CMS: Component Mixing Strategy for Augmentation on Motor Imagery Signal





Zhe Sun*‡ Zhiwen Zhang † Feng Duan‡ Binghua Li ‡ Jordi Solé−Casals‡§

Email: *zhe.sun.vk@riken.jp*

* *Head Office for Information Systems and Cybersecurity, Riken, Wako, Japan*

† *Tokyo Univerity, Japan*

‡ *College of Artificial Intelligence, Nankai University, Tianjin, China*

§ *Department of Engineering, University of Vic−Central University of Catalonia, Catalonia, Spain*

Nankai University

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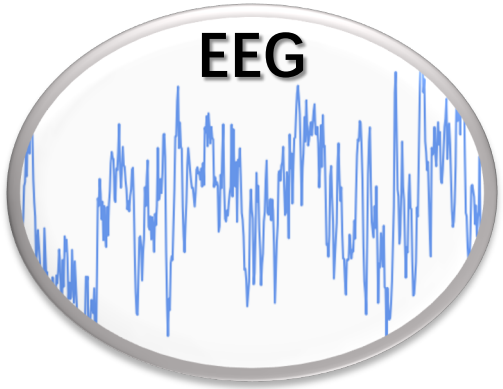
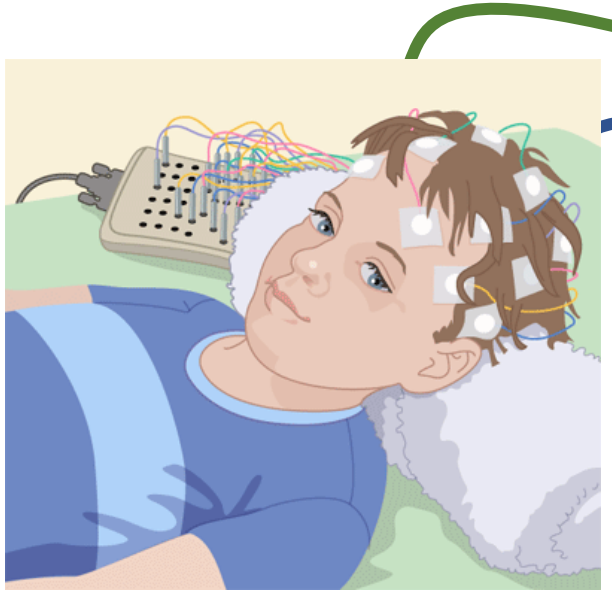
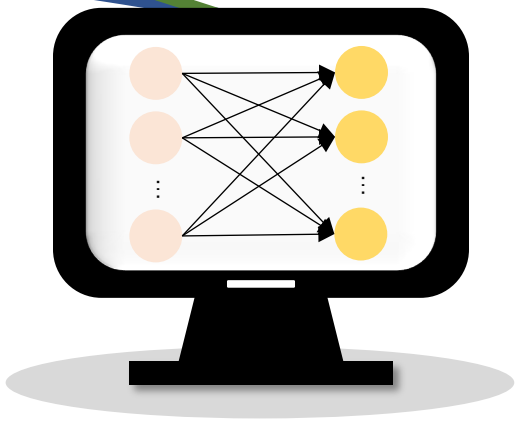
Electroencephalogram (i.e., EEG) Signal





