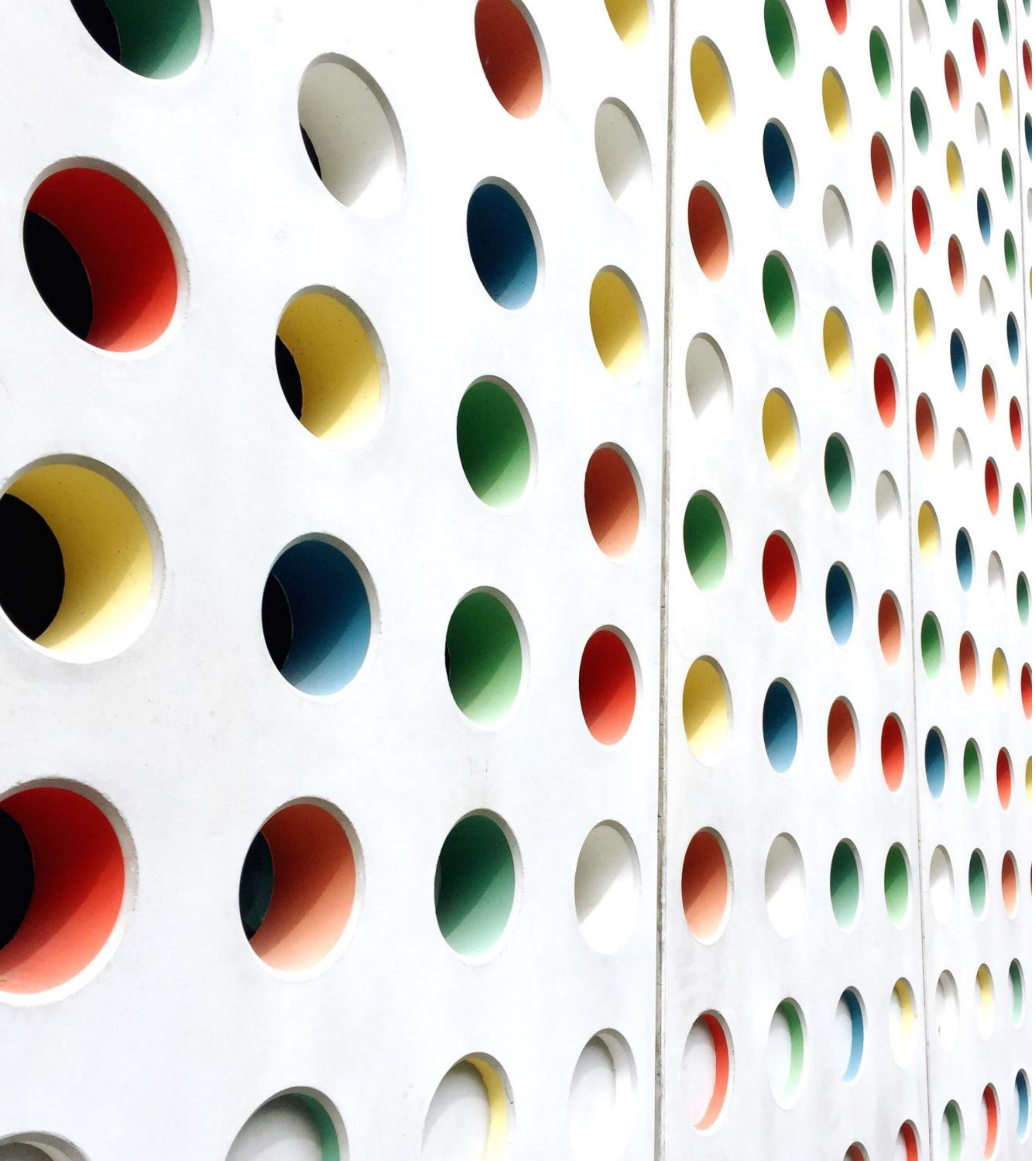

Recruiting Neural Field Theory for Motor Imagery Data Augmentation

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IARIA

Daniel Polyakov

I earned my Bachelor's Degree in Computer Engineering and a Master's Degree in Biomedical Engineering, both from the Technion, the Israel Institute of Technology. I worked for over 12 years in various R&D positions as a software and algorithm engineer in companies such as SCR and Camero. I developed products that included signal processing, computer vision and machine learning.

