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

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Introduction

Motivation

- Traditional CASA algorithms: designed using established underlying principles
  - E.g., Temporal Coherence [Krishnan et. al., 2014] models use timing cues → biologically inspired
  - E.g. Harmonicity and continuity in pitch [Vishnubhotla et al. 2009]
- Deep Neural Networks (DNN) models outperform CASA models but are black-boxes

Goal: Investigate the underlying principles of DNN based speech segregation models

Contributions

- DNNs fail to segregate inharmonic speech
- DNNs heavily rely on harmonicity of speech for segregation
- DNNs find it challenging to learn to segregate when trained on inharmonic speech
- DNNs diverge from humans and do not use Temporal Coherence for segregation
- Inharmonic speech → adversarial input to most end-to-end DNN models

Experiments

Inharmonic Sources

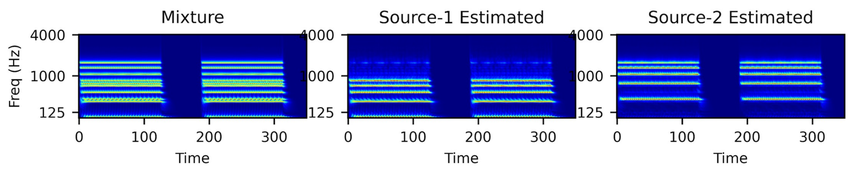
- Sounds with components not at integral multiples of fundamental frequency (F0)
  - Inharmonic speech → using STRAIGHT [Ellis et al. 2012]
  - Spectral components maximally jittered by $\pm$J% F0
  - . More J → More inharmonicity ; Harmonic source → J = 0
- Generate Inharmonic WSJ for different J:
  - Average spectral offset for male speakers: ±1.2 – ±40 Hz
  - Average spectral offset for female speakers: ±2.1 – ±65 Hz

Evaluation Metric: Signal-Distortion Ratio (SDR)

Empirical Analysis

- Evaluate Conv-Tasnet [Luo et al., 2019] and DPT-Net [Chen et al. 2020] trained on natural speech with:
  - Mixtures of inharmonic tones
  - Mixtures of inharmonic speech (inharmonic speech + inharmonic speech)
  - Mixtures of natural and inharmonic speech (inharmonic speech + harmonic speech)
  - Baseline: Mixtures of natural speech (harmonic speech + harmonic speech)
- Train Conv-Tasnet and DPT-Net on inharmonic speech mixtures and evaluate with:
  - Mixtures of inharmonic speech
  - Mixtures of natural speech

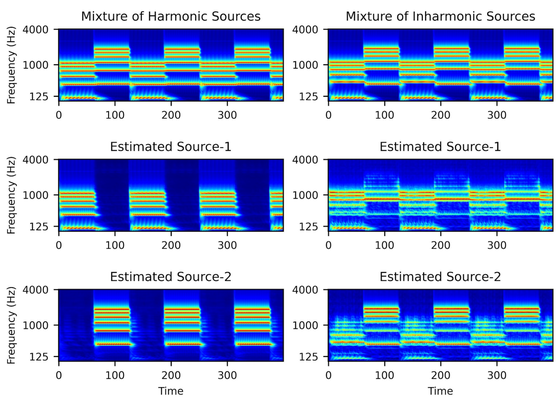
Results: Divergence of DNNs from Temporal Coherence