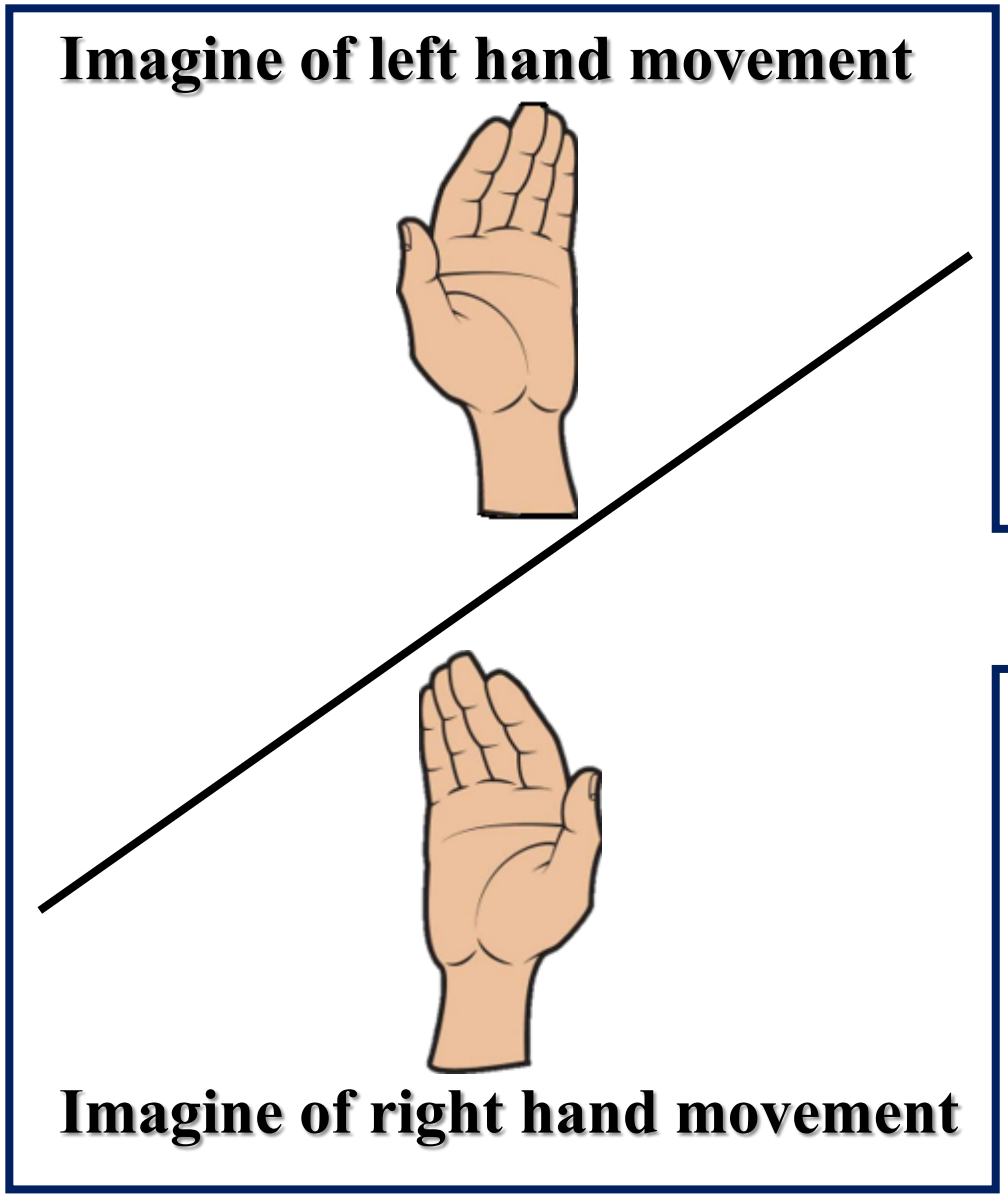


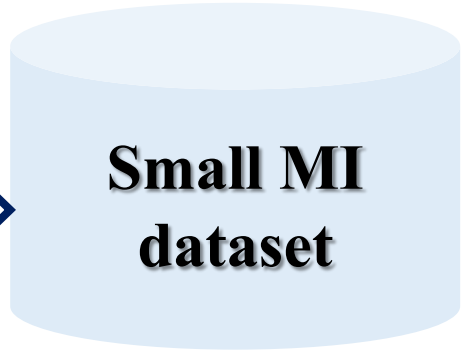
Brain Computer Interface (BCI)