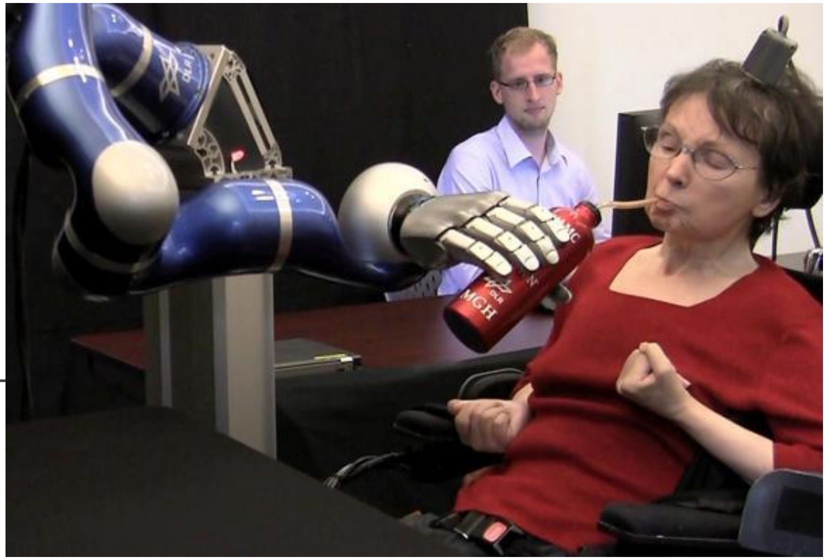
During the last 6 years, I routed my career to neuroscience research. I did a research internship at Robert Sanders anaesthesiology lab at the University of Wisconsin Hospital in Madison WI, collaborating with Giulio Tononi. Nowadays, I am a PhD student at Oren Shiki Computational Psychiatry lab at the Ben-Gurion University. In my research, I recruit Neural Field Theory to model large-scale neural activity. I use the model to augment data for brain-computer interfaces, to explore brain activity in states of disorders of consciousness (DOC) and to improve stimulation tactics in DOC treatment. I also teach courses in neural data analysis and computational neuroscience.

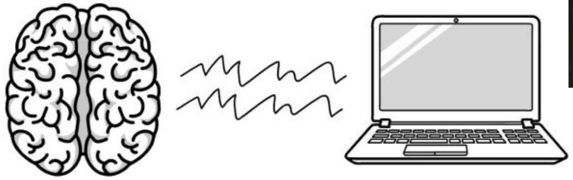
Computational Psychiatry Lab

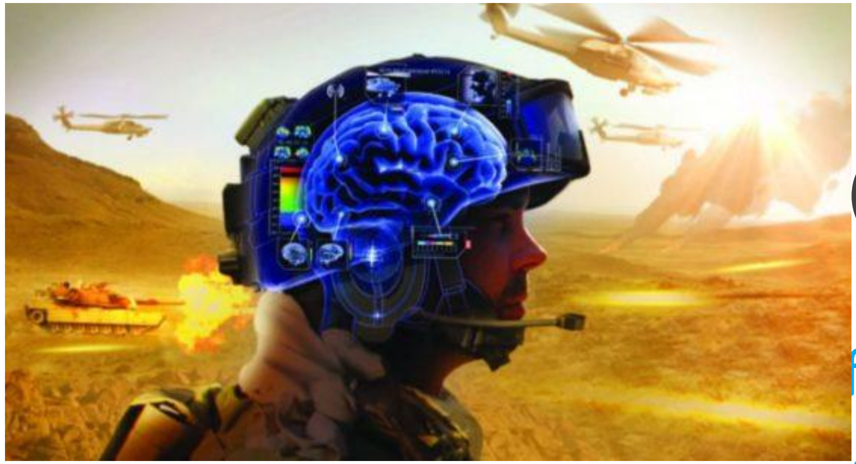
- Critical brain dynamics
- Computational models of brain activity
- Machine learning techniques in neuroscience
- Brain-Computer Interfaces
- Dynamics of the epileptic brain
- Computational approaches to schizophrenia, cognitive workload, sleep deprivation and more

