# A Comparative Study of Features and Classifiers in Single-channel EEG-based Motor Imagery BCI

○Suguru Kanoga, Atsunori Kanemura, and Hideki Asoh
AIST Japan

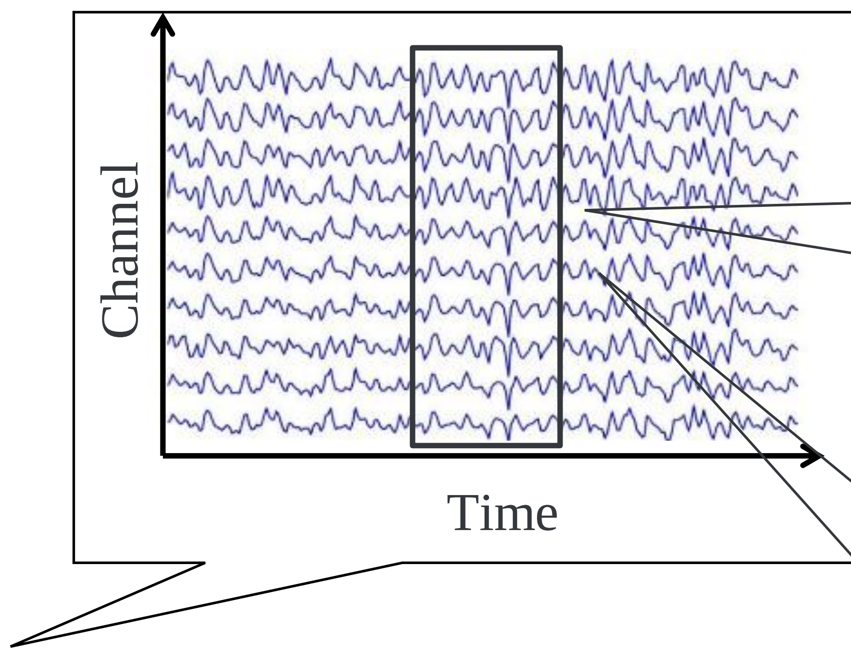
# Motor Imagery Brain—Computer Interfaces

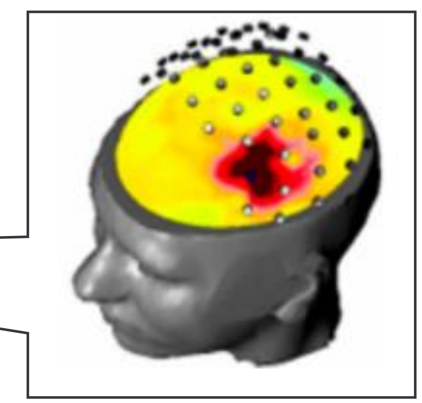
- Use rhythmic EEG features by motor imagery

  $\mu$ and $\beta$ rhythms in motor areas are discriminative features

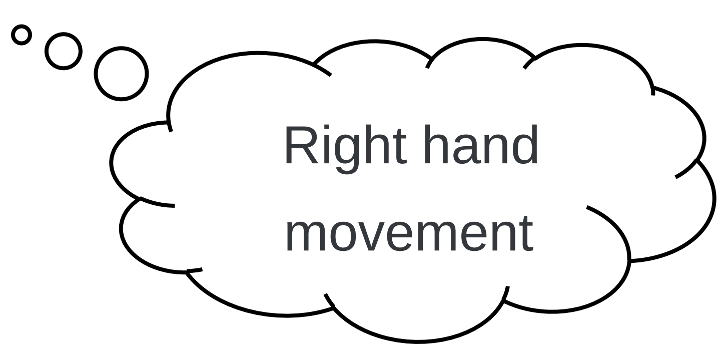
- Integrate spatial filter to emphasize the features

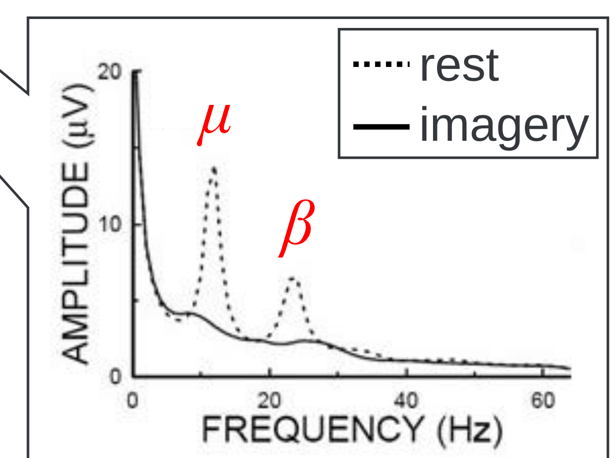
  But, … the filter needs multichannel information