Limitation in Motor-Imagery-based BCIs

Spirited

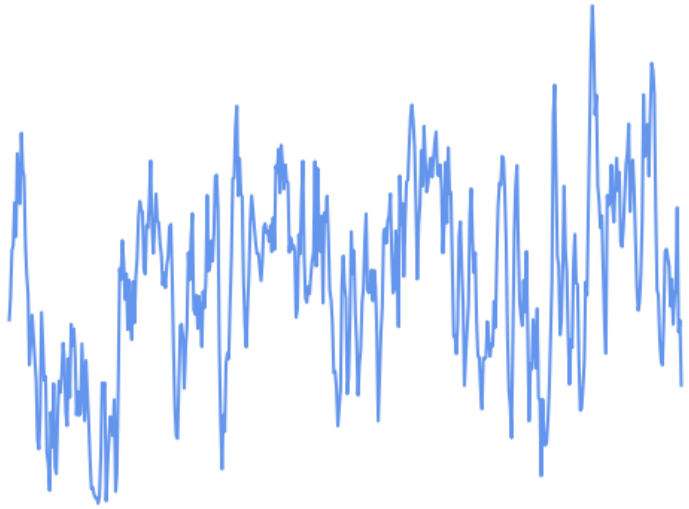
Fatigue



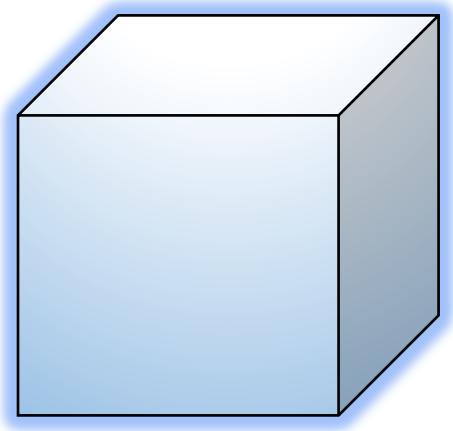


Previous Work

- **Tensor decompositions for feature extraction and classification of high dimensional datasets (Andrzej Cichocki, 2010)**



$Wavelet\ Transformation$



channels × smaples

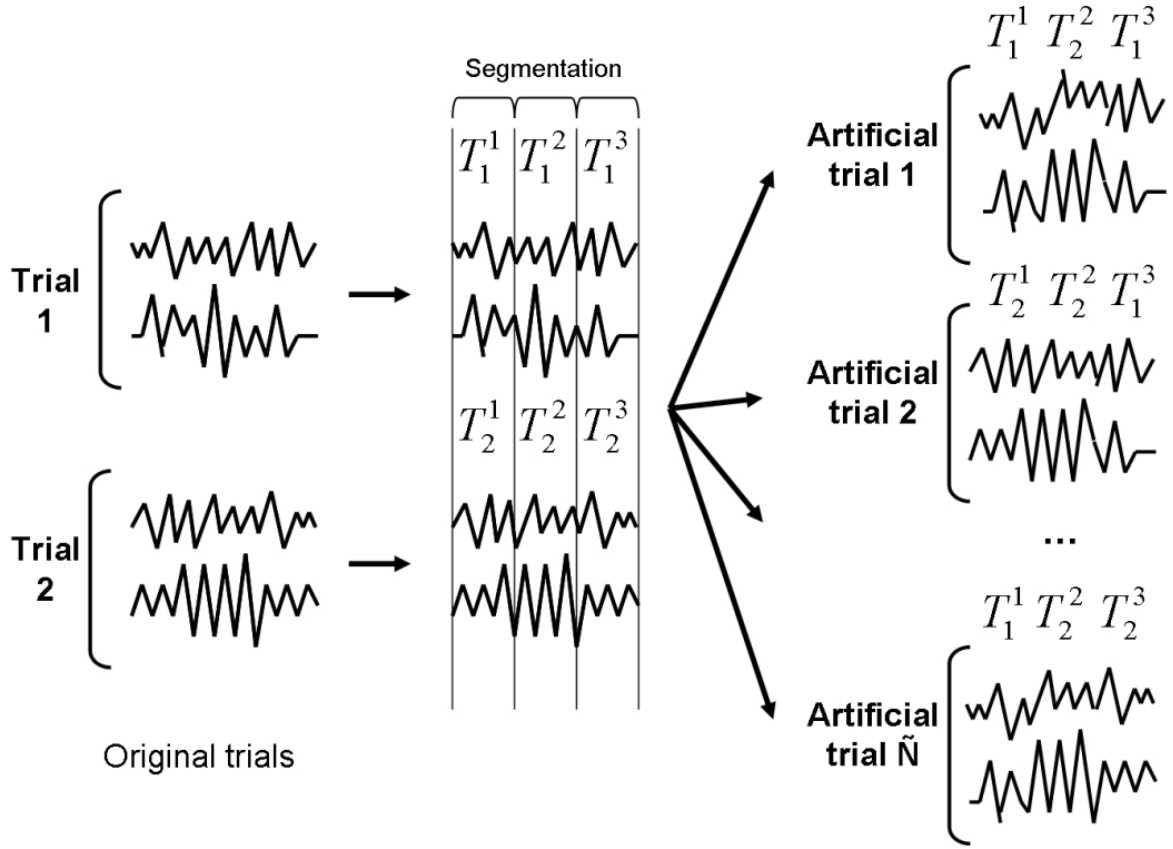
channels × frequency bins × time frames

Remark

Tensorize MI frames by wavelet transform help enrich the representation of trials.

