

Generative Adversarial Network-based Postfilter for STFT Spectrograms



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1 Introduction

Background

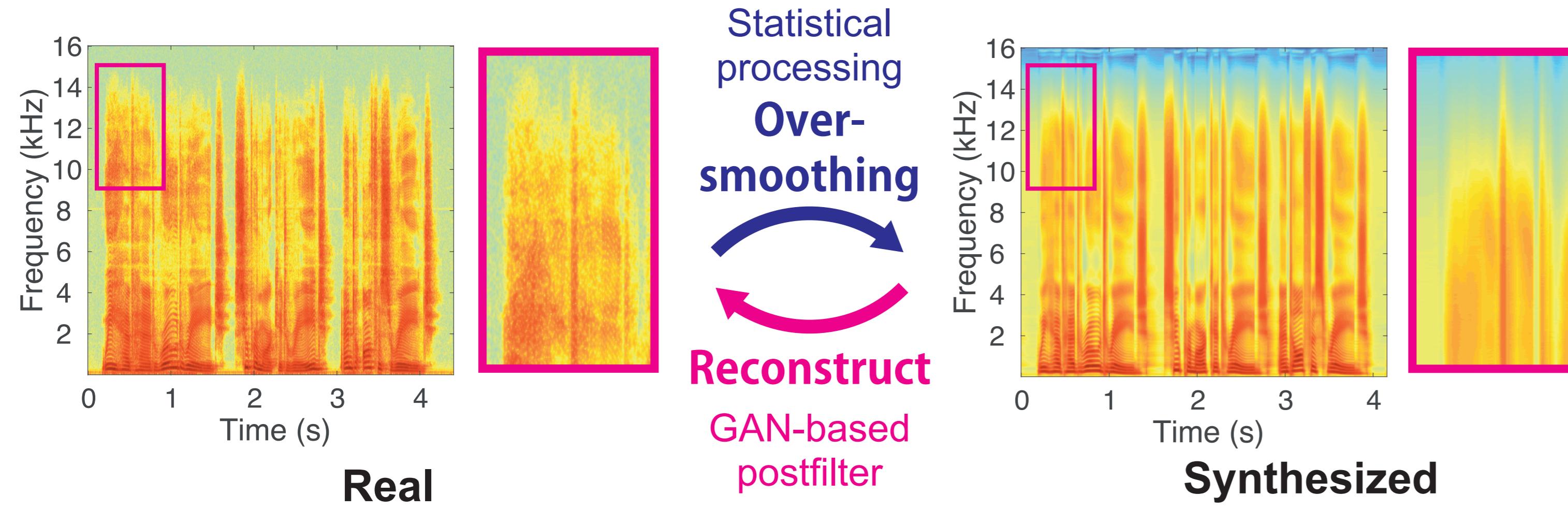
- In speech-processing systems, **STFT spectrograms** have been widely used as key acoustic representations.
- The aim with these systems is to produce spectrograms with quality indistinguishable from real ones, but typically they **lack fine structure** through statistical processing.

Objective

- Overcome these limitations and reconstruct **spectrograms having finer structure**.

Solution

- Generative adversarial network (GAN)-based postfilter for STFT spectrograms.



2 GAN-based Postfilter for STFT Spectrograms

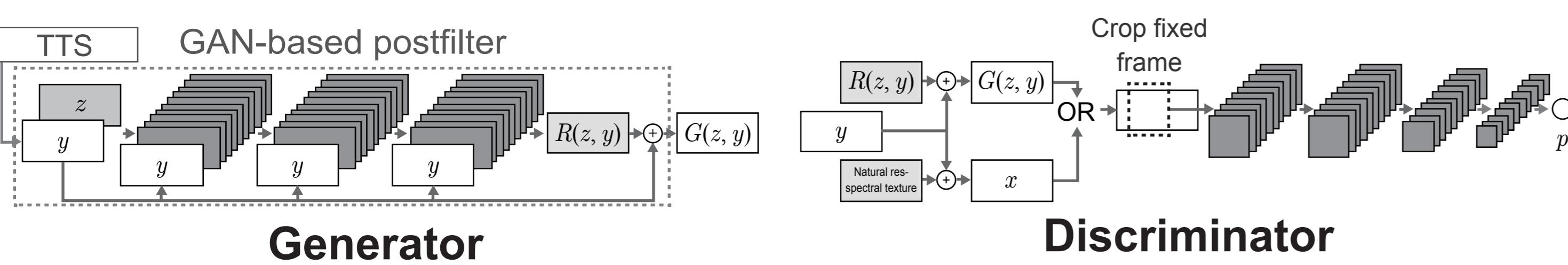
i GAN [Goodfellow+2014]

- The goal is to learn generative distribution $P_G(x)$ matching true data distribution $P_{\text{Data}}(x)$.
- Composed of two networks:
 - Generator** G : Map noise variable $z \sim P_{\text{Noise}}(z)$ to data space $x = G(z)$.
 - Discriminator** D : Assign probability p for “real” sample x , $1 - p$ for generated sample $G(z)$.
- D and G play two-player **minmax** game:

$$\min_G \max_D \mathbb{E}_{x \sim P_{\text{Data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim P_{\text{Noise}}(z)} [\log(1 - D(G(z)))].$$

ii GAN-based Postfilter for Vocoder Parameters [Kaneko+2017]

- The goal is to reconstruct convincing **vocoder parameters** from synthesized ones.



- (1) **Conditional**: Reconstruct natural spectral texture x from synthesized one y and noise z .

$$\min_G \max_D \mathbb{E}_{x, y \sim P_{\text{Data}}(x, y)} [\log D(x, y)] + \mathbb{E}_{z \sim P_{\text{Noise}}(z), y \sim P_y(y)} [\log(1 - D(G(z, y), y))].$$

- (2) **Residual**: Shorten the entire process of generating the spectral texture.