Topographical map




Spectra over left sensorimotor cortex [1]

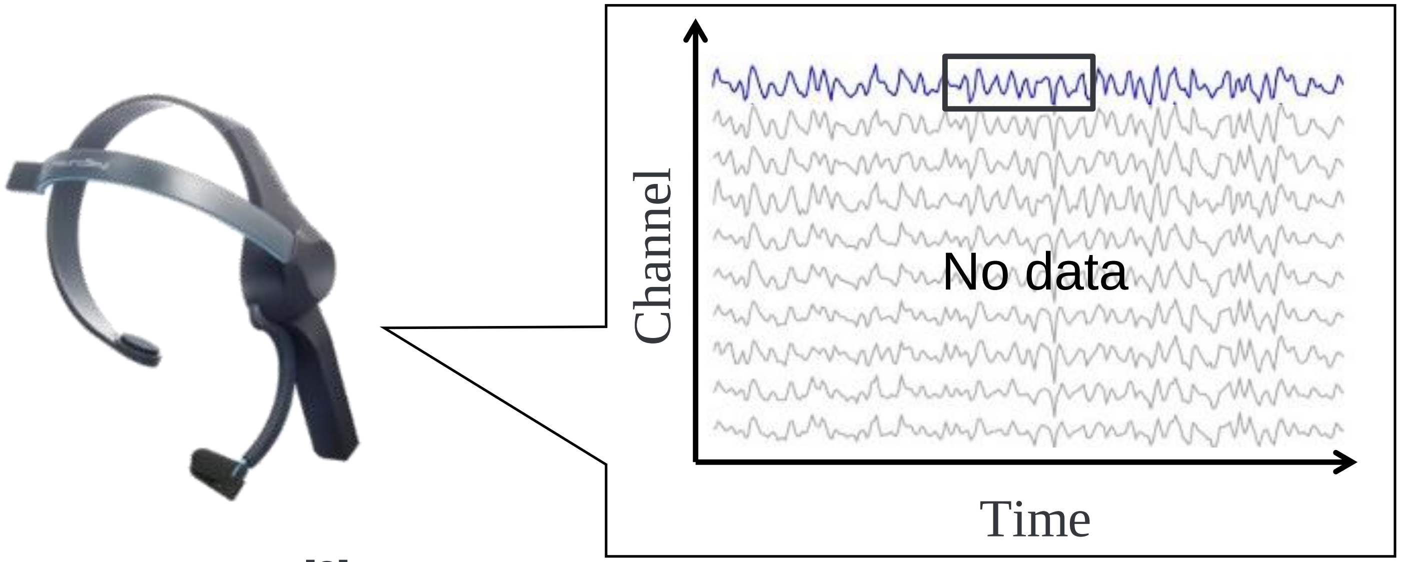
[1] http://web.media.mit.edu/~cvx/sht.htm, accessed 13-Nov.-2018.

# Single(/Few)-channel measurement devices

◆ Recently developed

- Portable
- Cheap
- Limited channel

  (Ultimately single)




MindWave [2]

→ **We can not use spatial filter for feature extraction**

◆ Only allow specialized feature extraction technique

to emphasize rhythmic features

→ **Comparative study by using the same dataset is required**

[2] http://store.neurosky.com/, accessed 1-Nov.-2018.

# Motivation

**Investigating how to build the best single-channel motor imagery BCI**

◆ Research objective

To find the best combination of **channel**, **feature**, and **classifier**

◆ Materials

EEG dataset: BCI competition IV dataset 2a [3]

◆ Analysis

- Epoch segmentation
- Artifact rejection
- Feature extraction : 3 types (PS, SCCSP, GLCM)
- Classifiers : 6 types (LDA, k-NN, GMM, RF, MLP, SVM)
- Evaluation : 2-class classification with 10-fold CV