Previous Work

- **Generating Artificial EEG Signals to Reduce BCI Calibration Time (Fabien Lotte, 2011)**

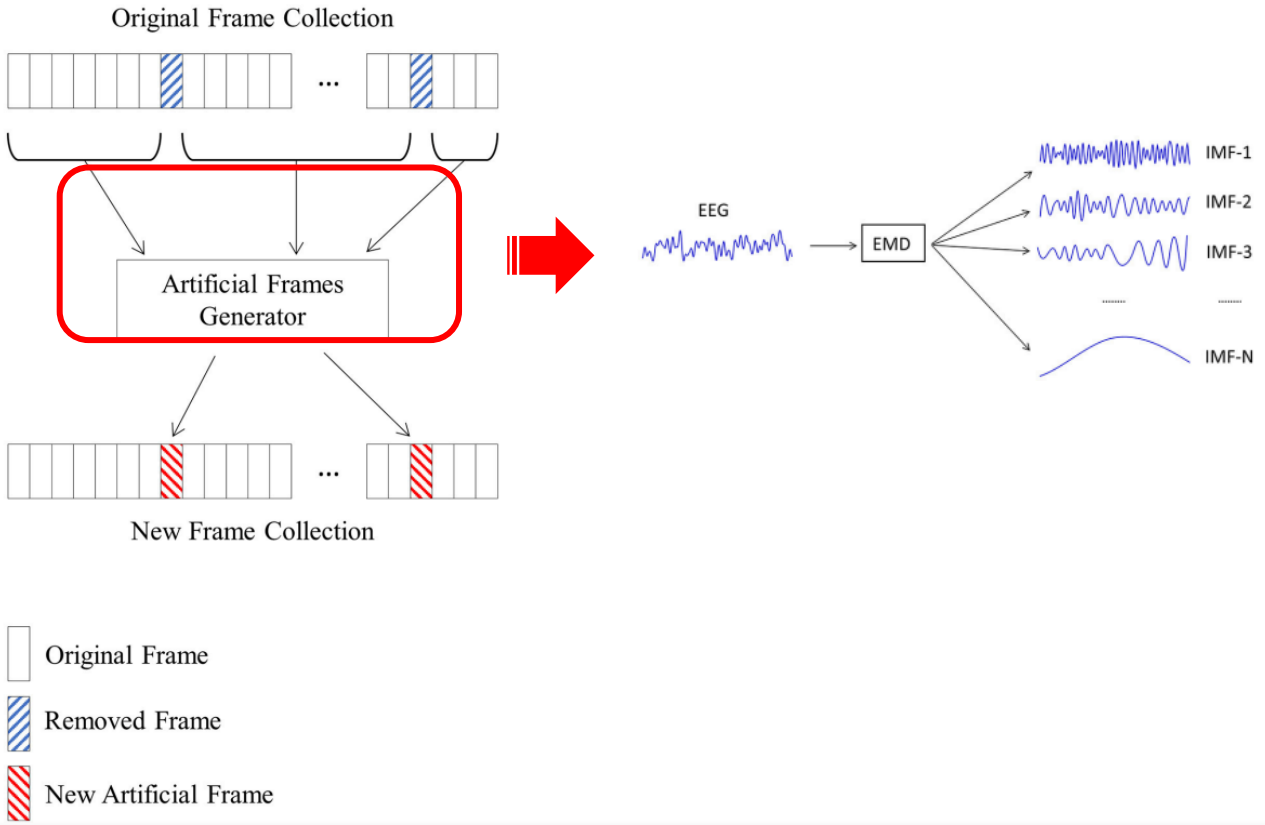


Remark

Generate artificial trials by information randomly selected from raw data help improve the performance

Previous Work

• **A New Method to Generate Artificial Frames Using the Empirical Mode Decomposition (EMD) for an EEG-Based Motor Imagery BCI (Josep Dinarès-Ferran et. al., 2018)**



Remark

Randomly mixing IMFs rather than segments allows artificial frame to contain time-frequency information of the raw data.

