Harmonicity Plays a Critical Role in DNN Based Versus in Biologically-Inspired Monaural Speech Segregation Systems

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Introduction

Monaural Speech Segregation Systems

Cocktail Party Problem → Computational Auditory Scene Analysis (CASA) → Speech Segregation

Traditional CASA Systems	
Harmonicity Model: • Continuity of pitch in time • Harmonic structure across frequency	Temporal Coherence Model • Biologically plausible • Features of a single source are modulated • Onset co-incidence and timing cues

Deep Neural Network Based Models		
Harmonicity ?	Temporal Coherence ?	Other ?

Goal: Bridge the gap between CASA systems and Deep Neural Network based speech segregation models

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✓	?	?

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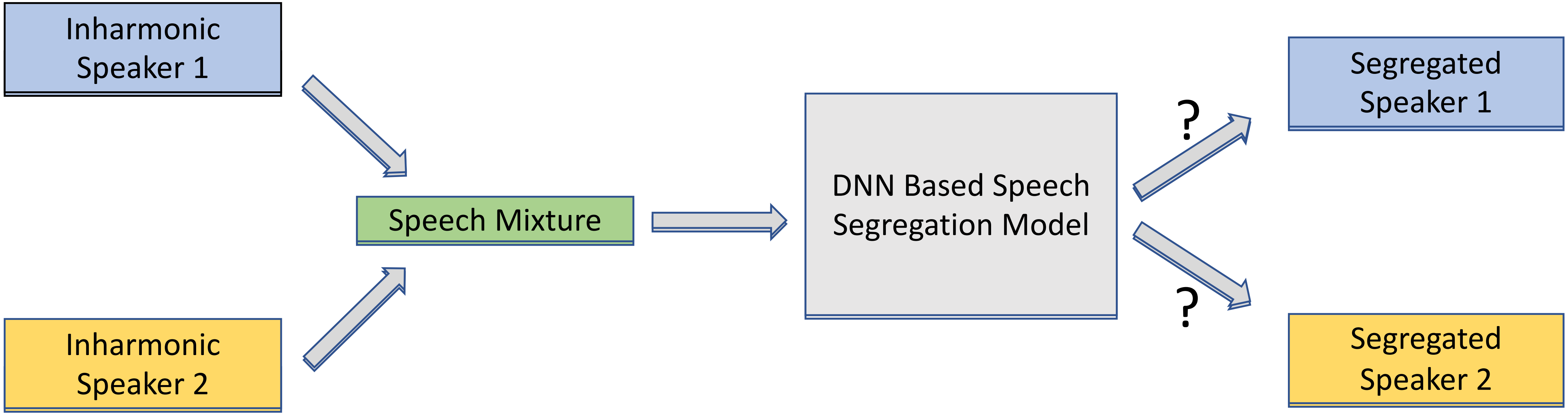

Investigate the importance of harmonicity for DNN-based speech segregation models

Inharmonic Sources

- Inharmonic sounds: components **not** at integer multiples F0

$$f_n(t) = n\, f_0(t) + J_n f_0(t);\ -J < J_n < J \qquad (1)$$

- Inharmonic Tones:

$$x_{tone} = \sum_{k=1}^{N} A_k \sin(2\pi f_n(t)t) \qquad (2)$$

- Inharmonic sources: $J \neq 0$

J ↑ → Inharmonicity ↑

- Natural speech: $J = 0$

Inharmonic Speech: Modified STRAIGHT Algorithm [Kawahara, 2018]

Experiments

Experiments

Dataset: WSJ0 and WSJ-2-Mix

Generate inharmonic versions of WSJ0 for each jitter: $0.01 < J < 0.30$:

- Average offset for male speakers: ±1.2 − ±40 Hz
- Average offset for female speakers: ±2.1 − ±65 Hz

Evaluate Conv-Tasnet and DPT-Net trained on natural (harmonic) speech mixtures with:

- Mixtures of inharmonic tones
- Inharmonic WSJ-2-Mix (inharmonic speech + inharmonic speech)
- Mixtures of inharmonic and natural WSJ0 (inharmonic speech + natural speech)
- Baseline: Natural WSJ-2-mix (natural speech + natural speech)

Evaluation Metric: Signal-Distortion Ratio (SDR)

Experiments

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Generate inharmonic versions of WSJ0 for each jitter: $0.01 < J < 0.30$:

