A Study of Salient Modulation Domain Features for Speaker Identification

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Speaker Identification

- 1-of-N problem
  - N training speakers, test speaker identified from those
  - closed-set here
- Single frame (e.g. MFCCs) v multiple frames (e.g. modulation spectrum features, x-vectors)

Modulation Spectrum

- Previous research identified 1-16 Hz range of temporal envelope modulation frequencies as containing most useful linguistic information about speech for automatic speech recognition (ASR)
- Temporal envelope v temporal fine structure (instantaneous frequencies)
  - more recent research on cochlear implants showed importance of latter for speaker identification

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Generating Modulation Spectrum Features

- 4-step process:
  - Stage 1: first stage of short-time Fourier transform (STFT)
  - Stage 2: either take amplitudes or use Hilbert transform envelope
  - Stage 3: second stage of STFTs, done in acoustic frequency bands
  - Stage 4: either take amplitudes or use Hilbert transform – latter necessary for instantaneous frequencies
- Reconstruct speech signal using constant overlap-add (COLA) without specific acoustic and/or modulation frequencies to see what effects are: https://swm1718.github.io/ModulationSpectrumAudio/
- See Figure 1 of paper for detailed diagram
- This research focused on 1 second modulation frames with 250 ms steps on top of wideband acoustic frames 3 ms long with 1 ms steps
  - 25 acoustic frequency bands up to 8 kHz
  - 501 modulation frequency bands up to 500 Hz

$$\boldsymbol{\Phi}(l) \in \mathbb{R}^{25 \times 501}$$
$$\boldsymbol{\Phi} = \text{modulation spectrum}$$
$$l = \text{modulation frame}$$

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Data

- TIMIT
  - Designed for ASR, but useful as arranged by speaker and utterance
  - 630 speakers
  - 10 utterances of ~3 seconds per speaker, 2 same for all speakers (SA1 and SA2), sampled at 16 kHz
  - Train set has 468 speakers, test set 162 – used in correlation analysis
  - When machine learning models, rearranged so train and test sets both comprise 630 speakers, with first 7 utterances in train set (inc. SA1, SA2) and last 3 utterances in test set

Methods Used

- Correlations
  - Spearman's rank among input features
  - One-way ANOVA for each input feature v output speaker
- Feature importances from random forest models
- Convolutional neural network (CNN) models
- Reconstructed speech signals with specific acoustic and/or modulation frequencies removed

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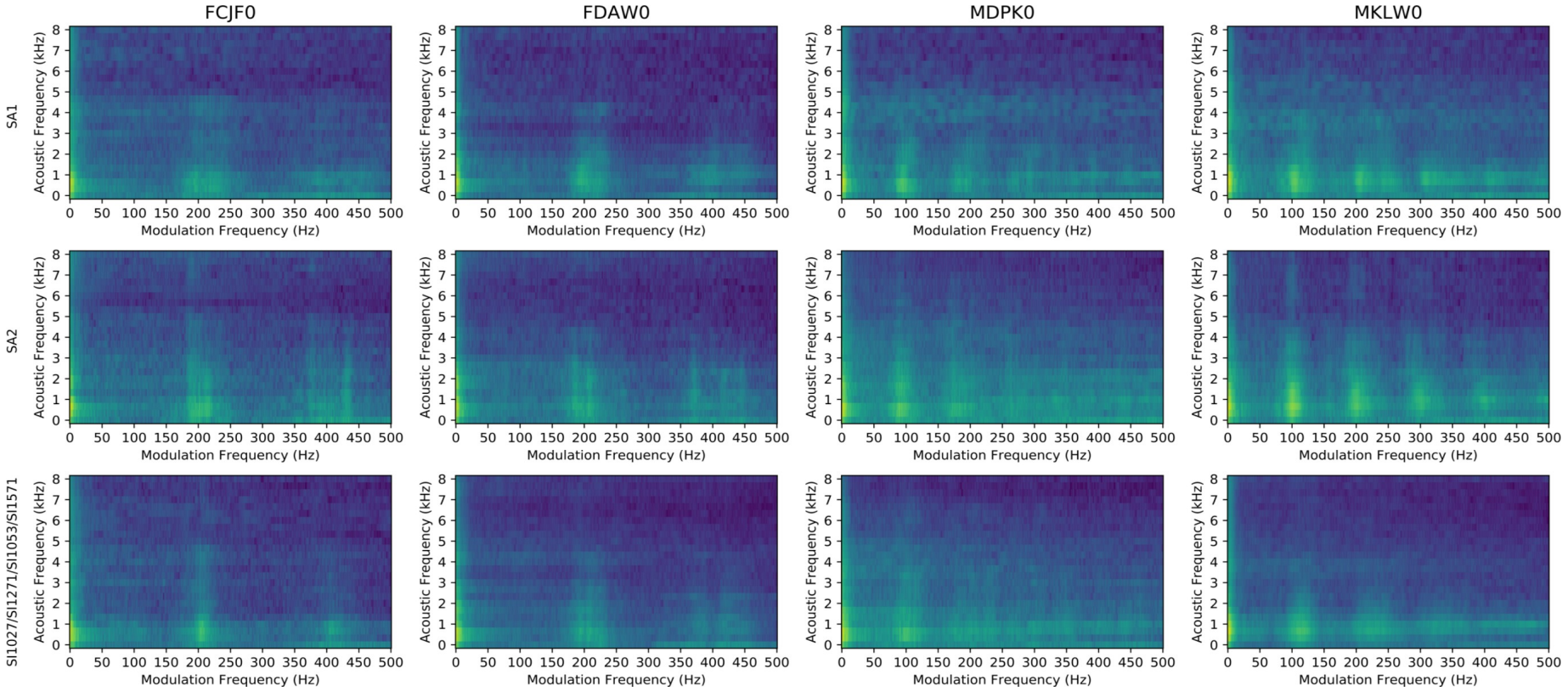
These are based on the amplitude envelope modulation spectrum