https://www.computational-psychiatry.com/

Prof. Oren Shriki



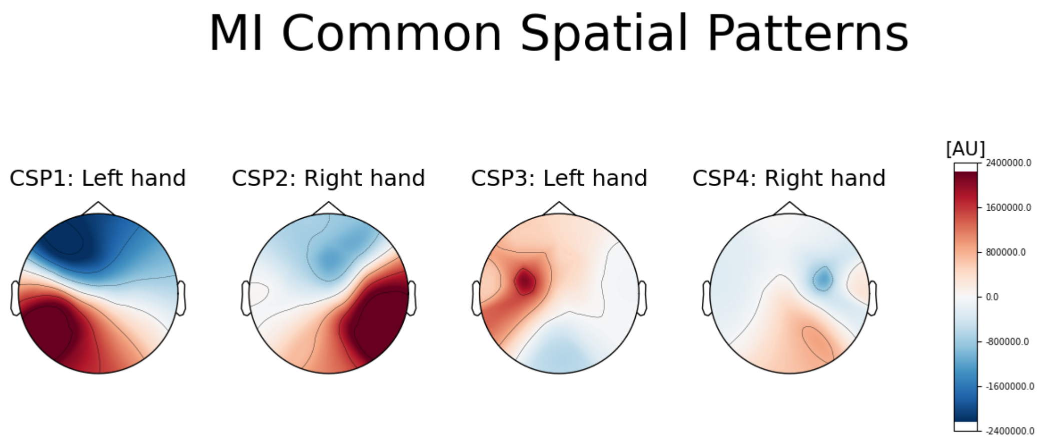




COMPUTER INT

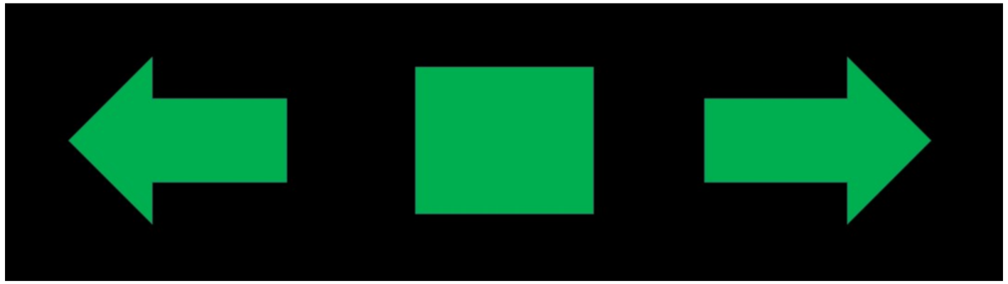
MOTOR IMAGERY PARADIGM

- The subject imagines a specific limb movement
- Activity at the central and parietal (motor) areas is modulated and reflected in the EEG signal
- A possible way to observe different activity for each limb MI is to fit Common Spatial Patterns (CSP). Each CSP is a linear combination of EEG channels signals
- A Linear Discriminant Analysis (LDA) classifier separates among features extracted from CSPs, e.g. total power
- Right hand MI is translated to *RIGHT* command
  Left hand MI is translated to *LEFT* command



THE PROBLEM

- Motor Imagery training process is very long and exhausting
  - Becomes more acute for people with illness
- Shorter training sessions → insufficient amount of training data → low classification accuracy