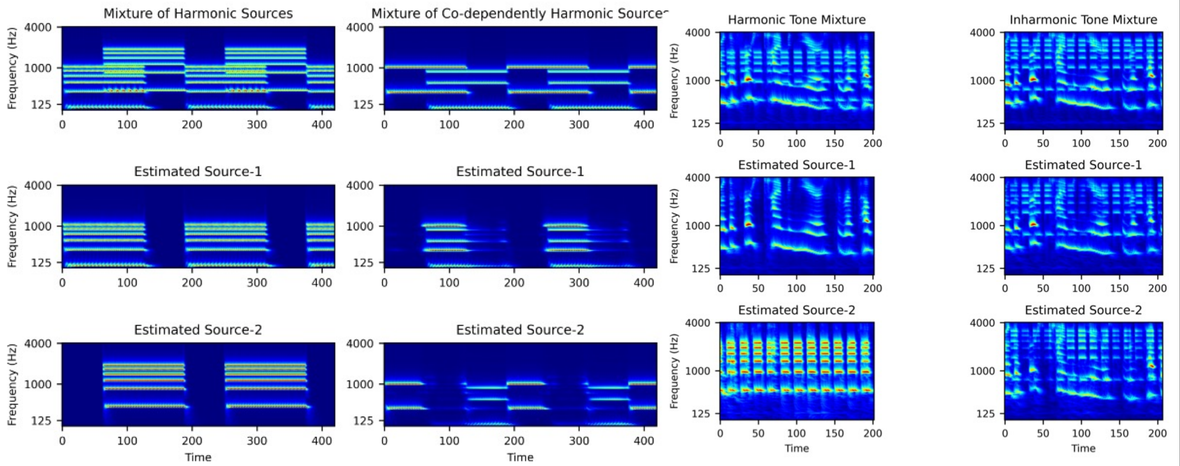
- Humans and Temporal Coherence models (Krishnan et al. 2014) group all sources with the same timing onset and offset as one source.
- Unlike humans, Conv-Tasnet **can** segregate two synchronous, harmonic sources

Results: Segregation Performance on Inharmonic Tones

DNN Models Trained on Natural Speech



- Conv-Tasnet can segregate a mixture of harmonic tones
- It cannot segregate inharmonic tones

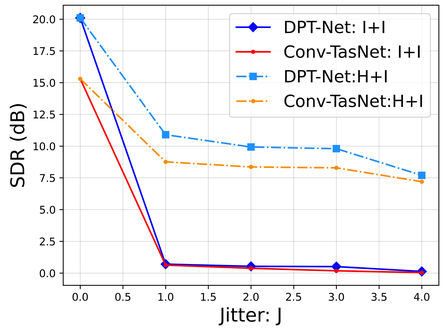


- Conv-Tasnet can segregate a mixture of harmonic overlapping tones
- A mixture of overlapping tones of- 200Hz, 600Hz and 100Hz, 300Hz, 500Hz contain the harmonics of 100Hz during the overlap.
- Conv-Tasnet segregates this overlap as one single source

- Conv-Tasnet can segregate a mixture of natural speech and harmonic tones
- It cannot segregate mixtures of natural speech and inharmonic tones

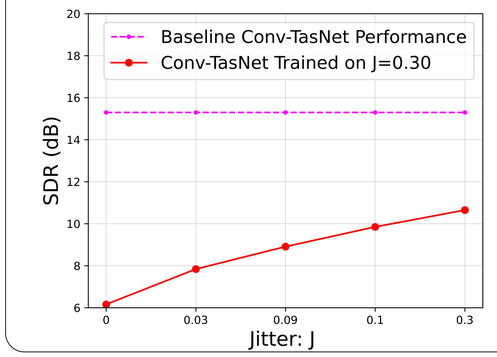
Results: Segregation Performance on Inharmonic Speech

DNN Models Trained on Natural Speech



- DNNs completely fail to segregate a mixture of inharmonic speech (I+I)
- DNNs perform below baseline if only one speaker is inharmonic (H+I)

DNN Models Trained on Inharmonic Speech



- DNNs finds it challenging to learn to segregate speech
- Model performance on natural speech deteriorates

Conclusion

Takeaways

- Unlike Temporal Coherence models, DNNs do not rely on timing information
- DNNs cue onto harmonicity for segregation
- SOTA models completely fail with inharmonic inputs
- DNNs implicitly perform pitch-tracking
- DNNs find it challenging to learn from inharmonic speech
- Inharmonic speech → adversarial input to DNN based models

Next Steps

- Investigate how DNNs perform harmonic analysis
- Investigate how DNNs perform harmonics tracking
- Study spectrogram-based speech segregation models

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