

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

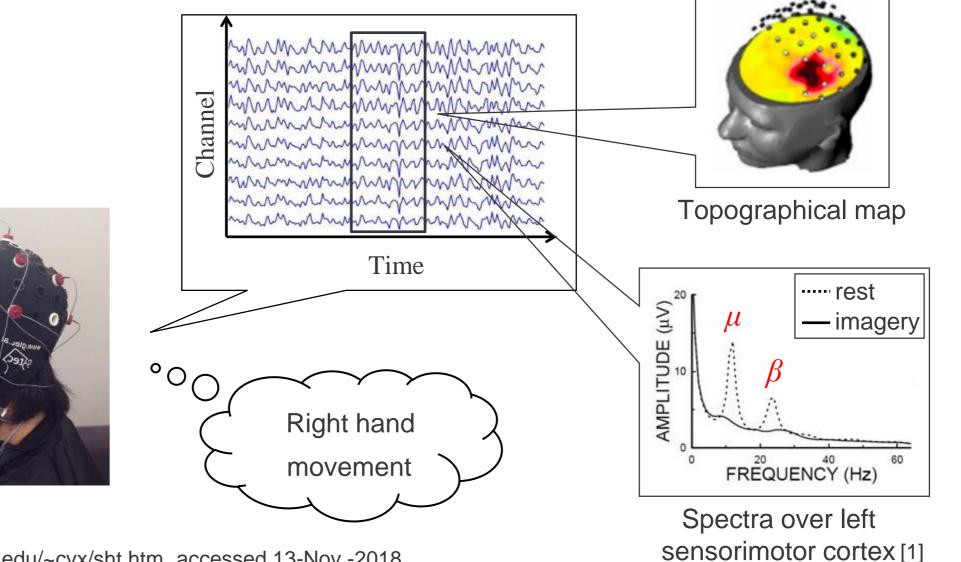
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Motor Imagery Brain—Computer Interfaces

- Use rhythmic EEG features by motor imagery μ and β rhythms in motor areas are discriminative features
- Integrate spatial filter to emphasize the features

But, ... the filter needs multichannel information



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

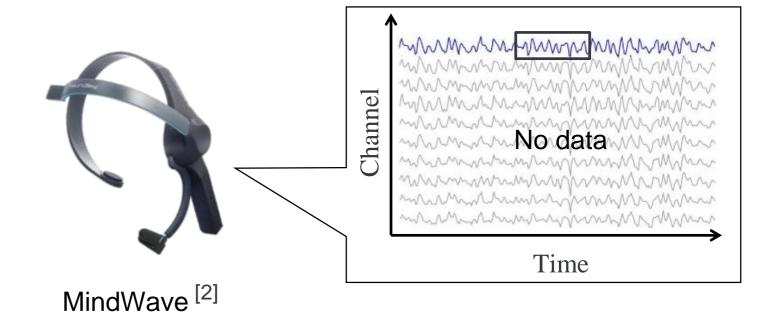


Single(/Few)-channel measurement devices

- Recently developed
 - Portable
 - Cheap

Artificial Intelligence Research Group

- Limited channel
 - (Ultimately single)



\rightarrow We can not use spatial filter for feature extraction

Only allow specialized feature extraction technique

to emphasize rhythmic features

 \rightarrow Comparative study by using the same dataset is required



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.



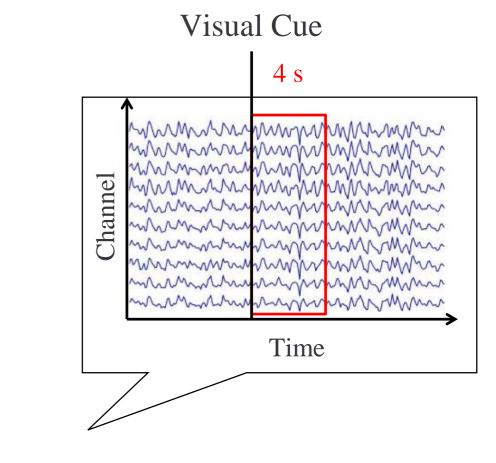
Materials (1/2)

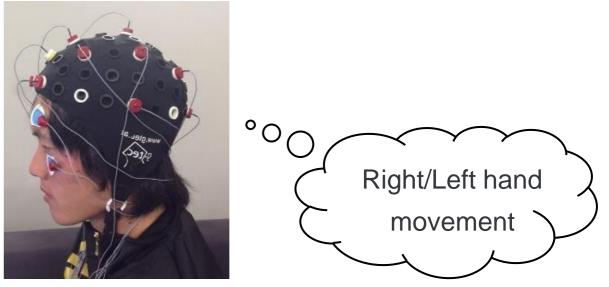
Open-access EEG dataset

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)

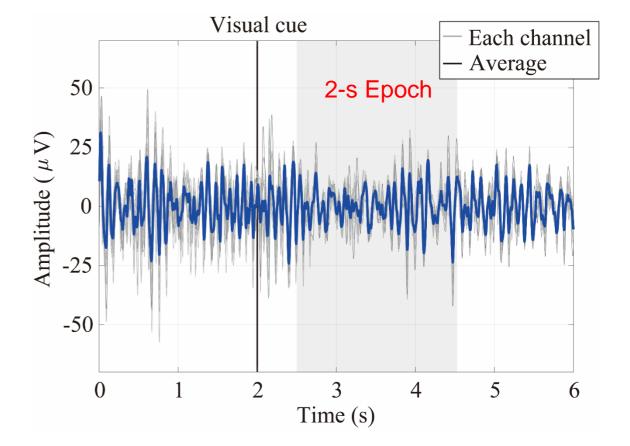




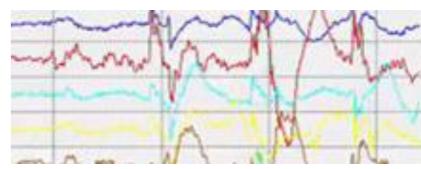


Materials (2/2)

- Epoch segmentation
 - 0.5-2.5 s after the cue $^{\scriptscriptstyle [4]}$
 - \rightarrow 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)
 - \rightarrow 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.