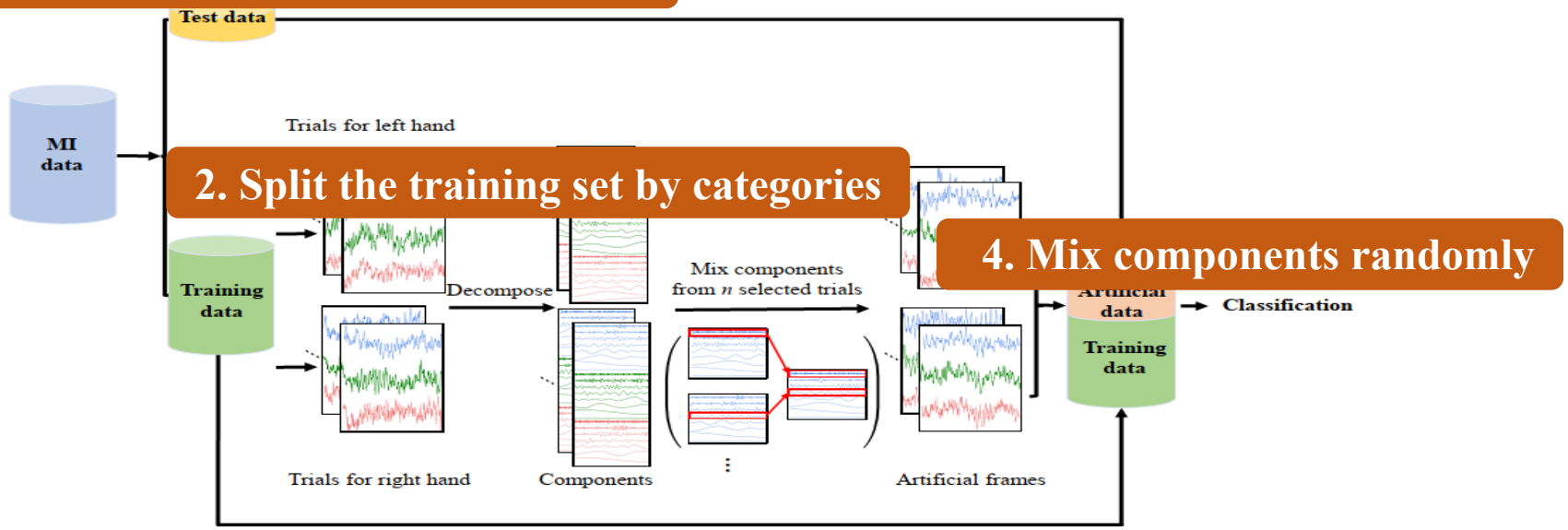
Previous Work

Question

- Can we tensorize the MI frames after augmented by mixing components?
- Do **other decomposition methods** except EMD take effect?

Component Mixing Strategy (CMS)

1. Split the test set and training set



3. Decompose parent signals with EMD\MEMD\ITD

Results on our experimental motor imagery EEG data

Results on EMD-based CMS

The combination of two strategy does improve the performance on accuracy

	Accuracy %(mean±std)	
	CNN	WNN
0×Dataset	77.9±0	88.0±0
1×Dataset	88.9±1.9	90.1±1
2×Dataset	85.6±2.2	86.7±2.5
3×Dataset	86.4±2.6	87.3±1.7
4×Dataset	83.6±2.9	85.0±2.6
5×Dataset	82.9±2.7	84.3±1.5

