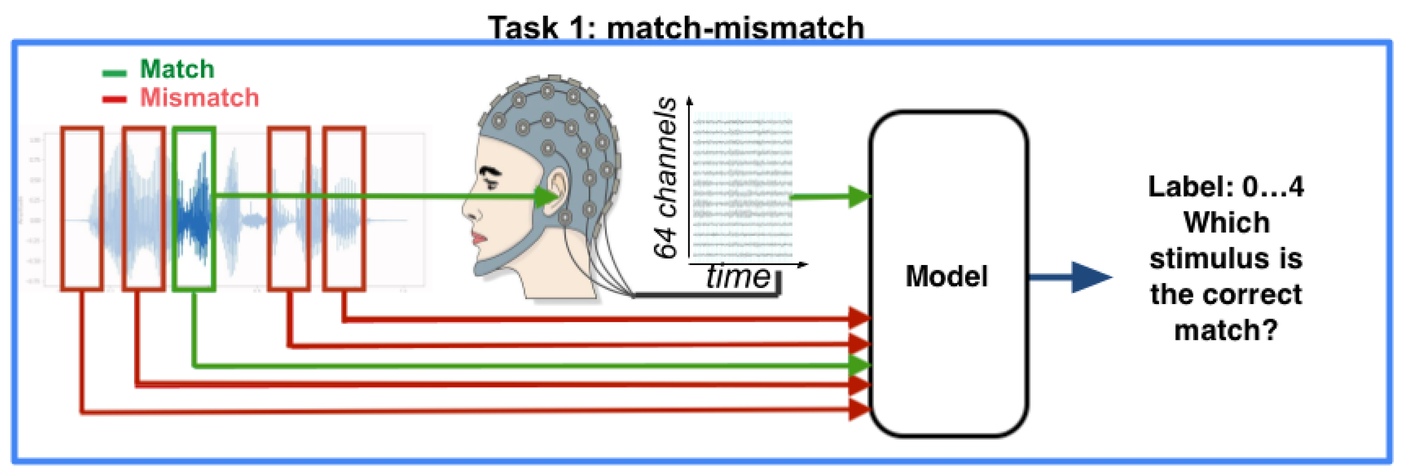
Improving Auditory EEG Decoding with Time-Frequency Analysis

Alexander Karbowski [1], Sophia Xiao [2], Corinne Orton [3], Dylan Marchlinski [4]

[1] Harvard University, [2] Emory University, [3] University of Utah, [4] University of Pennsylvania

Introduction

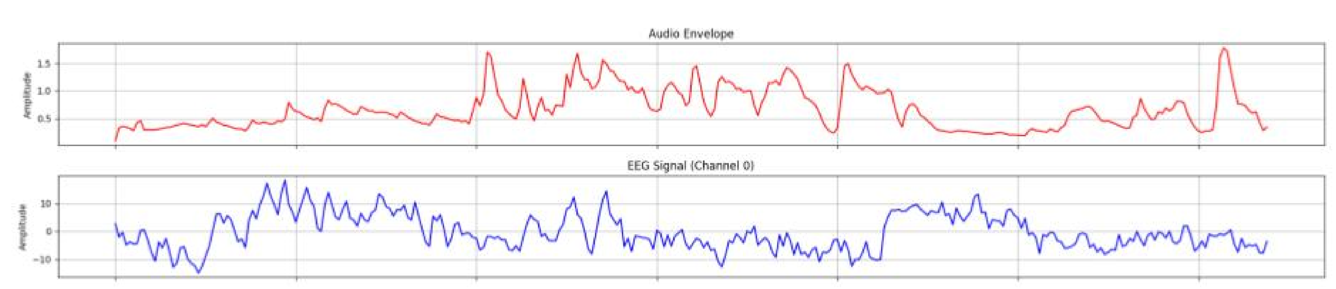
ICASSP 2024 Grand Challenge:
We address the matching task of the 2024 ICASSP Auditory EEG Grand Challenge: given a 5-second segment of EEG and five 5-second audio stimuli, determine which audio is the correct match.