Average Modulation Frame per Speaker/Meeting



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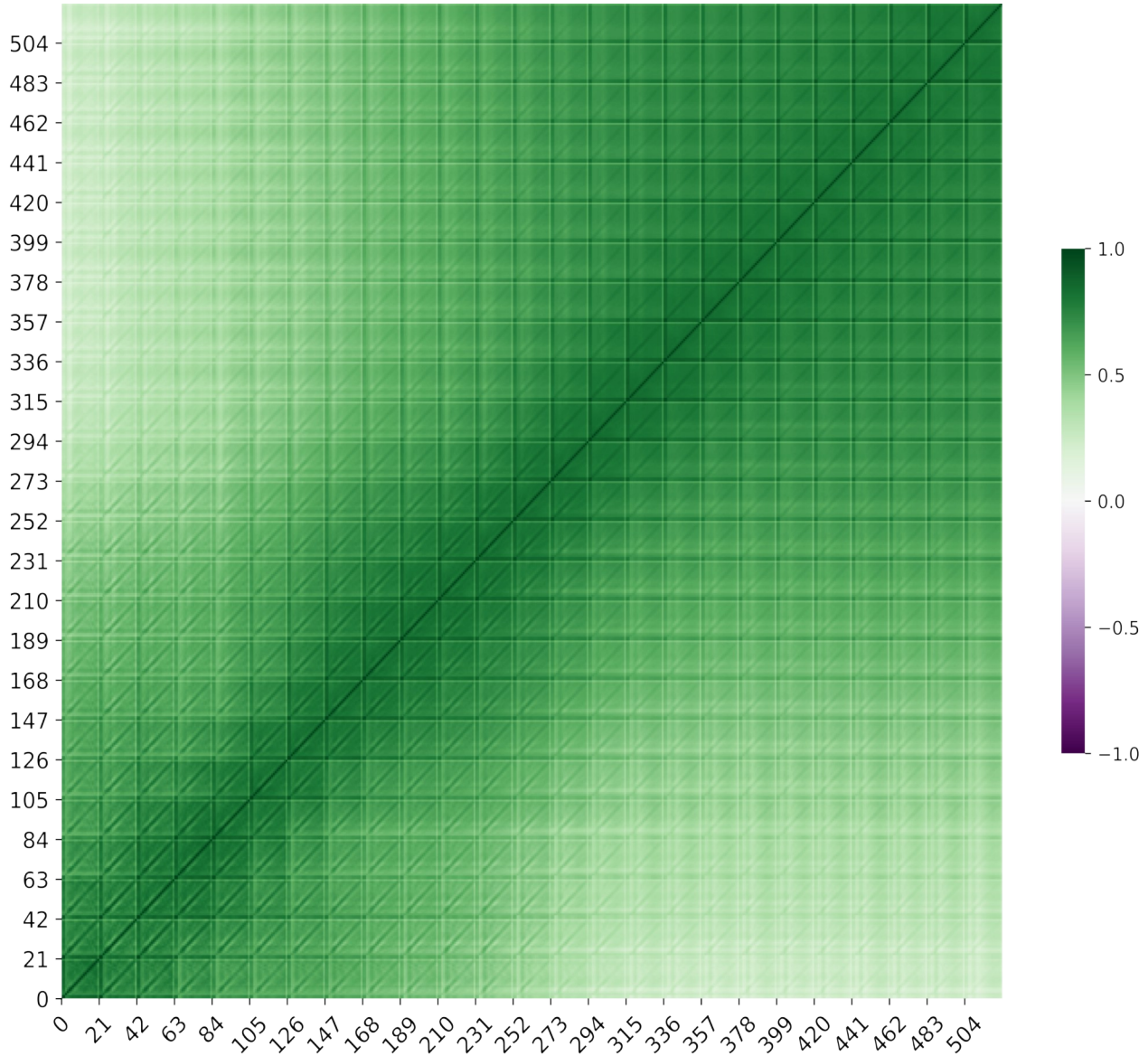
Spearman's Rank Between Feature Correlations