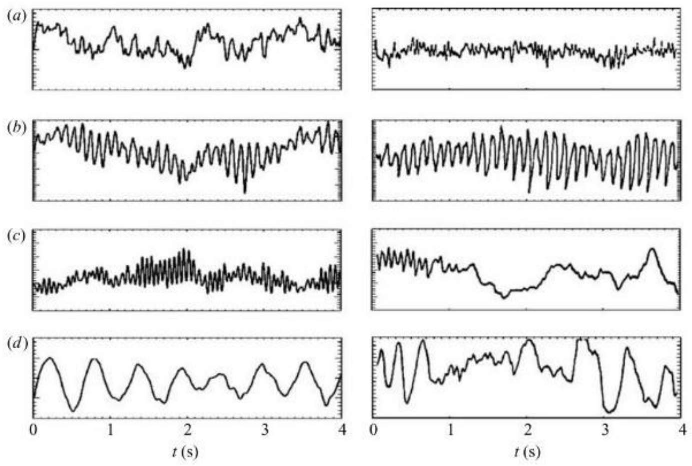


PROPOSED SOLUTION

Data Augmentation with Neural Field Theory (NFT) Model

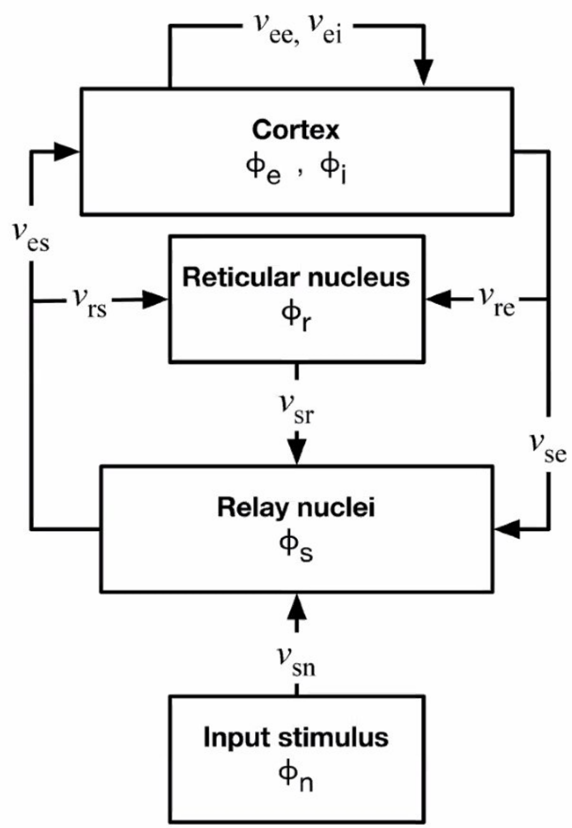
- Perform a short training session
- Use NFT to generate artificial EEG trials, based on the acquired training trials
  - Similar basic characteristics
  - Add variations to account for experimental signal diversity
- Combine experimental and artificial trials and train the classifier → Increase the classification accuracy

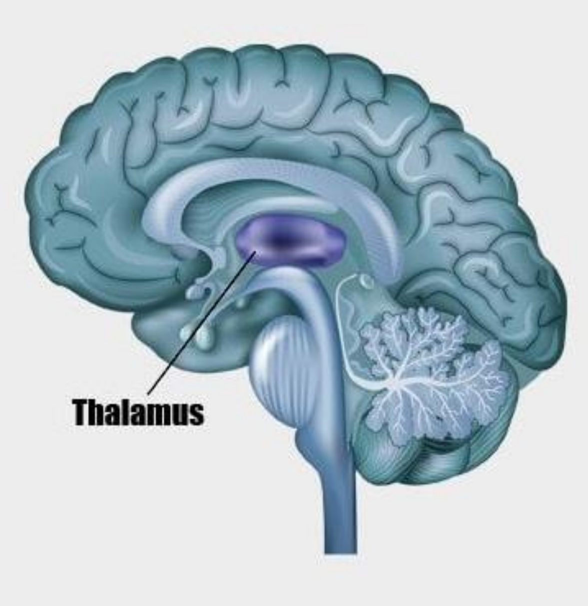
NFT – CORTICOTHALAMIC MODEL



Simulated VS Experimental
(eyes open/closed, spindles, slow-wave)

[Robinson 2005]