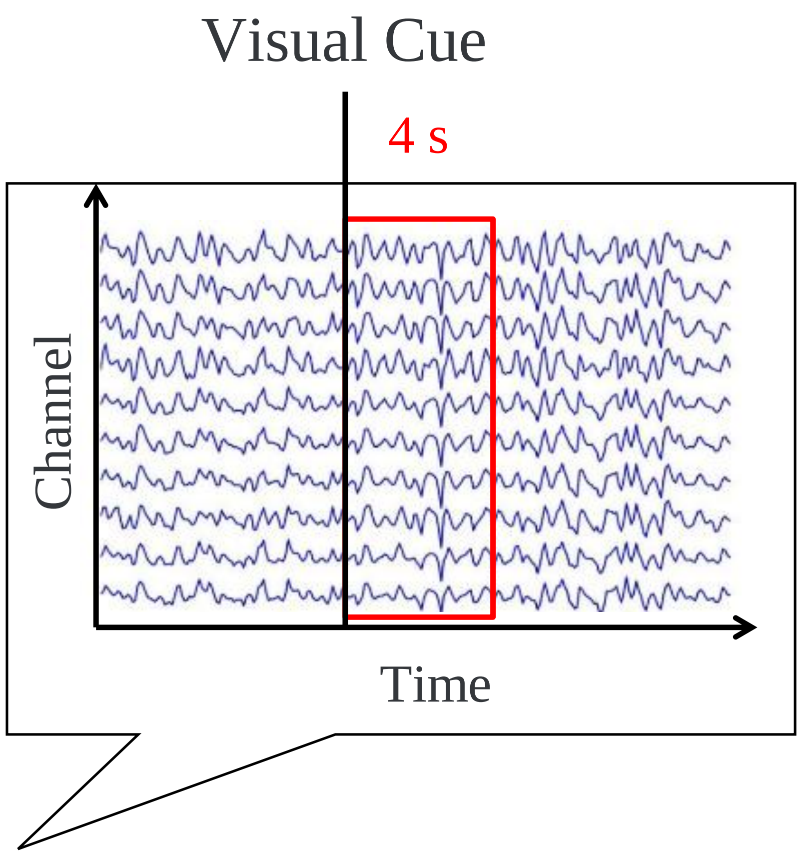
[3] M. Tangermann, et al., "Review of the BCI competition IV," Frontiers in Neuroscience, vol. 6, 2012.

# Materials (1/2)

◆ Open-access EEG dataset

BCI competition IV dataset 2a [3]

- # of channels: 22
- # of subjects: 9
- Task: Image a movement
- # of classes: 2 (left or right hand)
- Duration: 4 s
- # of trials: 288
- Sampling rate: 250 Hz
- Bandpass filter: 4 and 40 Hz
  (Fourth-order Butterworth filter)





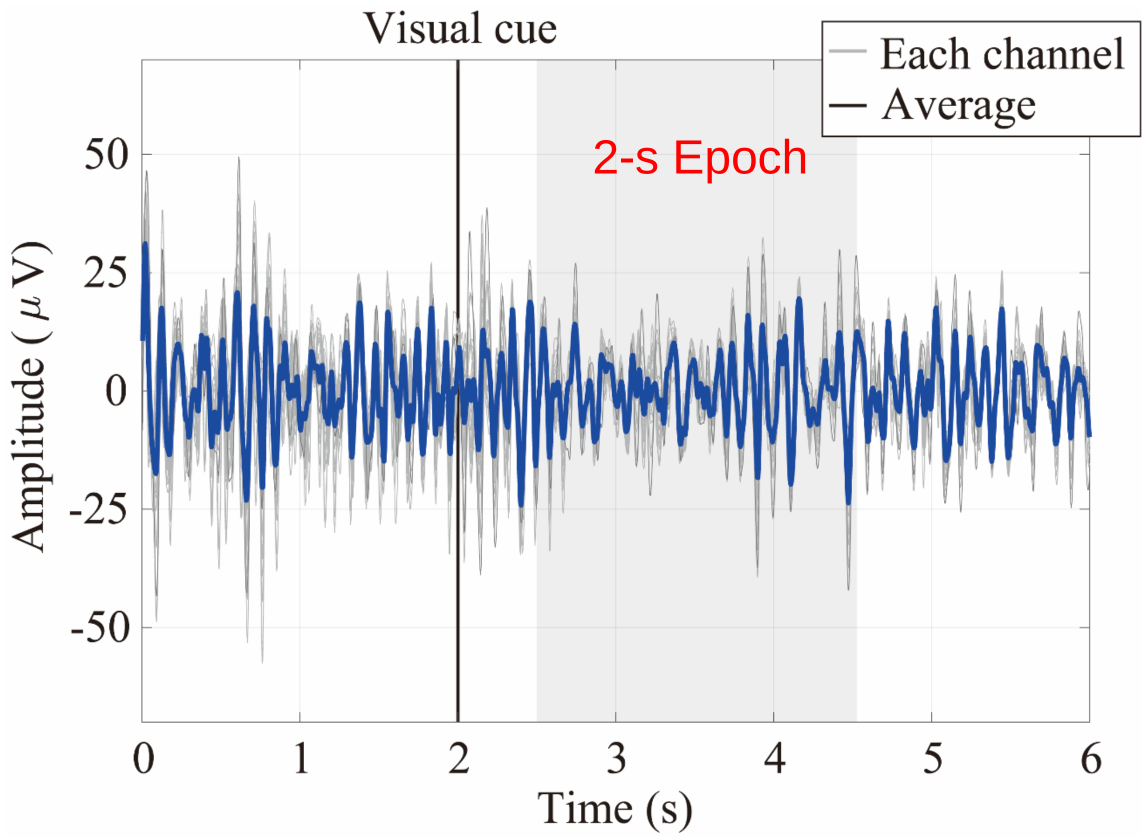
[3] M. Tangermann, et al., “Review of the BCI competition IV,” Frontiers in Neuroscience, vol. 6, 2012.