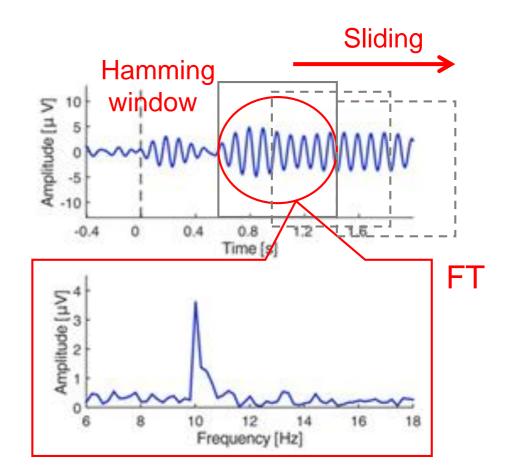


Feature Extraction (1/2)

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 W which maximize the variance of

two-class frequency bins

- Similar to classical CSP

(frequency bins as channels)

- \rightarrow Common 'spectral' pattern...?
- Log-scaled variance

of frequency bins $X_t \in \mathbb{R}^{d \times N}$ $\sum_t = X_t X_t^T \in \mathbb{R}^{d \times d}$ $w_c = \max_w w^t \sum_{w}^{(c)} w$ s.t. $w^t (\sum_{w}^{(c)} + \sum_{w}^{(c')}) w = 1$

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

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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 90° 45° 1. Contrast 135° 3 1 2. Correlation 3 5 0° 3. Energy 4. Homogeneity 8 8-level valued PS GLCM \rightarrow 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



Results and Discussion (1/2)

Classification accuracy

Subject	Feature	Classifier					
		LDA	k-NN	GMM	RF	MLP	SVM
				•			
				•			
				•			
S 3	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)
				•			
S 9	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)

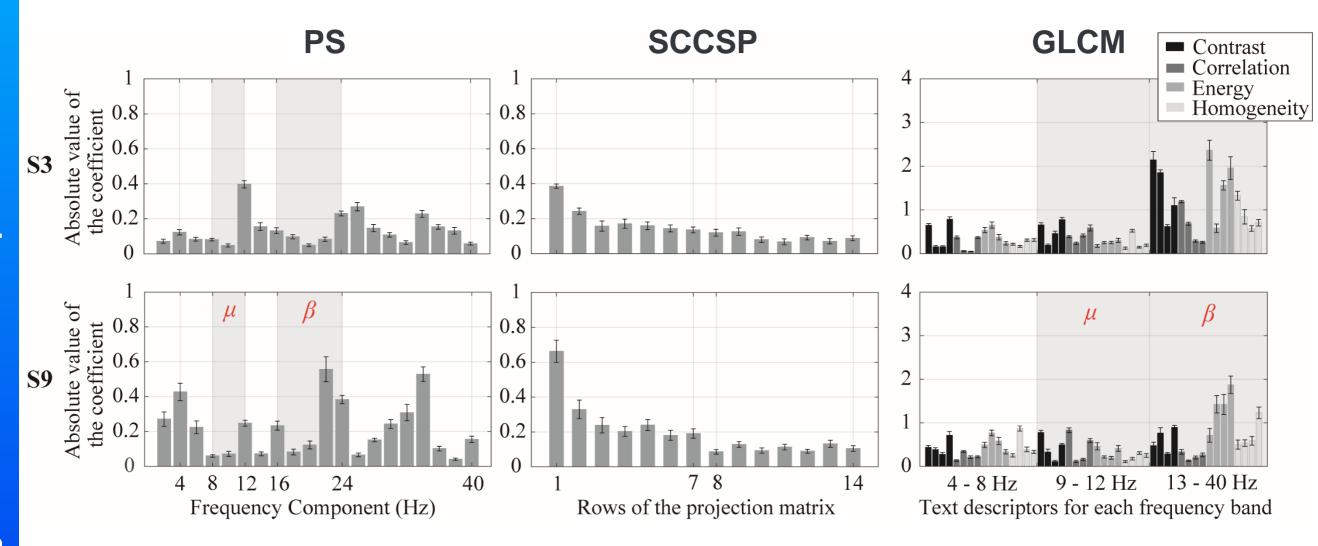
- MLP with SCCSP / SVM with PS effectively classified EEG data
 - \rightarrow Average: 63.5 ± 0.4%

Best : $86.6 \pm 0.4\%$ (C3 or C4 position)



Results and Discussion (2/2)

Absolute values of the coefficients in LDA



 μ and β rhythms would have large coefficients ...? \rightarrow 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 : $86.6 \pm 0.4\%$ (C3 or C4 position)

Limitation

Original dataset used multichannel environment (Not used single(/few)-channel measurement device)



Appendices