- Wideband acoustic frames
- For 0-20 Hz modulation frequencies
- Flattened to 25 x 21 = 525 features



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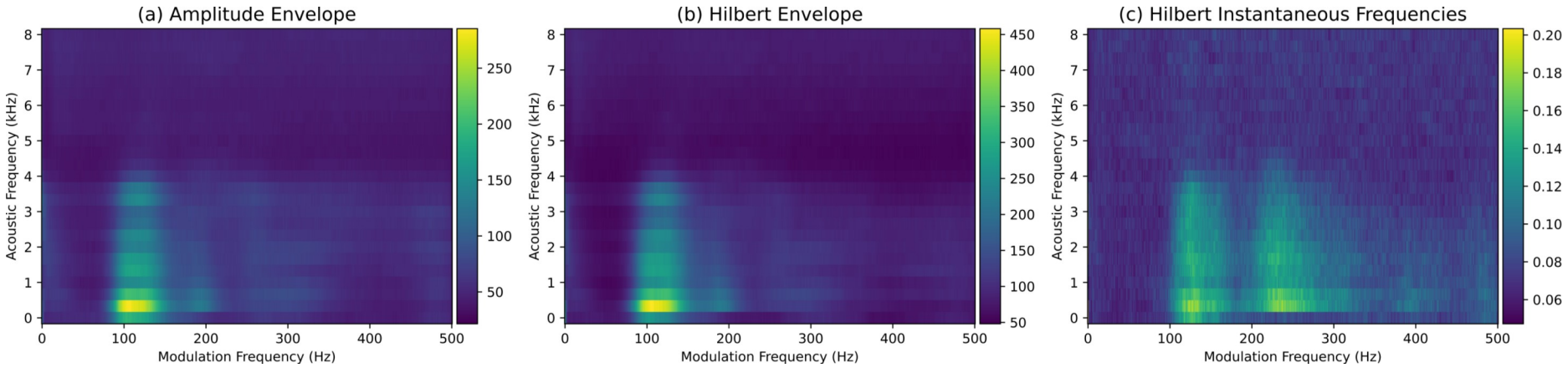
$$F_s = \frac{\text{between} - \text{speaker} - \text{means covariance}}{\text{intra} - \text{speaker covariance}}$$

Wideband One-Way ANOVA Correlations



- Based on original TIMIT training set of 462 speakers
- For temporal envelope, first two graphs show strong peak around male fundamental frequencies, with stronger correlation values and slightly lower frequencies for Hilbert envelope
- For temporal fine structure, third graph shows less strong peaks at higher frequencies, so not great on their own but may provide additional information