- Average offset for male speakers: ±1.2 – ±40 Hz
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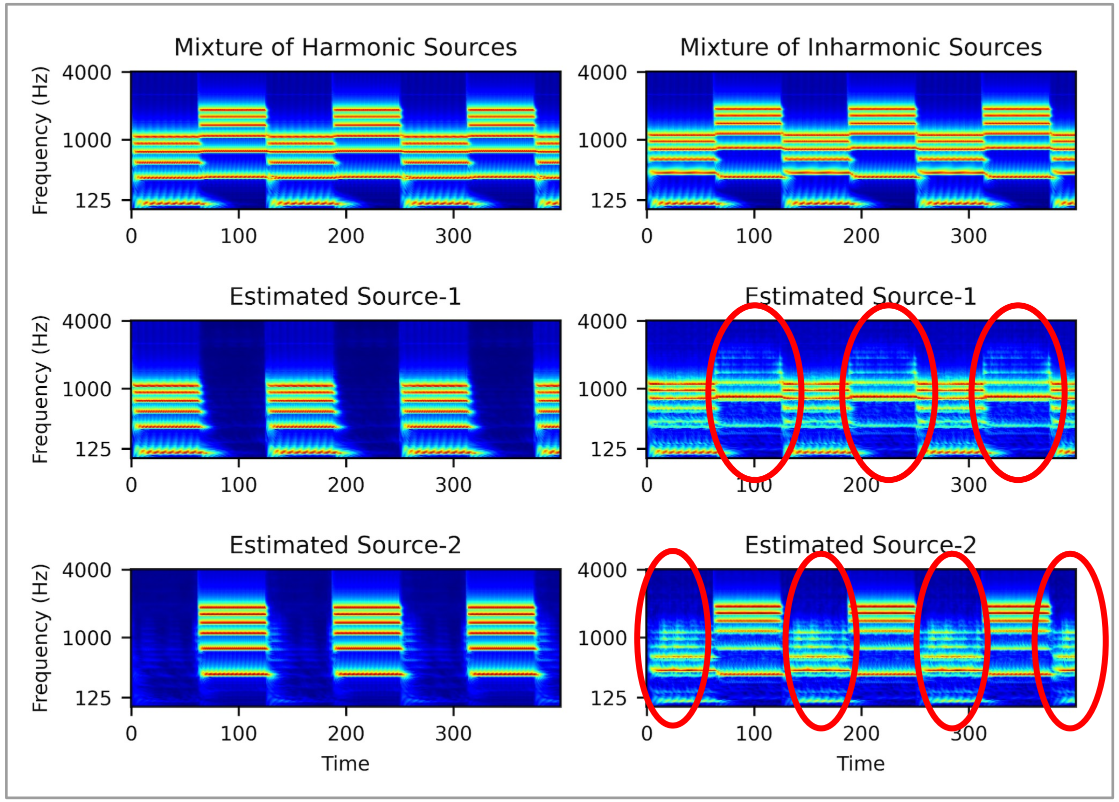
Evaluate Conv-Tasnet trained on inharmonic speech mixtures with:

- Inharmonic WSJ-2-Mix (inharmonic speech + inharmonic speech)
- Natural WSJ-2-mix (natural speech + natural speech)

Evaluation Metric: Signal-Distortion Ratio (SDR)

