BCI Comparative Analysis with multiple EEG domains

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Contents

Motivation

The paper about BCI Comparative Analysis:

Comparative Analysis of Features Extracted from EEG Spatial, Spectral and Temporal Domains for Binary and Multiclass Motor Imagery Classification

Seung-Bo Lee*, Hyun-Ji Kim*, Hakseung Kim, Ji-Hoon Jeong, Seong-Whan Lee and Dong-Joo Kim, PhD[1§]

Motivation

In discussion,

- "Future studies that aim to validate the findings of this study with similar designs could benefit from including enhanced variants of feature extraction techniques and classifiers **for multiple EEG domains**, preferably with larger cohorts from prospective experiments."

Objective

Comparing feature extraction methods that use multiple EEG domains

- Spatial & Spectral
- Spectral & Temporal
- Spatial & Temporal

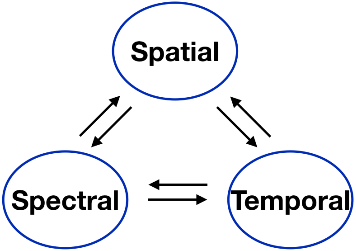

Figure 1. Three Feature Domains

Objective

Comparing feature extraction methods that use multiple EEG domains

- **Spatial & Spectral**
- Spectral & Temporal
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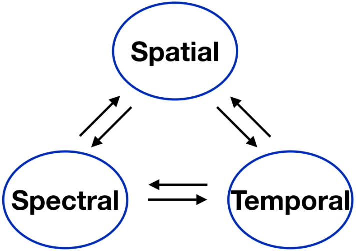

Figure 1. Three Feature Domains

Objective

The paper about **Spatial & Spectral** feature extraction method:

On the Use of Convolutional Neural Networks and Augmented CSP Features for Multi-class Motor Imagery of EEG Signals Classification

Huijuan Yang, Siavash Sakhavi, Kai Keng Ang and Cuntai Guan

⇒ **Augmented CSP (ACSP)[1]**

Objective

Comparing feature extraction methods that use multiple EEG domains

- Spatial & Spectral
- **Spectral & Temporal**
- Spatial & Temporal

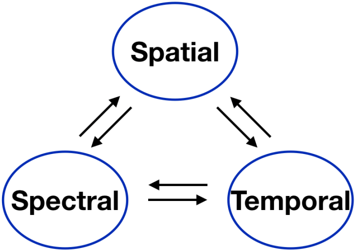

Figure 1. Three Feature Domains

Objective

The paper about **Spectral & Temporal** feature extraction method:

Journal of Neural Engineering

PAPER

A novel deep learning approach for classification of EEG motor imagery signals

To cite this article: Yousef Rezaei Tabar and Ugur Halici 2017 *J. Neural Eng.* **14** 016003

⇒ **Short-Time Fourier Transform (STFT)[2]**

Data set

Table 1. Data set description for each method

Method	ACSP	STFT
Dataset	Competition IV dataset IIa	Competition IV dataset IIb
Subjects	9	9
Channels	22 Ag/AgCl	C3, Cz, C4
Trials	288	400
Rate(Hz)	250	250
Tasks	left hand, right hand, feet and tongue	left hand and right hand
Classes	4-class	2-class

ACSP

Augmented CSP (ACSP):

- The proposed "Augmented CSP (ACSP)" features can be considered as extraction of the CSP features from a multi-level decomposition of the frequency ranges

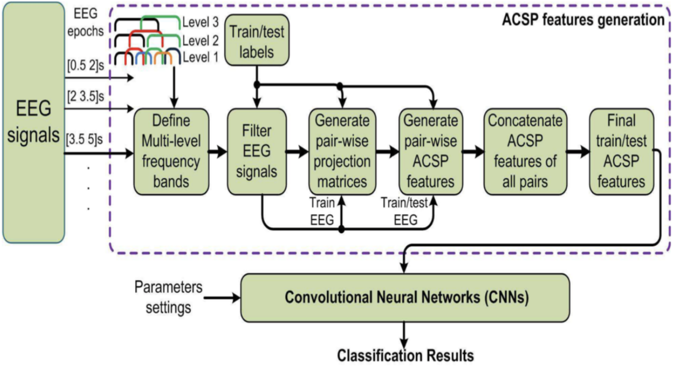

Figure 2. Schematic illustration of ACSP feature extraction

ACSP

The following steps are carried out to generate the ACSP features:

1. Define the overall starting frequency and ending frequency, width of each band, and width of each window shift.
2. Filter the EEG signals for all the frequency bands with a band-pass filter.
3. Generate the pair-wise projection matrix by applying CSP **pair-wisely**.
4. Generate the ACSP features based on pair-wise projection matrix.

Model (ACSP)

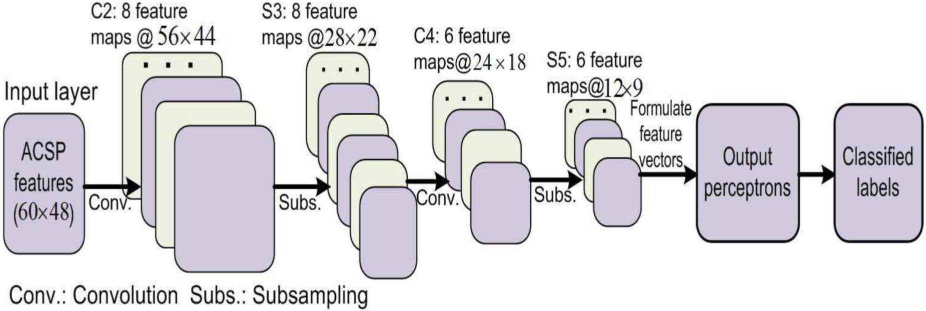

Figure 3. Architecture of CNN for measuring performance of ACSP

STFT

Short-Time Fourier Transform (STFT):

- Fourier Transform(FT) decomposes signal into frequency.
- However, if the frequency of signal changes as time passes, FT cannot catches **when** and **how** the signal changed.
- Employ STFT so that we can get **Spectral & Temporal** feature.