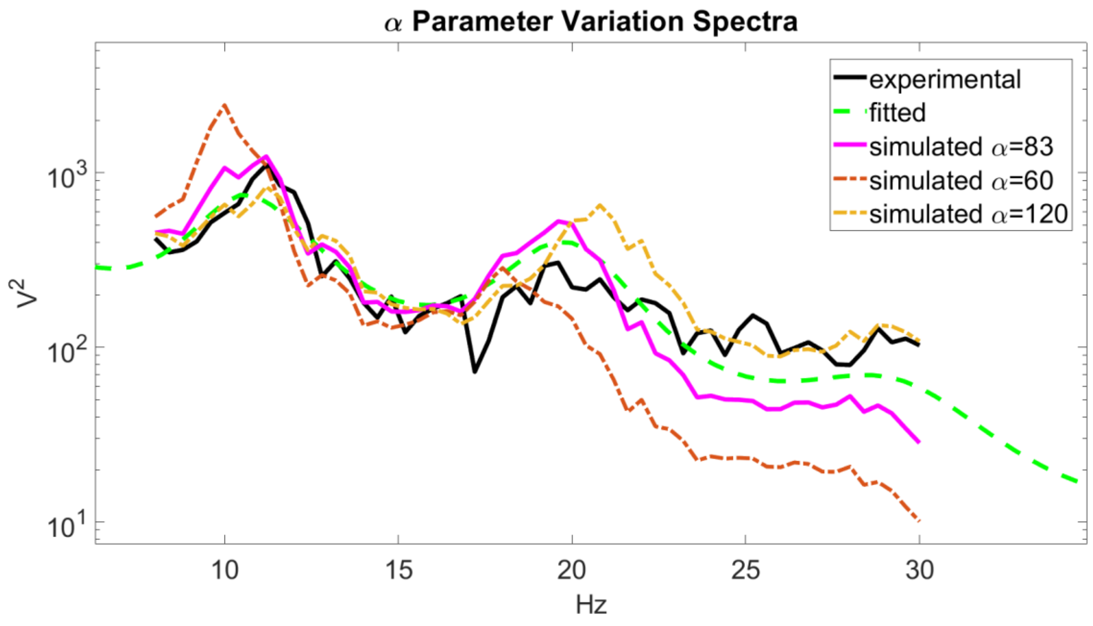


NFT MODEL ADVANTAGES

➢ The model has an analytical power spectrum representation, providing a fast and practical way for model fitting

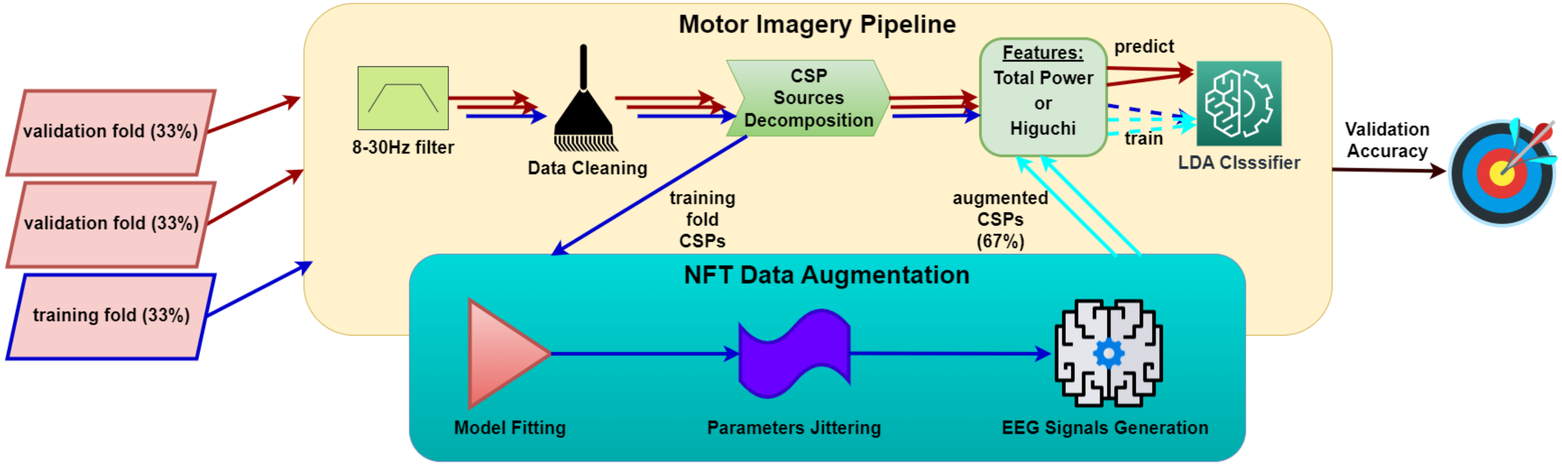
➢ A physiologically-inspired model:

- The output signal will always look like EEG with physiological characteristics and distributions
- The output signal can be controlled by parameters with a specific meaning
- Here we jitter parameters account for experimental signal diversity



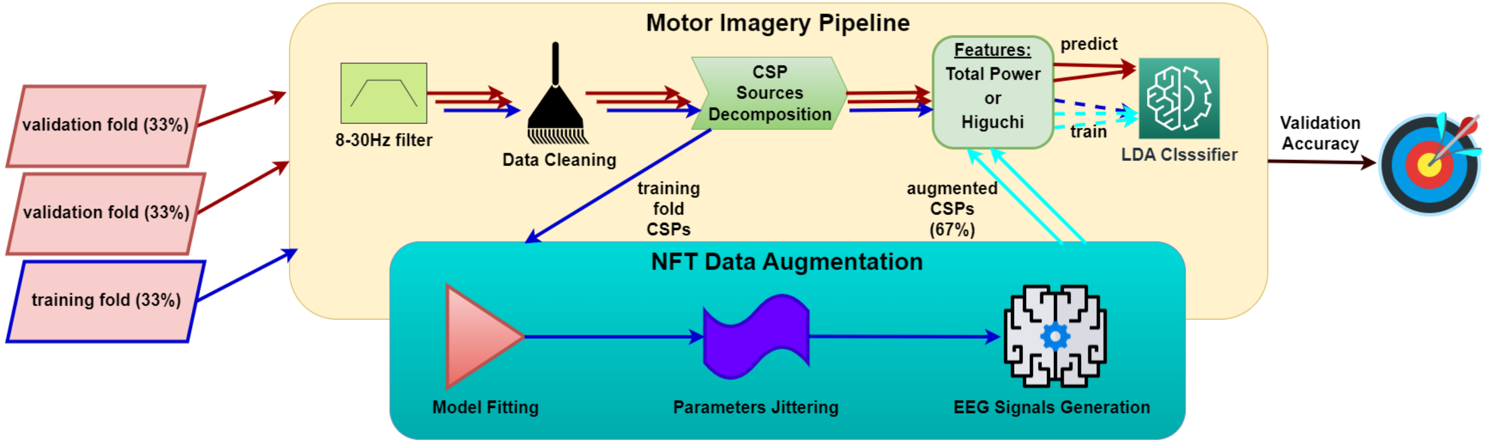
AUGMENTATION EXPERIMENT

1. Acquire an MI training set
2. Create a small training set: use 33% of trials for training and 67% for testing (3-fold inverse cross-validation)
3. Fit CSPs decomposition to the training fold
4. Fit the corticothalamic NFT model to MI training set average spectra; each CSP and each class separately.
5. Jitter model parameters