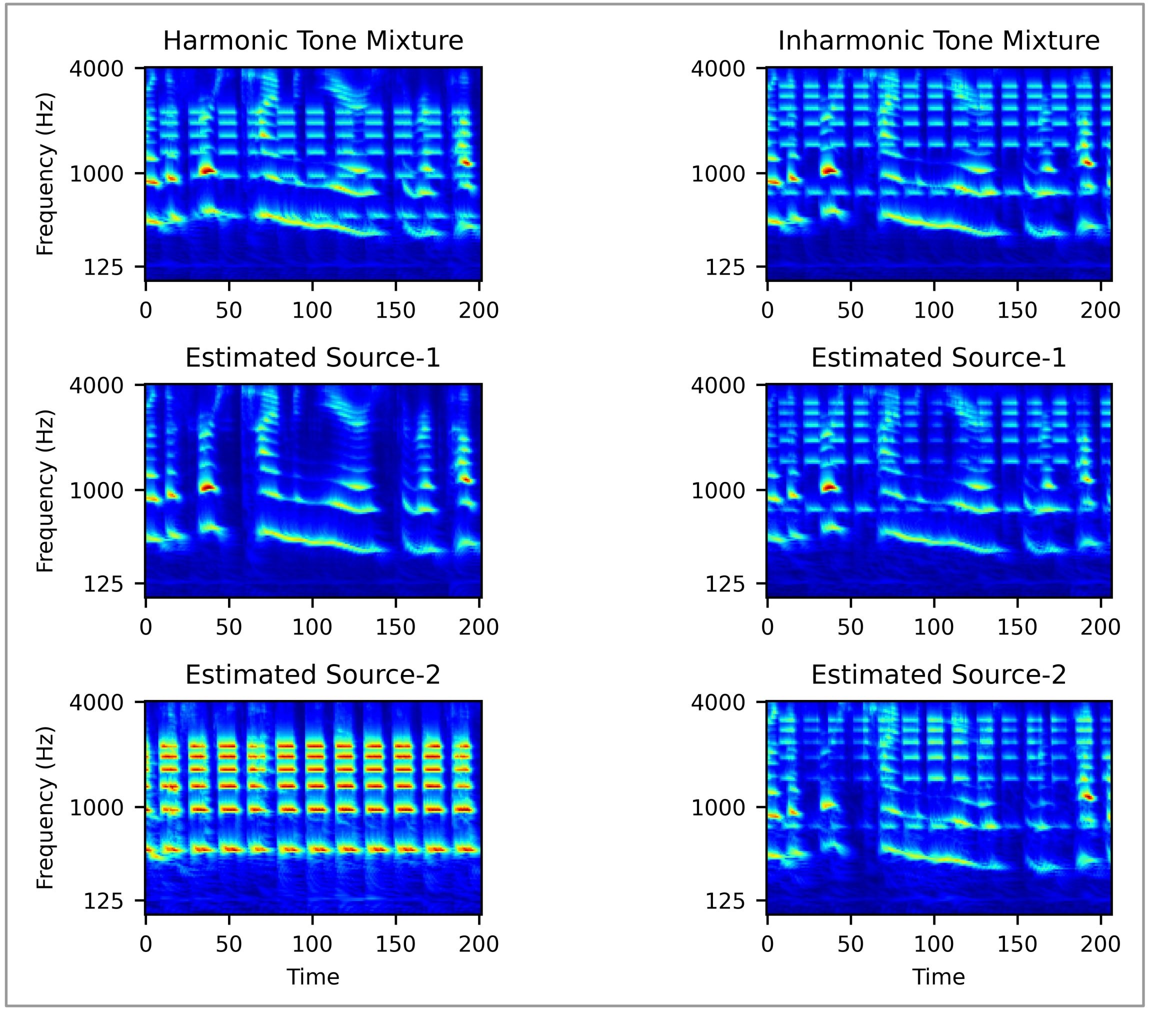
Results

DNN Models Trained on Natural Speech



Conv-Tasnet **fails** to segregate mixtures of inharmonic tones

DNN Models Trained on Natural Speech

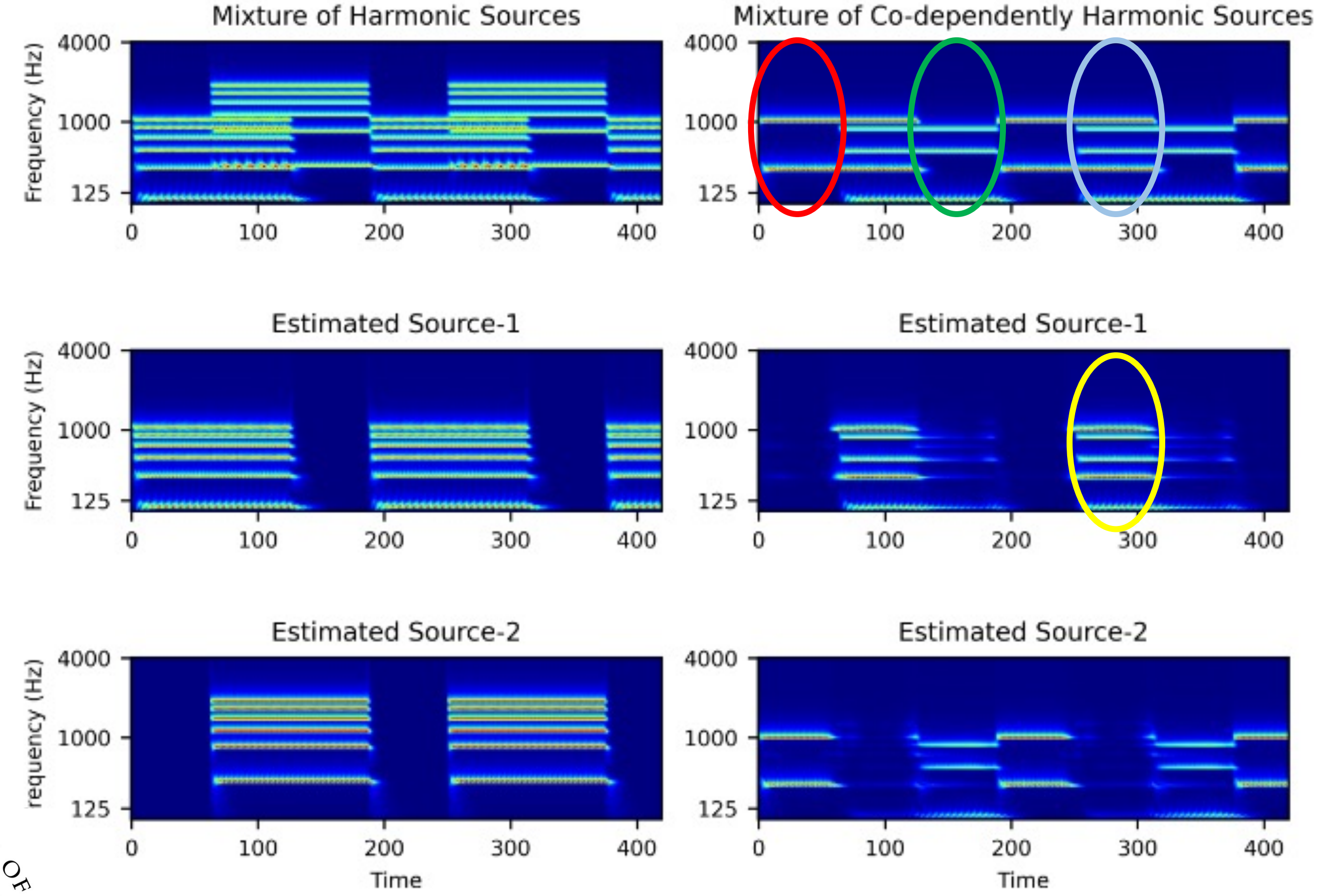