Experimental Settings

Dataset

- 6 subjects from BCI Competition IV dataset 2b[1], 300 MI frames for each

Ratio settings

- 20, 50, 100, 150 for training, respectively, the rest for test

Evaluation models

- EEGNet (Vernon J. Lawhern et. al., 2018)
- Wavelet Neural Network
- CSP + SVM

Decomposition methods

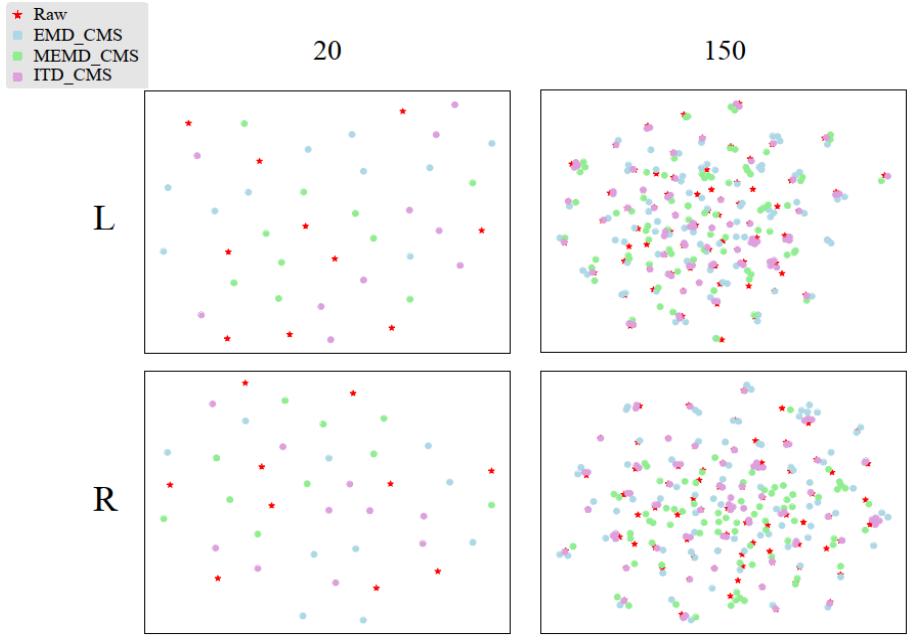
- EMD (Norden E. Huang et. al., 1998)
- MEMD (Naveed ur Rehman et. al., 2010)
- ITD (Mark G Frei et.al., 2007)

[1] http://www.bbci.de/competition/iv/#dataset2b

Distribution of Raw Data and Artificial Frames

Distribution visualized by t-distributed Stochastic Neighbor Embedding (t-SNE)

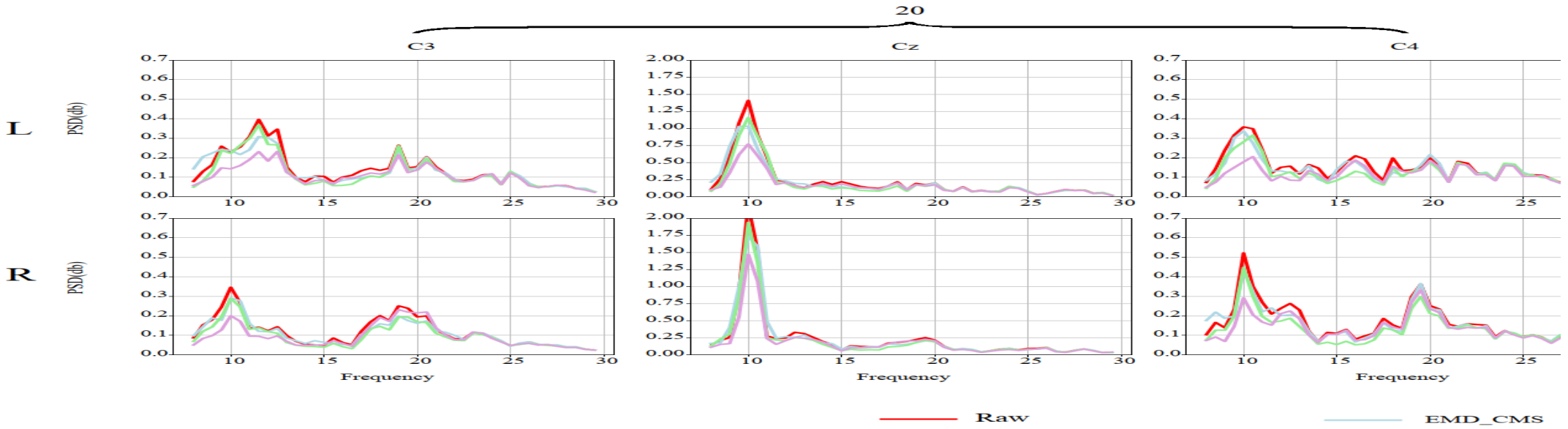
The artificial trials are clustered around raw frames.



Distribution of Raw Data and Artificial Frames

Comparison on mean power spectral density (PSD)

The generated data and real data share some similar traits on frequency.



Performance on Augmentation

Results on binary accuracy and area under curve (AUC) score

Improvement occurs in most cases.

Conclusion

Take-away messages

- Adding additional data generated by mixing components and then tensorize before classification help improve the performance.

- EMD, MEMD and ITD based CMS all take effect even when the training set is extremely small.

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