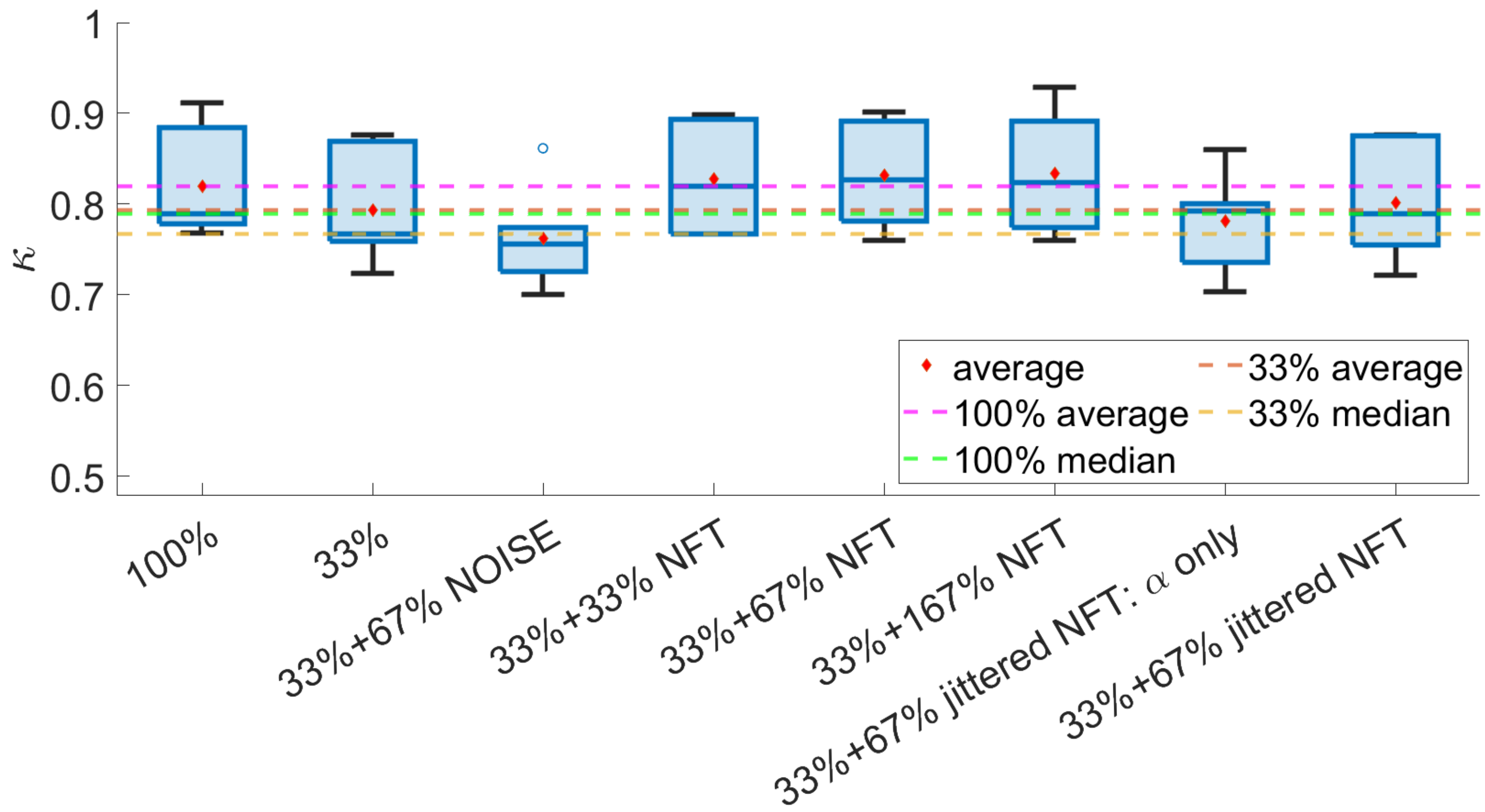


AUGMENTATION EXPERIMENT

6. Generate EEG time series, twice the size of the training set
7. Extract features: Total Power, Higuchi Fractal Dimension
8. Train the classifier on training + augmented data
9. Test on validation data; compare to the full (100%) training set classification accuracy
10. Compare to noise-based augmentation