# Materials (2/2)

◆ Epoch segmentation

- 0.5-2.5 s after the cue [4]

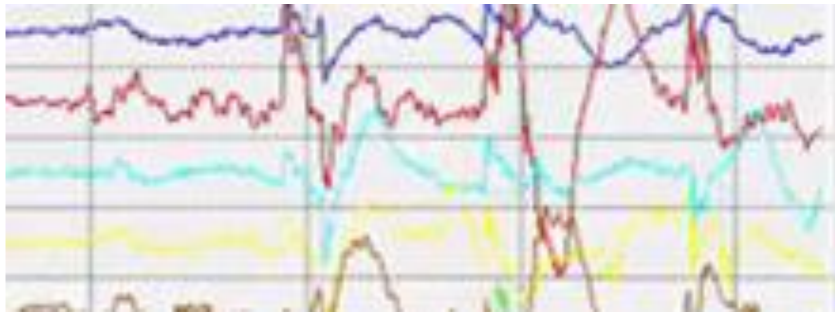
→ 288 2-s epochs




◆ Artifact rejection

- Some epochs were contaminated artifacts (e.g. muscular and ocular)
- The labels are given by the BCI competition (maybe visual inspection)

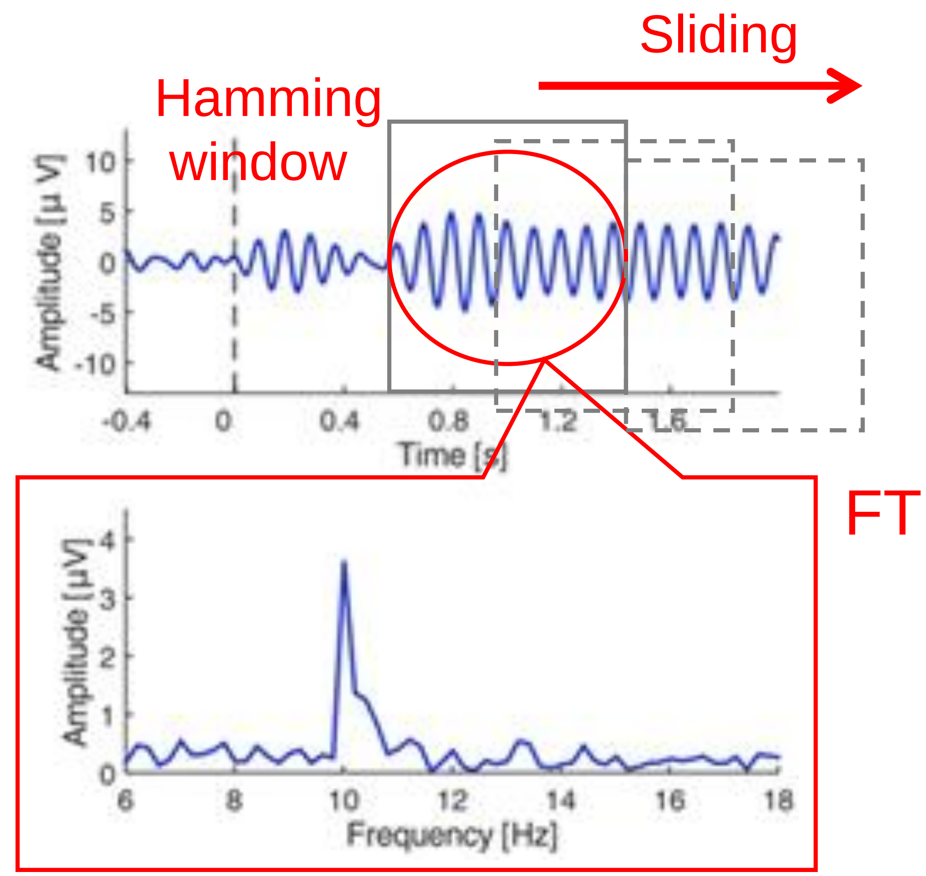
→ 221 to 279 epochs were used for classification



