineering*, vol. 17, no. 1, pp. 11, Feb, 2020.
- [18] A. Kachenoura, L. Albera, L. Senhadji, and P. Comon, "ICA: A potential tool for BCI systems," *Ieee Signal Processing Magazine*, vol. 25, no. 1, pp. 57-68, Jan, 2008.
- [19] L. Gang, "It may be time to improve the neuron of artificial neural network," *TechRxiv. Preprint*, <https://doi.org/10.36227/techrxiv.12477266>, 2020].
- [20] G. Pfurtscheller, and F. H. L. da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clinical Neurophysiology*, vol. 110, no. 11, pp. 1842-1857, Nov, 1999.
- [21] X. K. Shu, S. G. Chen, L. Yao, X. J. Sheng, D. G. Zhang, N. Jiang, J. Jia, and X. Y. Zhu, "Fast Recognition of BCI-Inefficient Users Using Physiological Features from EEG Signals: A Screening Study of Stroke Patients," *Frontiers in Neuroscience*, vol. 12, pp. 12, Feb, 2018.
- [22] R. Zhang, D. Yao, P. A. Valdes-Sosa, F. Li, P. Li, T. Zhang, T. Ma, Y. Li, and P. Xu, "Efficient resting-state EEG network facilitates motor imagery performance," *Journal of Neural Engineering*, vol. 12, no. 6, Dec, 2015.
- [23] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller, "Imagery of motor actions: Differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG," *Cognitive Brain Research*, vol. 25, no. 3, pp. 668-677, Dec, 2005.
- [24] H. Cho, M. Ahn, and S. Ahn, "Supporting data for "EEG datasets for motor imagery brain computer interface."," *GigaScience Database*, 2017.
- [25] X. Zhao, J. Zhao, C. Liu, and W. Cai, "Deep Neural Network with Joint Distribution Matching for Cross-Subject Motor Imagery Brain-Computer Interfaces," *Biomed Research International*, vol. 2020, Feb 24, 2020.
- [26] M. R. Xia, J. H. Wang, and Y. He, "BrainNet Viewer: A Network Visualization Tool for Human Brain Connectomics," *Plos One*, vol. 8, no. 7, pp. 15, Jul, 2013.
- [27] Y. He, A. Dagher, Z. Chen, A. Charil, A. Zijdenbos, K. Worsley, and A. Evans, "Impaired small-world efficiency in structural cortical networks in multiple sclerosis associated with white matter lesion load," *Brain*, vol. 132, pp. 3366-3379, Dec, 2009.
- [28] G. Liu, and J. Wang, "Dendrite Net: A White-Box Module for Classification, Regression, and System Identification," *arXiv e-prints*, <https://arxiv.org/abs/2004.03955>, [April 01, 2020, 2020].
- [29] G. Liu, and J. Wang, "A Relation Spectrum Inheriting Taylor Series: Muscle Synergy and Coupling for Hand," *arXiv e-prints*, <https://ui.adsabs.harvard.edu/abs/2020arXiv200411910L>, [April 01, 2020, 2020].
- [30] M. S. A. Graziano, "Ethological Action Maps: A Paradigm Shift for the Motor Cortex," *Trends in Cognitive Sciences*, vol. 20, no. 2, pp. 121-132, Feb, 2016.