Proposed Approach
Employ time-frequency and time-scale analysis for feature extraction to train shallow and lightweight neural networks to solve the challenge.

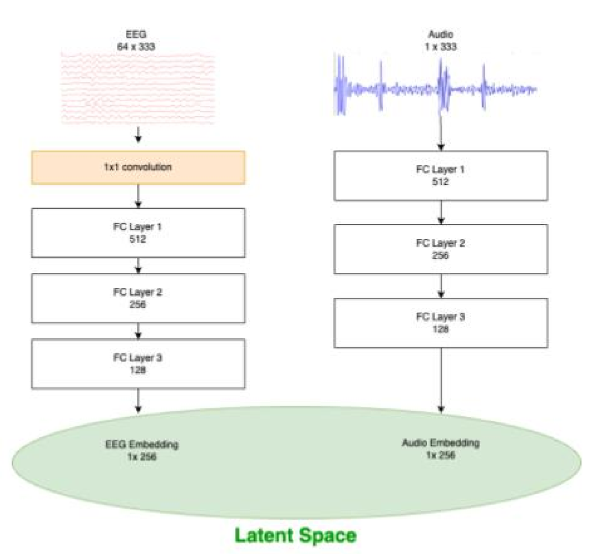
Dataset Details

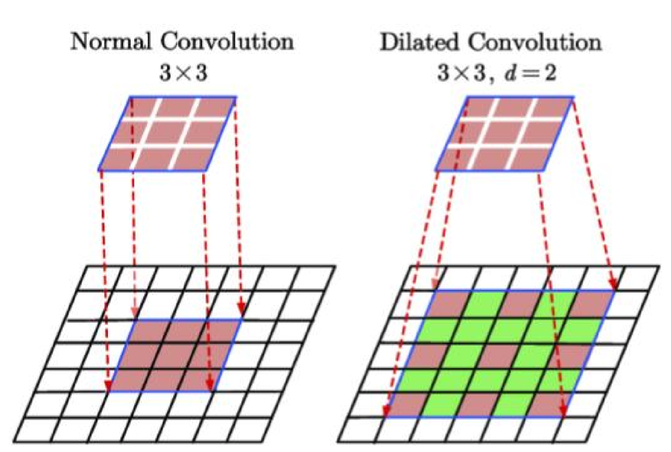
- 64-channel EEG recordings from 85 young individuals with normal hearing, each of whom listened to 90-150 minutes of natural speech.
- EEG collected at 8192 Hz, preprocessed with high-pass filter, downsampled to 1024 Hz, processed with a Wiener filter, re-referenced to a common average, and downsampled to 64 Hz.
- Audio collected at frequency 48kHz. The envelope was computed, then downsampled to 64 Hz.



Neural Networks

Two Branch Encoder: fully connected layers are applied to the EEG signals and audio separately, and outputs are embedded in latent space.
Dilated Convolutional Neural Network (DCNN): fully connected layers replaced by 2D dilated convolutional layers.