Artifactual epoch

[4] K. K. Ang et al., “Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b,” *Front Neurosci.*, vol. 6, 2012.

# Feature Extraction (1/2)




- Power spectra (PS)

  Fourier transform

  - 100 sample points (and 28 zeros)
  - 50% overlap Hamming window
  - Log-scaled variance ranged 4 - 40 Hz

- Single-channel common spatial pattern (SCCSP)[5]

  Calculates filter $\boldsymbol{W}$ which maximizes the variance of two-class frequency bins

  - Similar to classical CSP (frequency bins as channels) → Common 'spectral' pattern…?
  - Log-scaled variance

\# of frequency bins

$$\boldsymbol{X}_t \in \mathbb{R}^{d \times N}$$

$$\Sigma_t = \boldsymbol{X}_t \boldsymbol{X}_t^{\mathrm{T}} \in \mathbb{R}^{d \times d}$$

$$\boldsymbol{w}_c = \max_{\boldsymbol{w}} \boldsymbol{w}^t \Sigma^{(c)} \boldsymbol{w}$$

$$\text{s.t. } \boldsymbol{w}^t \left(\Sigma^{(c)} + \Sigma^{(c')}\right) \boldsymbol{w} = 1$$

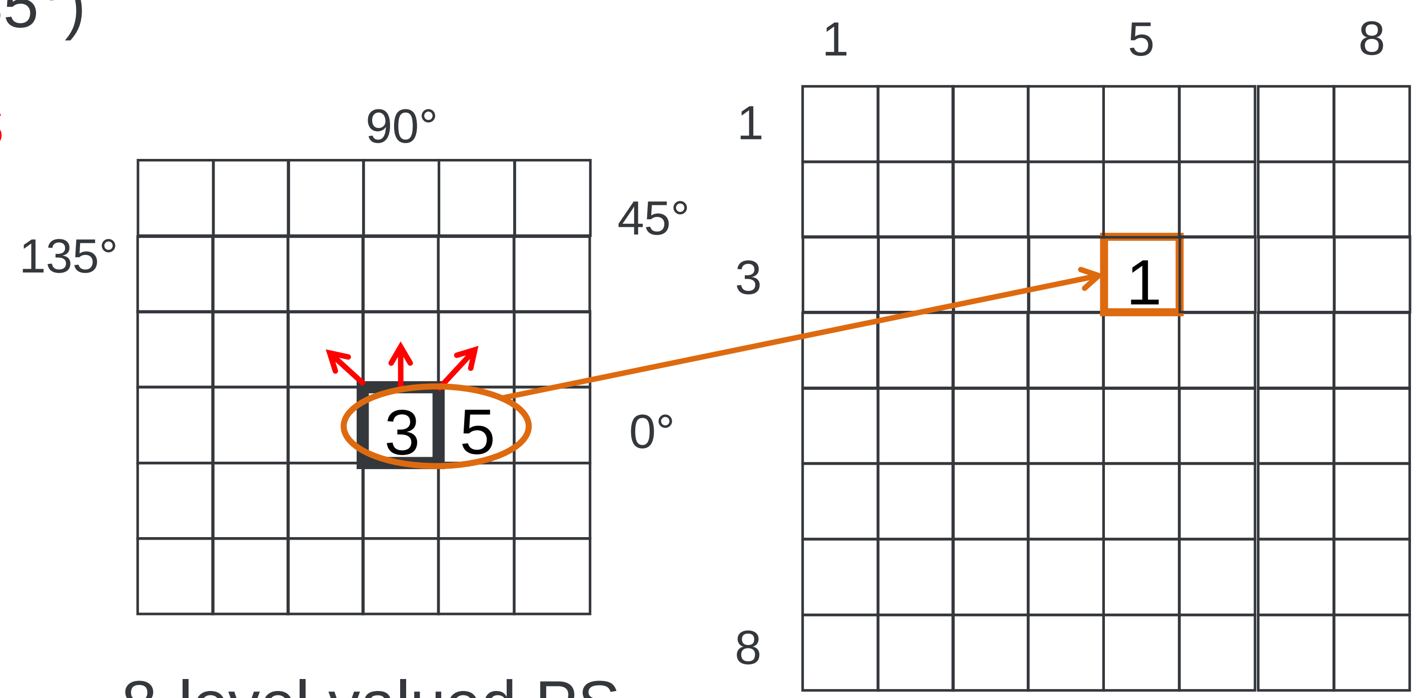
[5] S. Ge et al., "Classification of four-class motor imagery employing single-channel electroencephalography," *PloS ONE*, vol. 9, no. 6, e98019, 2014.