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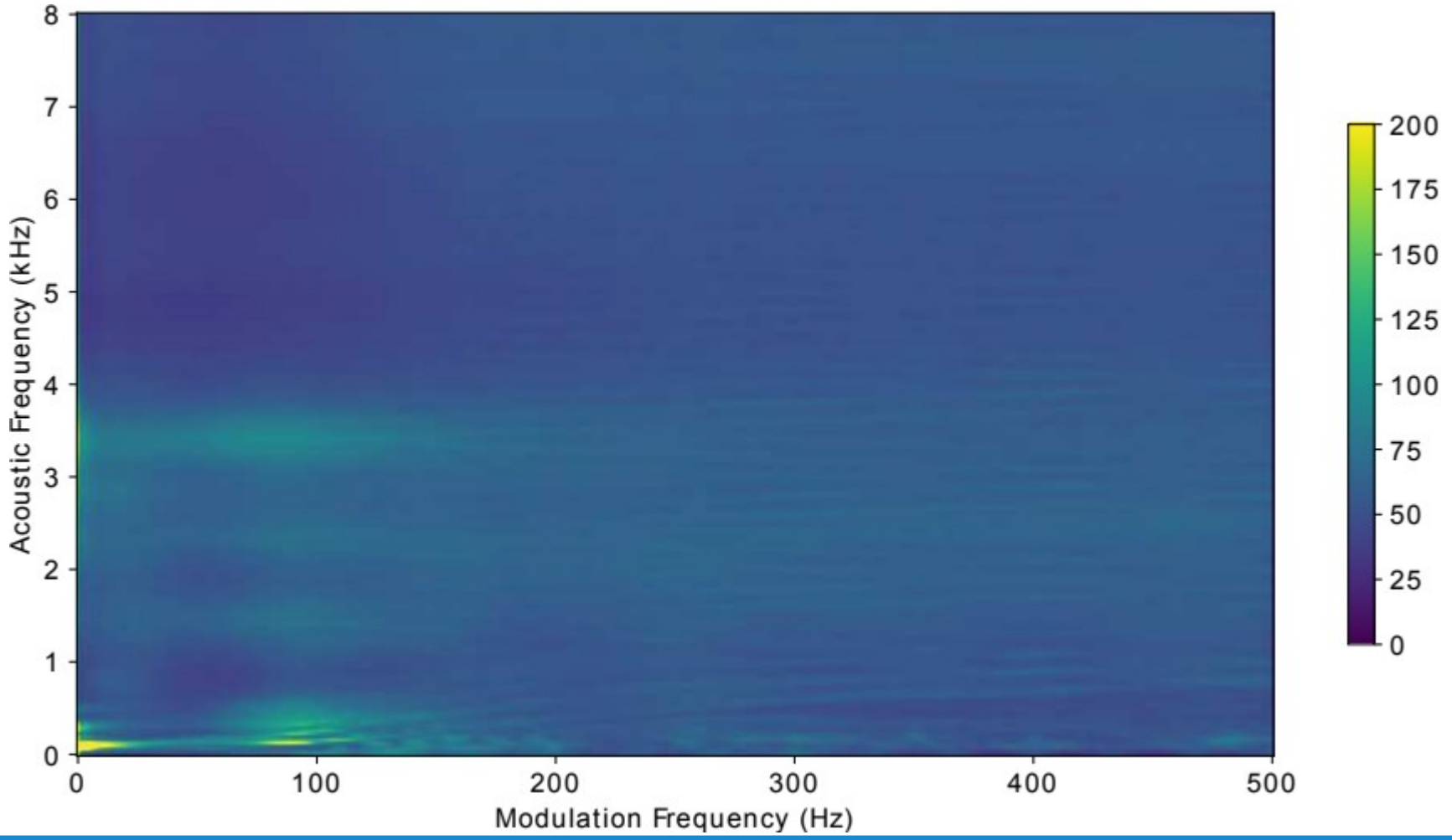
Narrowband ANOVA Correlations for Amp. Env.