Conv-Tasnet **can** segregate mixtures of natural speech + harmonic tones

Conv-Tasnet **cannot** segregate mixtures of natural speech + inharmonic tones

Both sources need to be harmonic

DNN Models Trained on Natural Speech



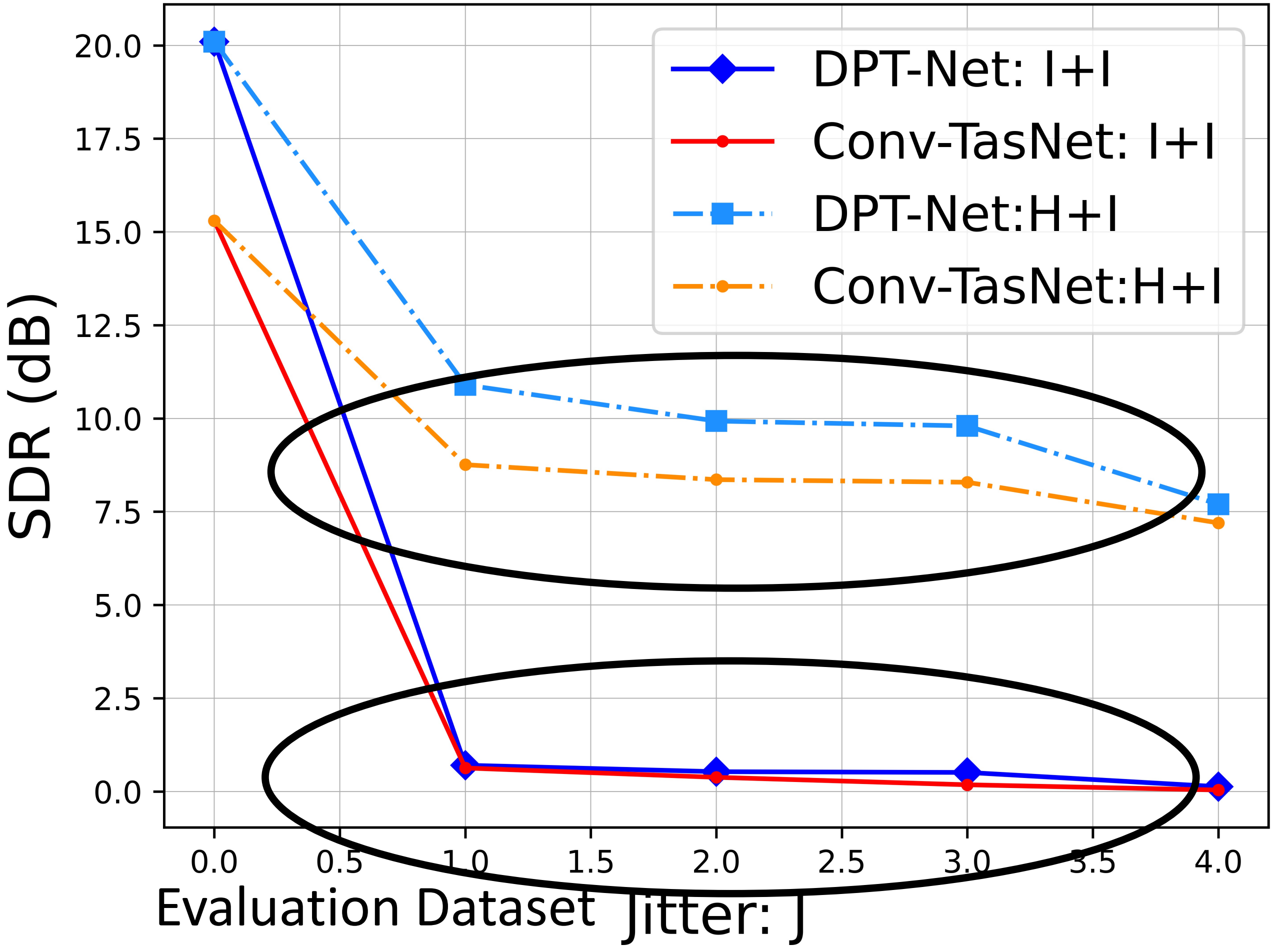
Tone 1: 200Hz, 600Hz,

Tone 2: 100Hz, 300Hz, 500Hz

At overlap: harmonic series of 100 Hz

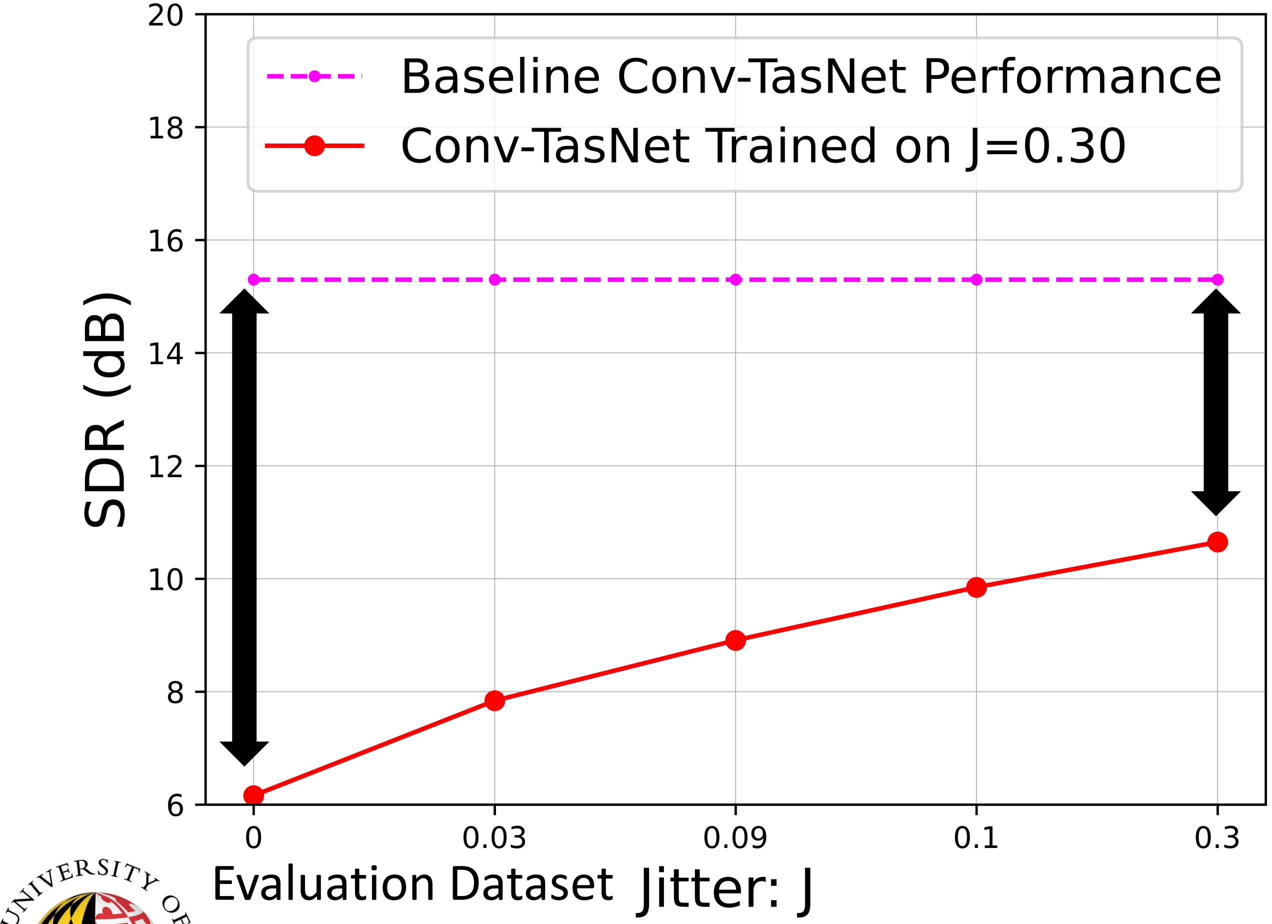
Network groups overlapping harmonic region as one source