# Feature Extraction (2/2)

◆ Gray-level co-occurrence matrix (GLCM) [6]

- Concatenates PS to be a spectrogram
- Translates spectrogram into 8-level values
- Sums co-occurrence counts from the 8-level values

  4 directions (0, 45, 90, and 135°)
- Used for 4 text descriptors
  1. Contrast
  2. Correlation
  3. Energy
  4. Homogeneity




8-level valued PS

GLCM

→ To capture

co-occurrence power fluctuation (by event-related (de)synchronization)

[6] J. Camacho et al., "Real-time single channel EEG motor imagery based brain computer interface," *World Automation Congress* pp.*1-6,* 2016.

# Classification

- Six classifiers:
  1. Linear discriminant analysis (LDA)
  2. $k$-nearest neighbor ($k$-NN)
  3. Gaussian mixture model (GMM)
  4. Random forest (RF)
  5. Multi-layer perceptron (MLP)
  6. Support vector machine (SVM)

- Assessments
  - Independent validation for each subject and channel
  - 10-fold cross validation (10 times to avoid selection bias)

The best combination of **channel**, **feature**, and **classifier**

AIST

# Results and Discussion (1/2)

◆ Classification accuracy

| Subject | Feature | Classifier | | | | | |
|---|---|---|---|---|---|---|---|
| | | LDA | $k$-NN | GMM | RF | MLP | SVM |
| ⋮ | | | | | | | |
| S3 | **PS** | 70.6±0.8 (C3) | 67.9±0.8 (C3) | 60.7±0.7 (C3) | 69.2±0.8 (C3) | **71.4±0.7 (C3)** | 70.8±0.7 (C3) |
| | SCCSP | 67.0±0.7 (C3) | 64.4±0.8 (C3) | 62.1±0.9 (C6) | 65.6±0.9 (C3) | 71.1±0.8 (C3) | 66.6±0.6 (C3) |
| | GLCM | 64.4±0.7 (C4) | 64.3±1.2 (C3) | 60.5±0.5 (C3) | 63.5±0.8 (C3) | 64.0±0.7 (C3) | 65.9±0.7 (CP4) |
| ⋮ | | | | | | | |
| S9 | PS | 85.0±0.5 (C3) | 82.2±1.4 (C4) | 80.6±0.8 (C4) | 83.0±0.7 (C4) | 85.4±0.7 (C4) | 85.0±0.7 (C4) |
| | **SCCSP** | 83.8±0.5 (C3) | 84.2±0.5 (C4) | **86.6±0.6 (C4)** | 85.0±0.6 (C4) | 86.2±0.5 (C4) | **86.6±0.4 (C4)** |
| | GLCM | 68.0±0.8 (CP3) | 72.3±1.0 (CP4) | 69.1±0.9 (CP4) | 71.6±0.9 (C4) | 71.7±0.9 (CP4) | 73.7±0.8 (C4) |
| Mean | **PS** | 61.8±0.5 | 62.3±0.4 | 60.0±0.4 | 61.8±0.4 | 63.1±0.4 | **63.5±0.4** |
| | **SCCSP** | 61.8±0.4 | 62.2±0.4 | 61.6±0.4 | 61.2±0.42 | **63.5±0.4** | 63.3±0.4 |
| | GLCM | 61.4±0.4 | 60.7±0.3 | 58.5±0.3 | 58.7±0.3 | 60.3±0.4 | 61.4±0.3 |

