Zero-Calibration BCI Project

Main Project I

2016-2018

Zero-Calibration BCI Project Summary

Korea University
Pattern Recognition & Machine Learning Lab

- I performed this research project during Korea University and this project was my representative brain research.
- In graduate school, I developed a subject-independent non-invasive brain-computer interface (BCI) based on deep convolutional neural networks that classified a user's imagined movements.
- I mainly implemented this entire system (Matlab, Python, and Tensorflow) from the experimental environment (paradigm) to analysis functions.
- I contributed to one of the prominent journals (TNNLS, 0.97%, 1 of 104 in CS) as the first author.
- I demonstrate that the classification accuracy of our subject-independent (or calibration-free) model outperforms that of subject-dependent models using various methods [common spatial pattern (CSP), common spatiospectral pattern (CSSP), filter bank CSP (FBCSP), and Bayesian spatio-spectral filter optimization (BSSFO)].
- It indicated that this system can reduce approximately 20–30 min to collect enough data to build a reliable decoder.
- Through this experience, I realized the importance of statistical and practical integration when creating ML models for real-world applications.

Zero-Calibration BCI Project Summary

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- **Contribution**
  - Developing a subject-independent BCI framework for motor imagery
- **Implementation tools**
  - Matlab, Python & TF1
- **Development issues**
  - Common feature algorithm design & Deep learning architecture design
- **Major achievements**
  - ML 1% journal (TNNLS) 1st author publication