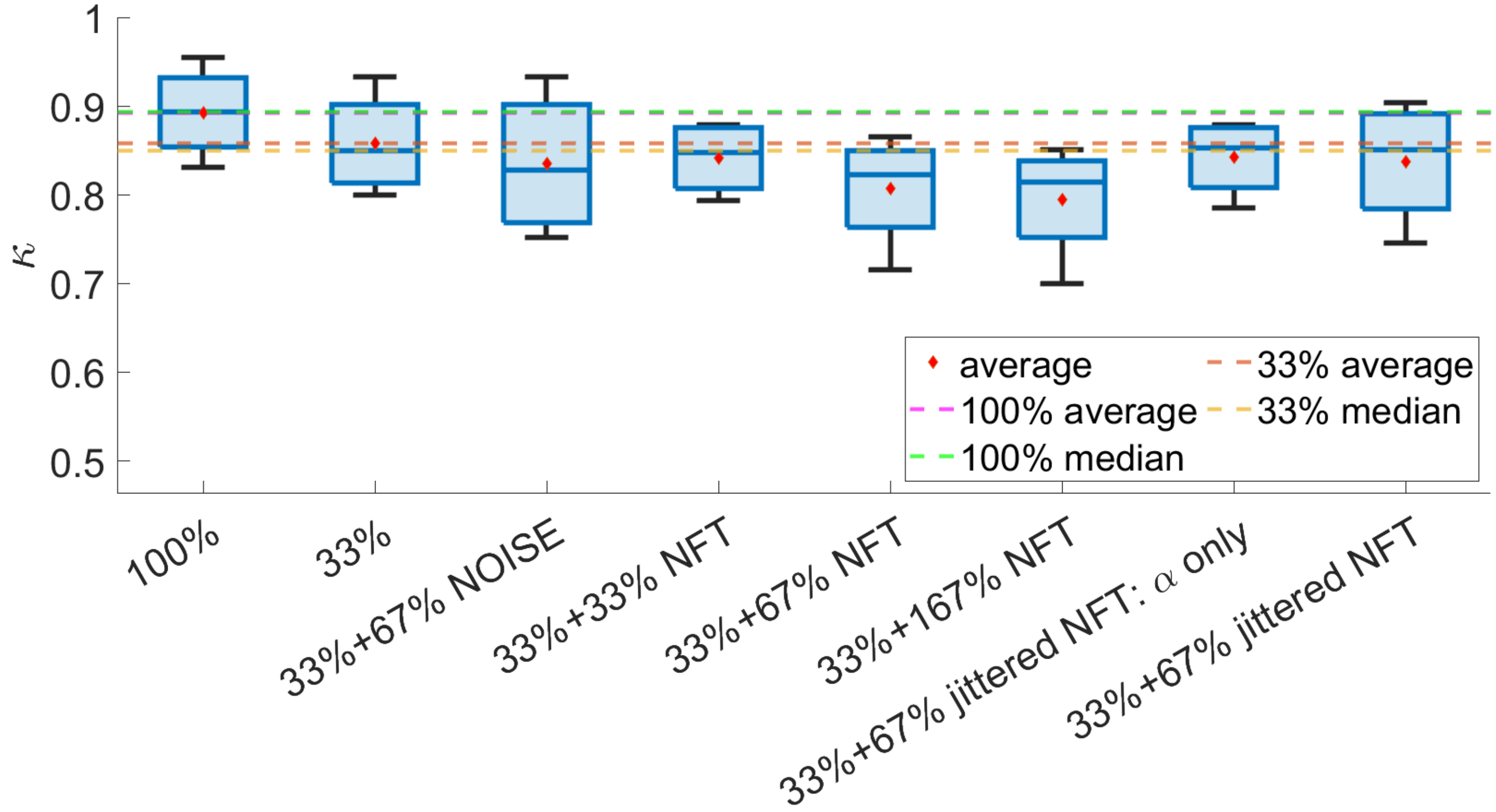
Results: TOTAL POWER



$$\kappa \equiv \frac{P_{acc} - P_{chance}}{1 - P_{chance}}$$

[Average/ Median]	$\boldsymbol{\kappa}$	$\Delta\boldsymbol{\kappa}$
100% (target)	0.82/0.79	N/A
33% (baseline)	0.79/0.77	0.03/0.03
Best *NFT* Augmentation	0.83/0.83	0.04/0.02
NOISE Augmentation	0.76/0.76	-0.03/ -0.02

Results: HIGUCHI FRACTAL DIMENSION



[Average/ Median]	$\boldsymbol{\kappa}$	$\Delta\boldsymbol{\kappa}$
100% (target)	0.89/0.89	N/A
33% (baseline)	0.86/0.85	0.04/0.03
Best *NFT* Augmentation	0.84/0.85	-0.02/ -0.01
NOISE Augmentation	0.84/0.83	-0.02/ -0.01

CONCLUSIONS

- ✓ NFT Data Augmentation works
- ✓ NFT generated EEG signals encompass some features better than others
  - Total Power feature results are a bit better than Higuchi feature results
  - The fit is on the spectrum, so NFT replicates spectral features better than time-domain features
- ✓ In most of the scenarios NFT augmentation performed better than noise augmentation
  - NFT generates a signal with more realistic distribution, rather than just noise
- ✓ Next step: evaluate this augmentation method with other BCI paradigms, such as SSVEP and P300

THANK YOU!