- **PS** and **SCCSP** showed superior performance than GLCM ($p<0.001$)
- **MLP** with SCCSP / **SVM** with PS effectively classified EEG data

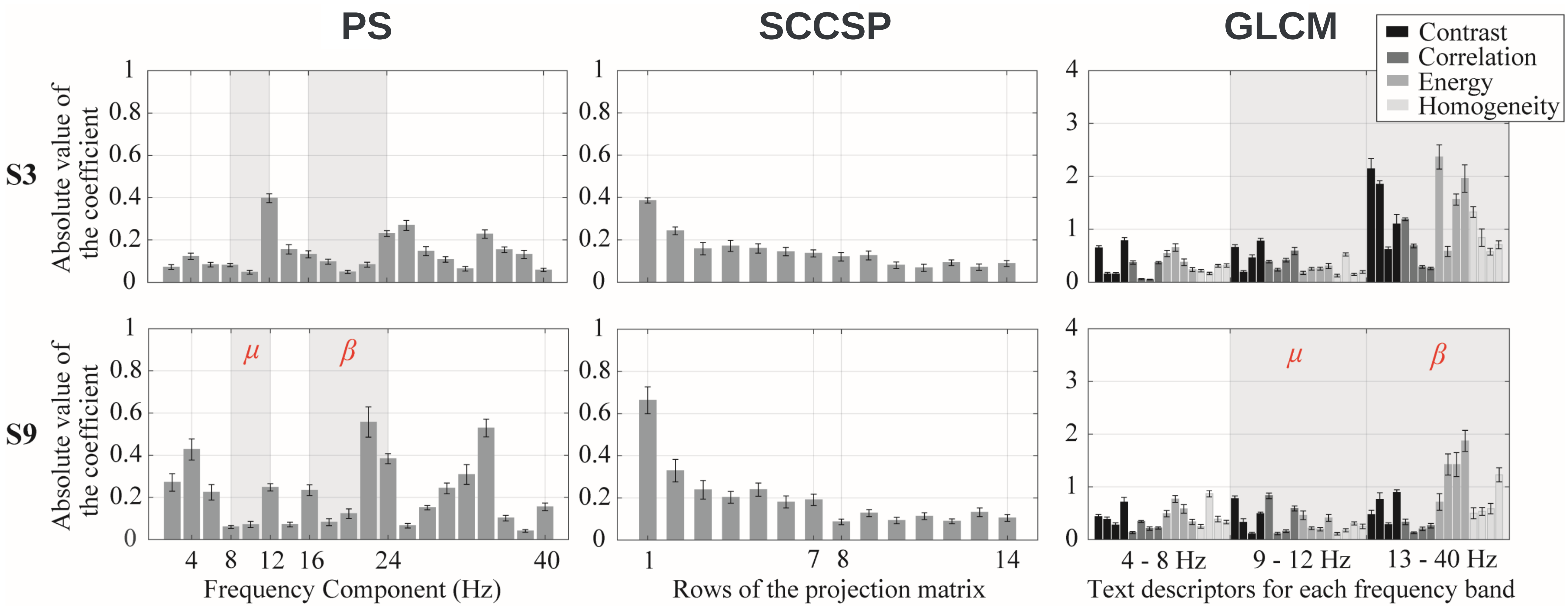
→ Average: 63.5 ± 0.4%

Best : 86.6 ± 0.4% (**C3** or **C4** position)

Artificial Intelligence Research Group

# Results and Discussion (2/2)

◆ Absolute values of the coefficients in LDA




**$\mu$ and $\beta$ rhythms would have large coefficients …?**

→ The relationship between features and classifiers should be further investigated.

# Conclusions

**Investigating how to build the best single-channel motor imagery BCI**

## ◆ Results

- PS and SCCSP showed superior performance than GLCM ($p$<0.001)
- MLP with SCCSP / SVM with PS effectively classified EEG data

Average: 63.5 ± 0.4%

Best : 86.6 ± 0.4% (C3 or C4 position)

## ◆ Limitation

Original dataset used multichannel environment

(Not used single(/few)-channel measurement device)

# Appendices