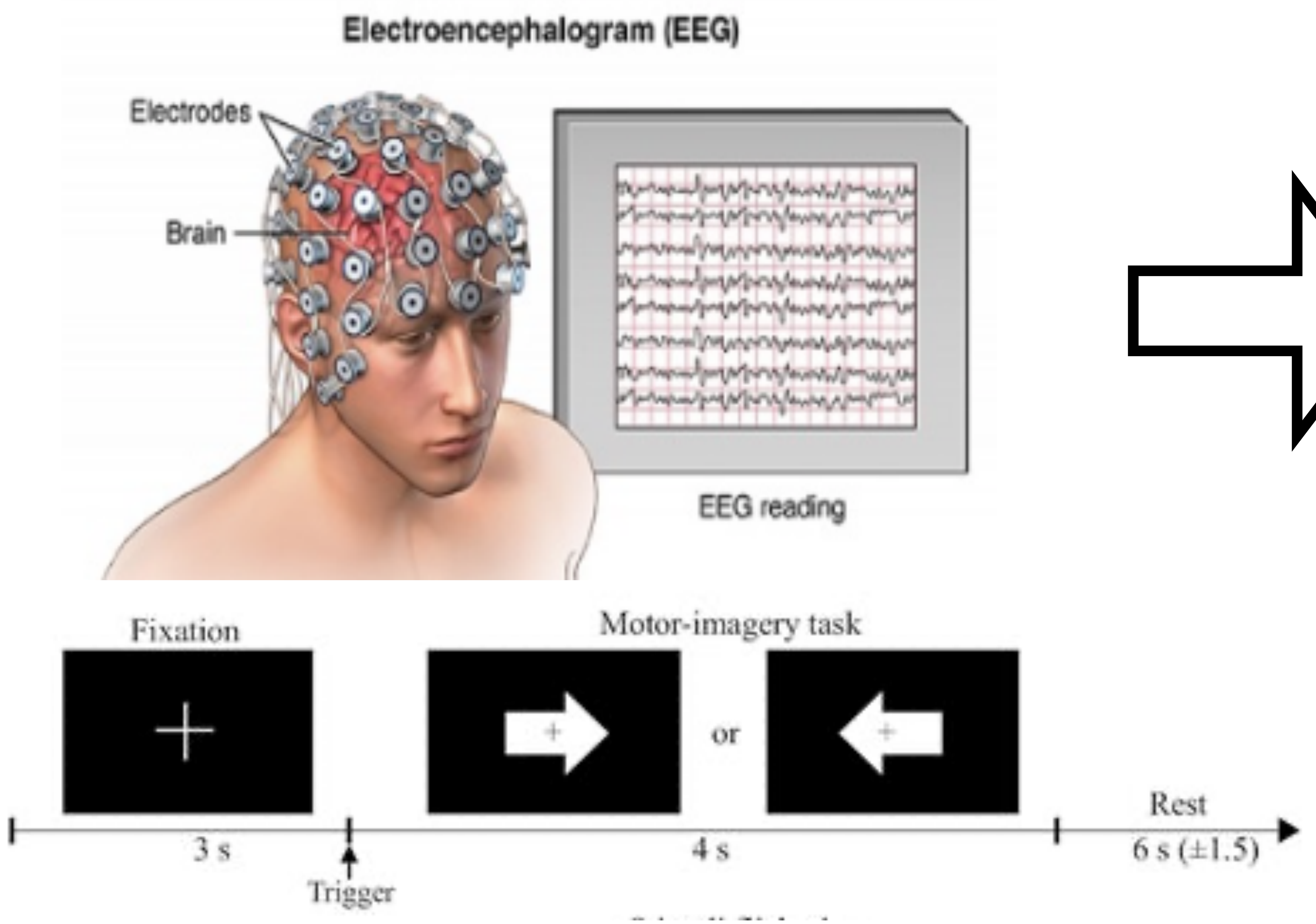
Input & Output definition

- Input: Time-series multi-dimensional data (Time by ECG Channels)
- Output: Motor imagination (binary classification; right or left motor imagination)

Motivation

- A calibration procedure is required for the use of BCI, which requires approximately 20–30 min to collect enough data to build a reliable decoder.

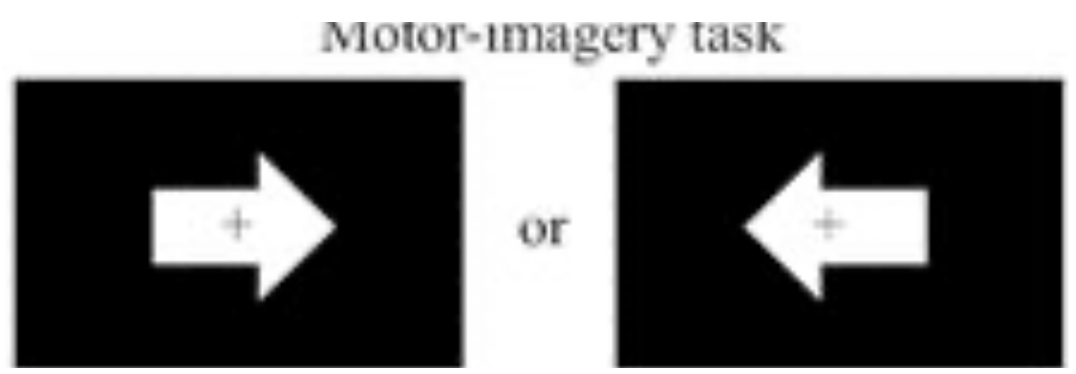
Input



20~30 min.

Model

Output



Zero-Calibration BCI Project
Limitation of previous research

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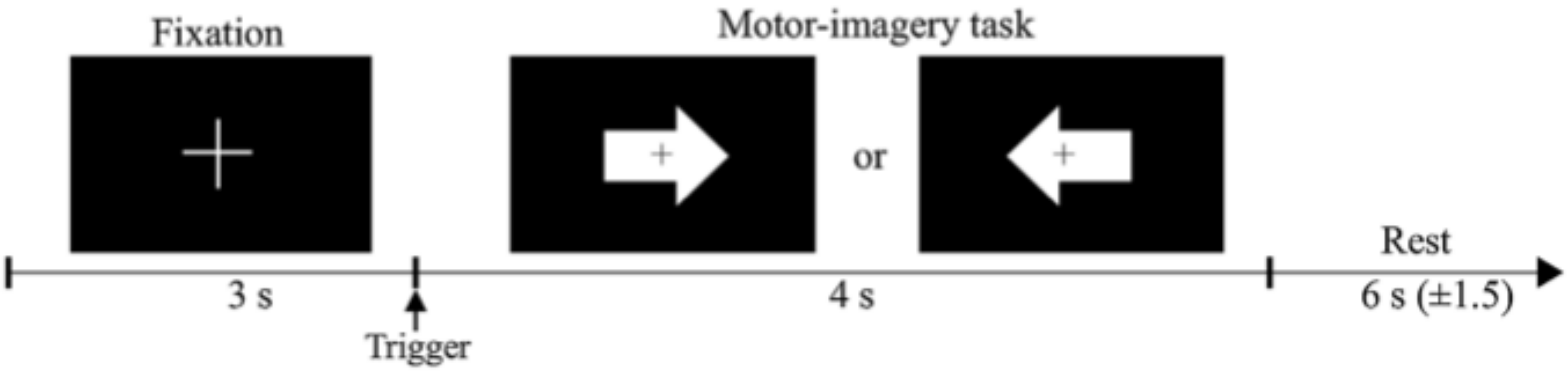
- **Previous approaches**
  - Previous approaches mainly utilized the linear characteristics of the given samples (log-variance of raw data).
    - I thought that there were limitations to building a classifier using only linear information from a data pool composed of different people.
    - Thus, I focused on considering the non-linear characteristics of the data and combining them with deep learning.
  - There were two major problems when trying to solve the calibration issue through deep learning.
    - First, there were no databases with a large number of subjects.
    - Second, there were scarce studies on zero-calibration BCIs based on deep learning, which required strategies for extracting discriminative brain features from a large-scale database.