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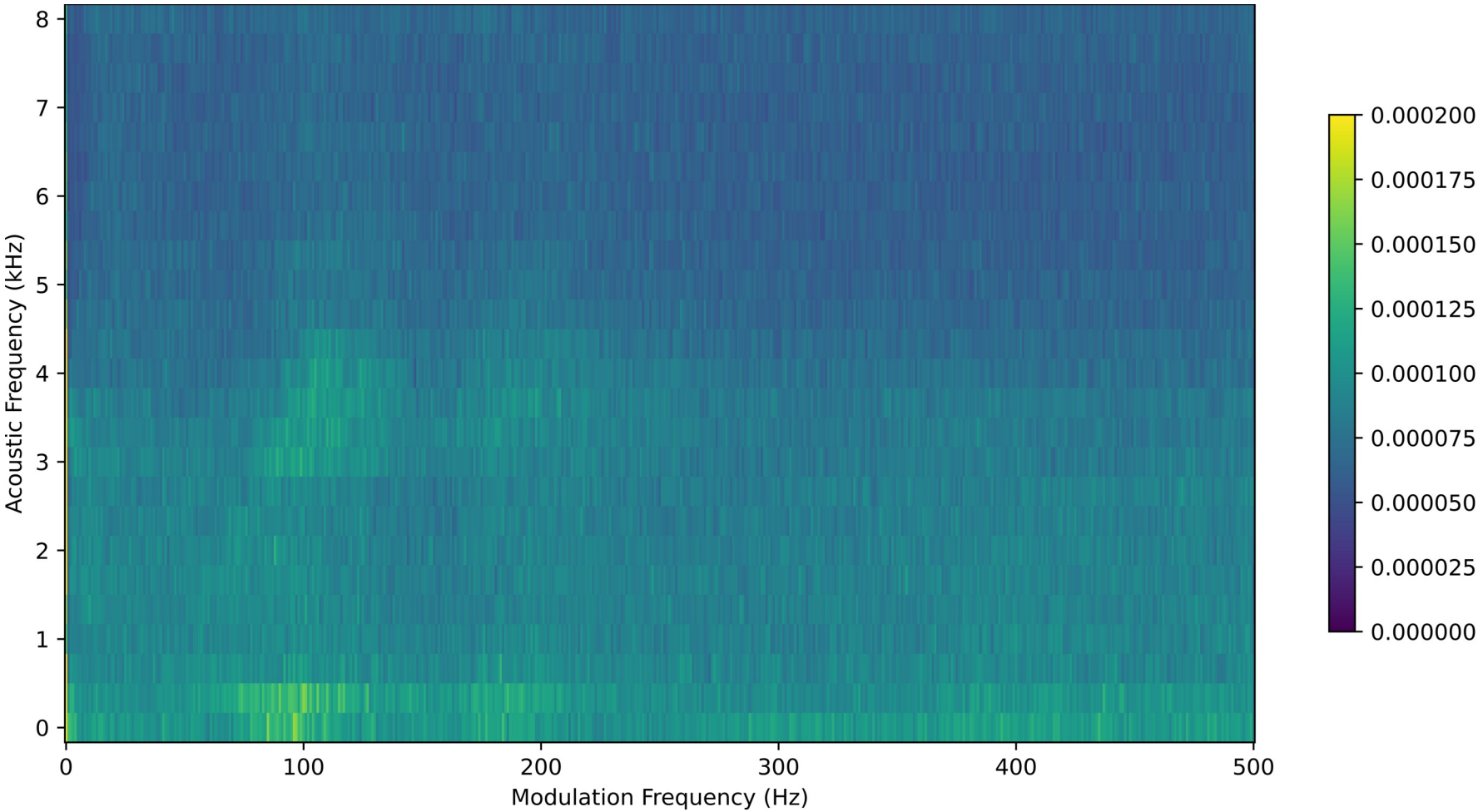
Feature Importances from Random Forest



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Fitting Random Forest and CNN Models

	Mode	Mean	
	Per MF	**Per Utt.**	**Ave. MF**
RF $\mathbf{\Phi}_{AE}$	12.34	27.63	26.20
CNN $\mathbf{\Phi}_{AE}$	29.03	42.40	26.36
CNN $\mathbf{\Phi}_{HE}$	27.97	48.39	32.77
CNN $\mathbf{\Phi}_{IF}$	5.75	12.20	0.69
CNN $\mathbf{\Phi}_{HE}$ and $\mathbf{\Phi}_{IF}$	31.05	49.26	32.17

MF = modulation frame
Utt. = utterance
Ave. = average
RF = random forest

CNN = convolutional neural network
Φ = modulation spectrum features
AE = amplitude envelope
HE = Hilbert envelope
IF = instantaneous frequency

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Conclusion

- Range of modulation frequencies associated with the fundamental frequency is more important than the 1-16 Hz range most commonly used in automatic speech recognition
- 0 Hz modulation frequency band contains significant speaker information
- Temporal envelope more discriminative among speakers than temporal fine structure, but temporal fine structure still contains useful additional information for speaker identification

Next steps

- See if using filterbanks and discrete cosine transforms (DCTs) in acoustic and modulation domains improve performance
- Test whether modulation spectrum features give as good results as single frame MFCCs and whether using both together improves performance