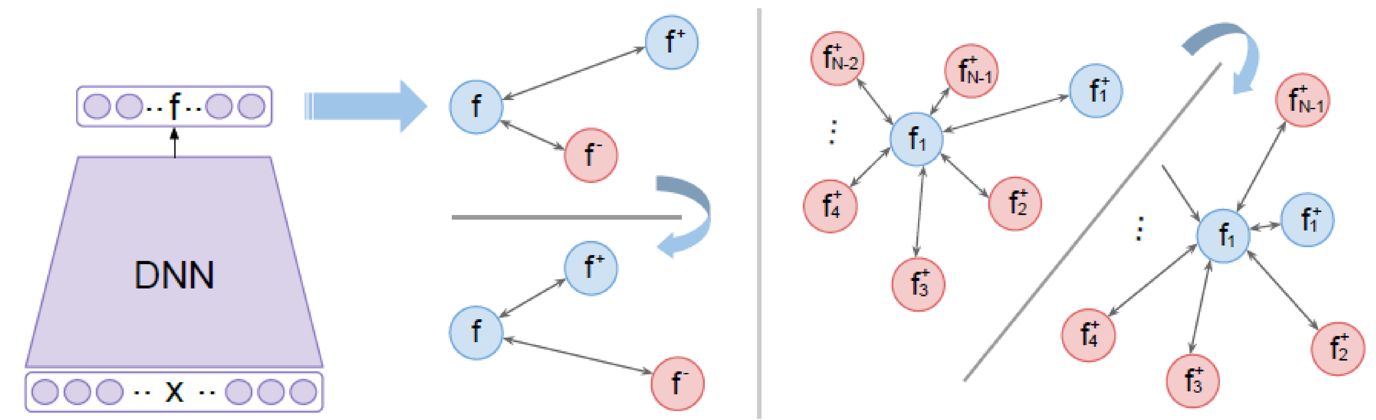




InfoNCE Loss Function

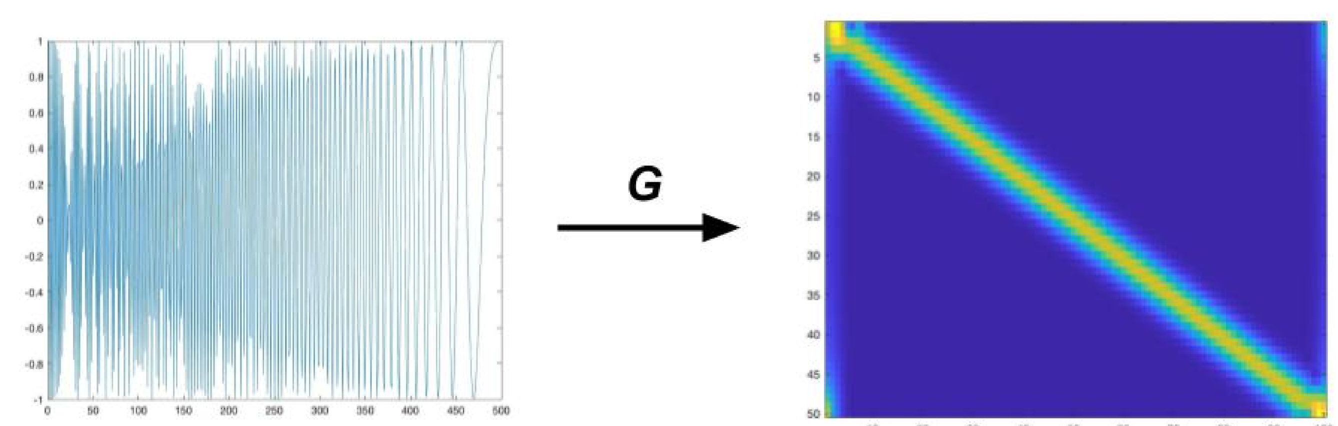
The networks are trained by minimizing the **InfoNCE Loss Function**, which ensures that matched data are close together and mismatched data are far apart in the latent space. Let x_i denote the normalized output of the EEG encoder, y_i^+ the matching normalized output of the audio encoder and y_j^- mismatched normalized outputs of the audio encoder. The InfoNCE loss is defined as

$$\mathcal{L}_{\text{InfoNCE}} = -\log \frac{\exp\left(x_i \cdot y_i^+\right)}{\sum_{j=1}^{5} \exp\left(x_i \cdot y_j^-\right)}$$