- **Our approach**
  - We built a large amount of data and for about a year and then opened the database, representing the largest BCI dataset thus far reported in the literature.
  - We built a novel algorithm “how to extract common features from a large number of data pools” and “how to deliver these features as the input of deep learning”.

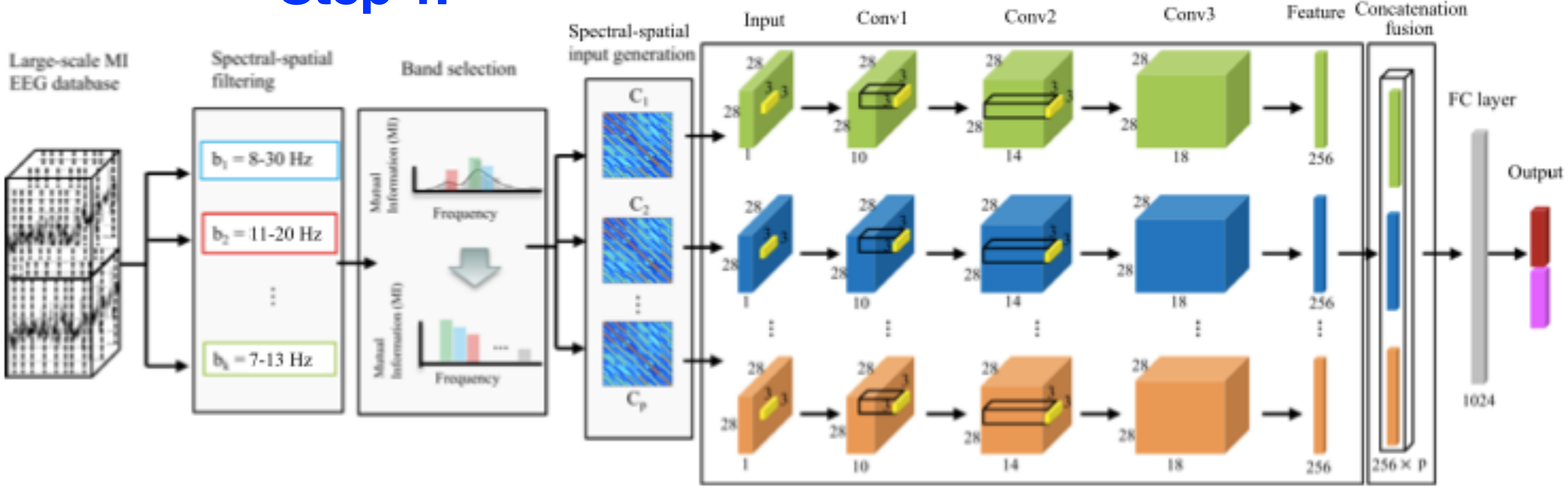
- **Subjects**
  - In the experiment, 54 healthy subjects (aged 24–35: 29 male and 25 female) participated in experiments of two sessions.



Zero-Calibration BCI Project Contribution

- 1) Extract discriminant features from a large number of data pools
- 2) Deliver these features as the input of deep learning
- 3) Train the transformed inputs with deep learning

Step 1. Step 2. Step 3.