DNN Models Trained on Natural Speech



- Model Performance drops to ≈ 0 dB if both speakers are inharmonic
- Model Performance drops to ≈ 8 dB if one speaker is inharmonic

DNN Models Trained on Inharmonic Speech

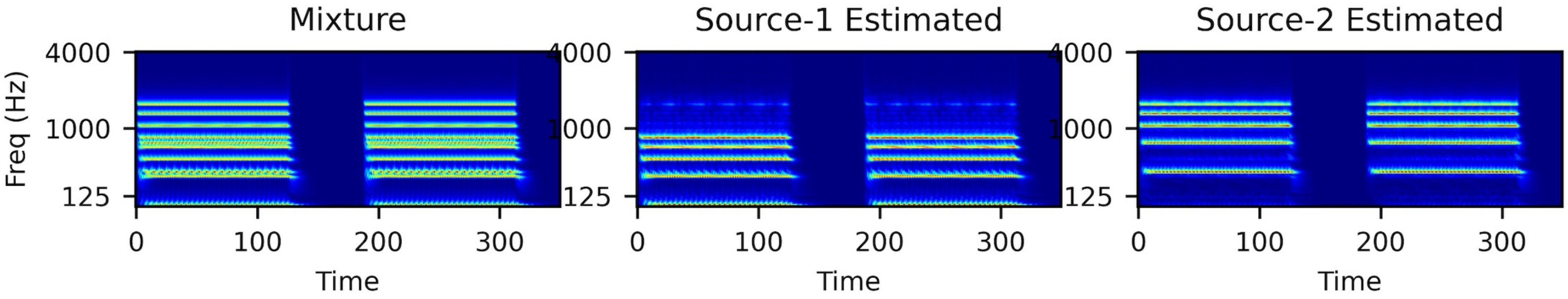


- The network finds it challenging to learn to segregate speech
- Model performance on natural speech deteriorates
- Harmonicity is critical for segregation

DNN Models Diverge from Temporal Coherence

- Humans and TC models (Krishnan et al. 2014) group all sources with the same timing onset and offset as one source, regardless of harmonicity

- Conv-Tasnet **can** segregate two synchronous, harmonic sources



Conclusion

Conclusion and Future Work

- DNNs cue onto the harmonic structure for segregation
- SOTA models completely fail with inharmonic inputs (adversarial inputs)
- DNNs implicitly learn the non-trivial task of pitch-tracking
- DNNs diverge from biologically inspired CASA models

Next Steps:

- Analysis on spectrogram-based DNN networks
- Investigation on how DNN models perform harmonic analysis

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