STFT

However, not only applying STFT to the signal,

- but also **augmented** spectrogram of each channel.

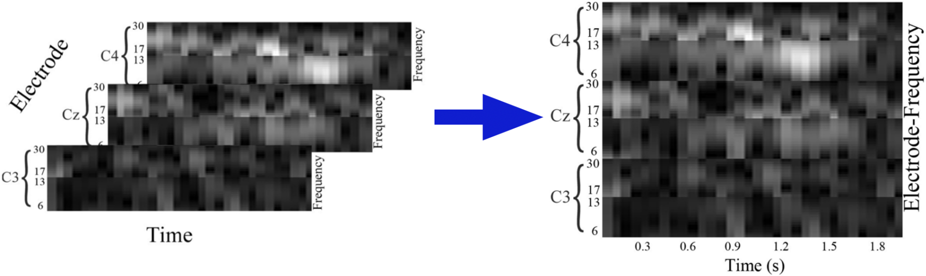

Figure 4. Spectrogram, after applying Short-Time Fourier Transform

Model (STFT)

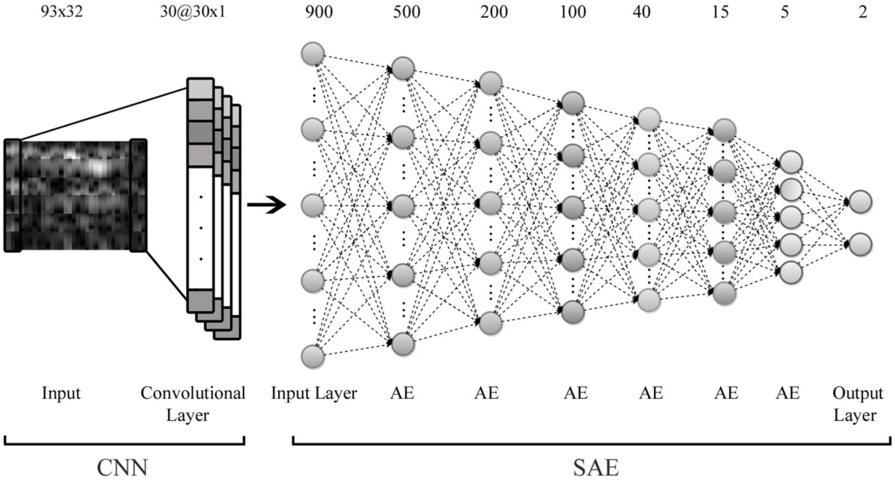

Figure 5. Architecture of CNN-SAE for measuring performance of STFT

Result (ACSP)

Table 2. 4-class classification result of ACSP(Diff = Proposed - ACSP)

Sub.	Mean accuracy [%]		Diff [%]
	ACSP	Proposed	
S1	75.8	97.2	21.4
S2	48.7	72.5	23.8
S3	79.0	94.4	15.4
S4	52.7	68.4	15.7
S5	64.0	74.6	10.6
S6	49.0	65.9	16.9
S7	80.8	90.6	9.8
S8	83.2	96.5	13.3
S9	82.5	95.8	13.3
Avg.±std.dev.	68.4±14.9	84.0±13.3	15.6±4.6

Result (STFT)

Table 3. 2-class classification result of STFT(Diff = Proposed - STFT)

Sub.	CNN			CNN-SAE		
	Mean accuracy [%]		Diff [%]	Mean accuracy [%]		Diff [%]
	STFT	Proposed		STFT	Proposed	
S1	74.5	72.5	-2.0	76.0	71.8	-4.2
S2	64.3	51.5	-12.8	65.8	52.8	-13.0
S3	71.8	56.3	-15.5	75.3	57.5	-17.8
S4	94.5	93.9	-0.6	95.3	84.9	-10.4
S5	79.5	52.3	-27.2	83.0	50.8	-32.2
S6	75.0	70.3	-4.7	79.5	71.8	-7.7
S7	70.5	71.3	0.8	74.5	67.3	-7.2
S8	71.8	50.8	-21.0	75.3	50.8	-24.5
S9	71.0	72.3	1.3	73.3	73.0	-0.3
Avg.±std.dev.	74.8±8.5	65.7±14.3	-9.1±10.4	77.6±8.1	64.5±12.0	-13.1±10.1

Discussion

1. ACSP
   - Our result showed much better accuracy that of original ACSP.
   - There would be other unseen reasons, but the reason being seen is **the number of frequency band**.
2. STFT
   - Our Result is not the same with that of original STFT.
   - **Since some of them are similar**, implemented method is not wrong at all.
   - Model is not well optimized.

Future plans

- Some modifications for ACSP(frequency band chunking), STFT(optimization)
- Implement remainder(feature extractor for **Spatial & Temporal** features)

Reference

1. Yang, H., Sakhavi, S., Ang, K. K., Guan, C. (2015, August). On the use of convolutional neural networks and augmented CSP features for multi-class motor imagery of EEG signals classification. In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 2620-2623). IEEE.
2. Tabar, Y. R., Halici, U. (2016). A novel deep learning approach for classification of EEG motor imagery signals. Journal of neural engineering, 14(1), 016003.