Zero-Calibration BCI Project Contribution

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- Step1: To extract discriminant features from a large number of data pools
  - Discover data-specific optimal frequency subsets representing the large data
    - In each person, optimal frequency range (e.g., A=7-13Hz, B=8-30Hz) of brain signals was different due to their respective neurophysiological basis.
    - From the large dataset, since it is uncertain which frequency bands can compose discriminative brain features, I **encode these uncertainties using mutual information** over frequencies and features
    - This is the first approach to extracting unique features from the large dataset

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- Step2: To deliver discriminant features as the input of deep learning
  - Convert inputs to 2D formats like images that had clear class information and spatial relationships
    - CNN was designed to compress spatial information of a certain region within the input.
      - Our input consisted of temporal and channel dimensions, so it was required to convert inputs to 2D formats such as images that had clear class information and spatial relationships.
    - Applying **a linear spatial transformation maximized the variance differences** between classes.
    - Designing the input to consider **spatial relationships of itself by taking the covariance**
    - This is also the first approach to transform time series input into 2D inputs

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- Step3: Data augmentation
    - Be able to provide different distinctive transformations of raw data while preserving inherent signal characteristics
- Step3: Feature fusion by integrating discriminant spectral–spatial inputs
    - Integrating all the discriminant features that contain the discriminant ERD patterns
    - Inputs are individually trained through the CNN and then combined by a concatenation fusion technique.

Zero-Calibration BCI Project Conclusion

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- For the performance comparison, we evaluated the decoding accuracy of the proposed method by comparing the previous subject-independent approaches as well as subject-dependent approaches

- Our zero-calibration method showed superior classification performance than other calibration methods [common spatial pattern (CSP), common spatiospectral pattern (CSSP), filter bank CSP (FBCSP), and Bayesian spatio-spectral filter optimization (BSSFO)].

Approach	Method	Mean (SD)	Median	Range (Max-Min)
Subject-dependent	CSP [23]	68.57 (17.57)	64.50	58.00 (100.00-42.00)
	CSSP [29]	69.68 (18.53)	63.00	58.00 (100.00-42.00)
	FBCSP [28]	70.59 (18.56)	64.00	55.00 (100.00-45.00)
	BSSFO [30]	71.02 (18.83)	63.50	52.00 (100.00-48.00)
	Proposed method (dependent)	71.32 (15.88)	66.45	53.10 (99.00-45.90)
Subject-independent	Pooled CSP [32]	65.65 (16.11)	58.00	55.00 (100.00-45.00)
	Fused model [31]	67.37 (16.01)	62.50	57.00 (98.00-41.00)
	MR FBCSP [32]	68.59 (15.28)	63.00	49.00 (97.00-48.00)
	Proposed method (independent)	74.15 (15.83)	75.00	60.00 (100.00-40.00)

- This study is the first approach to solving a zero-calibration issue by combining a large dataset with deep learning, which provides a novel feature representation method.

- This was my representative brain research, and it will be expanded to a variety of BCI applications.

IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, VOL. 31, NO. 10, OCTOBER 2020 3839

Subject-Independent Brain–Computer Interfaces Based on Deep Convolutional Neural Networks

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***Abstract*—For a brain–computer interface (BCI) system, a calibration procedure is required for each individual user before he/she can use the BCI. This procedure requires approximately 20–30 min to collect enough data to build a reliable decoder. It is, therefore, an interesting topic to build a calibration-free, or subject-independent, BCI. In this article, we construct a large motor imagery (MI)-based electroencephalography (EEG) database and propose a subject-independent framework based on deep convolutional neural networks (CNNs). The database is composed of 54 subjects performing the left- and right-hand MI on two different days, resulting in 21 600 trials for the MI task. In our framework, we formulated the discriminative feature representation as a combination of the spectral–spatial input embedding the diversity of the EEG signals, as well as a**

I. Introduction

BRAIN–COMPUTER interface (BCI) is a system that enables a direct communication pathway between a human brain and external devices [1]. BCIs have shown great potential in a variety of clinical applications for communication, control, and rehabilitation [2]–[9]. Furthermore, recent BCI studies have attracted great attention as future technology for the next generation [10]–[15]. Over the course of numerous BCI studies [16]–[21], growing attention has been dedicated to the analysis of electroencephalography (EEG)

IEEE Transactions on Neural Networks and Learning Systems

IF:11.683; 0.97% 2019: 1 of 104, Computer Science, Theory and Methods.

160 citations (on 2022.11.14), 1st author