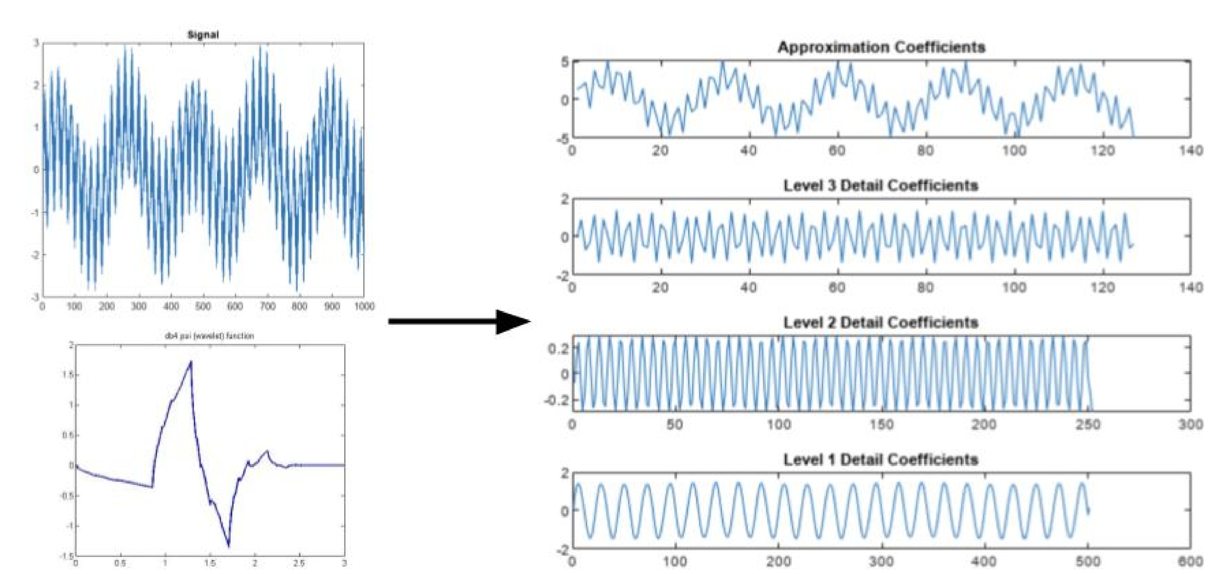


Time - Frequency Analysis

Discrete Gabor Transform: transforms a signal from the time domain to time-frequency domain, $G : \mathbb{C}^L \to \mathbb{C}^{M \times N}$. Captures change in frequency over time. Main parameters are the frequency (M) and time (N) resolutions.



Discrete Wavelet Transform: measures the *scale* of a wave over time, by projecting signals onto wavelets. Main parameter is type of wavelet used.



Results

Matching Accuracy:

	Raw	Gabor	Wavelet
2-Branch	33.8	32.4	**34.19**
DCNN	34.16	**39.15**	30

- The 2-branch model's accuracy was highest with the wavelet data.
- The baseline DCNN's accuracy was highest with the Gabor data, and this was the highest accuracy attainedd.

Overlap of Correct Guesses:

		DCNN Gabor	
		Correct	Incorrect
2-Branch Wavelet	Correct	0.19	0.15
	Incorrect	0.20	0.46

- Of the two top-performing configurations, at least one is correct 54% of the time.

Discussion

- Using transformed data to train networks provides an advantage over raw data.
  - Using the Gabor transform, we reach nearly 40% accuracy with a small DCNN, compared to around 34% accuracy on the raw data.
  - Gabor data may yield higher accuracy because it is higher-dimension (redundant), giving the model more information to work with.
- Fourier features achieve better performance than wavelet features
- Mathematically transforming data before feeding it into a neural network is a computationally cheap way to improve matching accuracy and interpretability overall.
  - Feature extraction can be used in conjunction with DNNs to reach higher accuracy, improve transparency, and lower computational cost.

Acknowledgements

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References

[1] Bernard Accou et al. "SparrKULee: A Speech-evoked Auditory Response Repository of the KU Leuven, containing EEG of 85 participants". In: *bioRxiv* (2023). Now published in *Data*, doi: 10.3390/data9080094. DOI: 10.1101/2023.07.24.550310. URL: https://www.biorxiv.org/content/10.1101/2023.07.24.550310v1.

[2] Bernd Accou et al. "Modeling the relationship between acoustic stimulus and EEG with a dilated convolutional neural network". In: *2020 28th European Signal Processing Conference (EUSIPCO)*. 2021, pp. 1175–1179. DOI: 10.23919/Eusipco47968.2020.9287417.