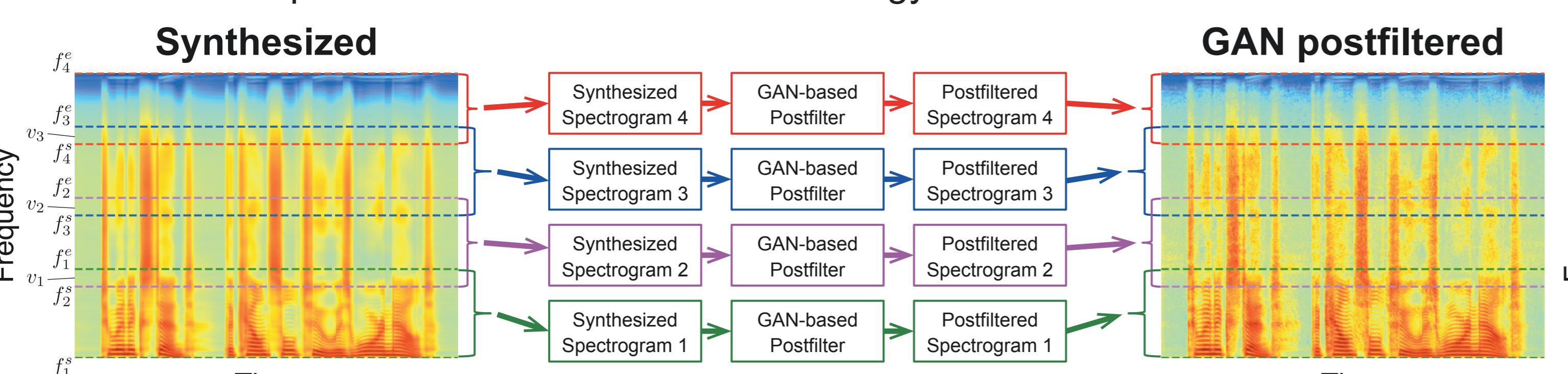
$$G(z, y) = y + R(z, y).$$

- (3) **Convolutional**: Represent spectro-temporal structures with reasonably small parameters.

Fully Convolutional Network for G : Allow input segments to take an arbitrary length.

iii GAN-based Postfilter for STFT Spectrograms

- The goal is to reconstruct convincing **STFT spectrograms** from the synthesized one.
- Challenges**: High dimensional, different structures depending on the frequency bands.
=> Take a simple **divide-and-concatenate** strategy.



- (1) **Partition**: Divide the spectrograms into N frequency bands with **overlap**.
- (2) **Postfiltering**: Reconstruct the individual bands using the GAN-based postfilter trained for each band.
- (3) **Concatenation**: Apply a **window function** to each band to smoothly connect and then concatenate them.

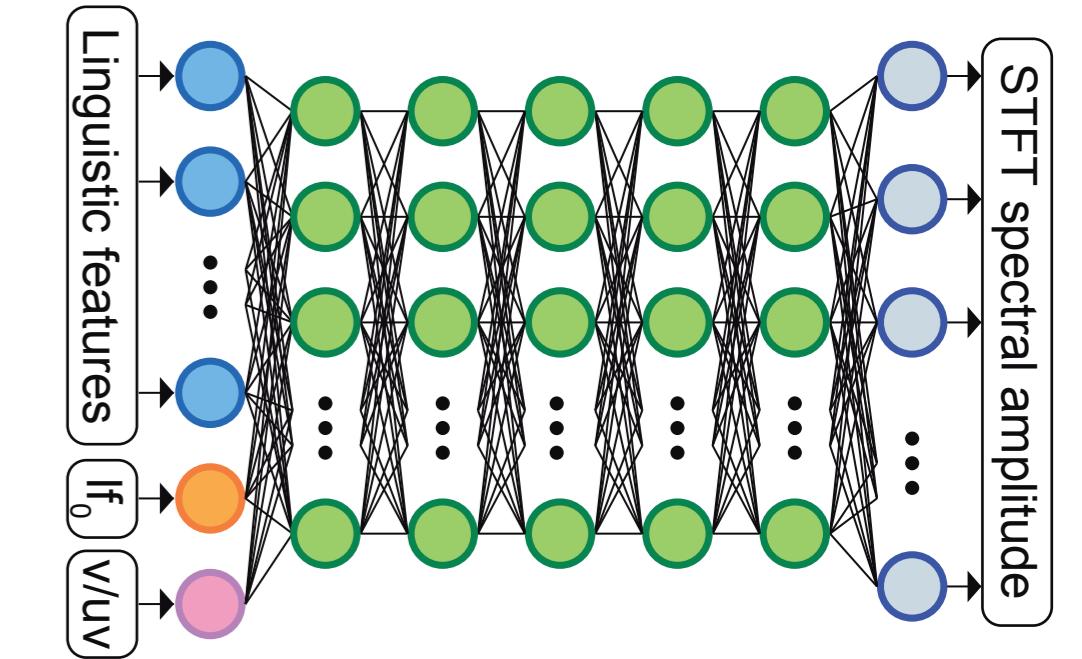
* In the model without overlap, the reconstructed spectrogram tends to have discontinuity between bands, causing a popping sound.

3 Application to Speech Synthesis

STFT-based speech synthesis

[Takaki+2017, Interspeech 2017 Tue-O-4-1-3]

- Instead of vocoder features, STFT spectra are directly predicted from text.
- Experimental results show that this method outperforms vocoder-based method.



STFT-based speech synthesis with GAN-based postfilter

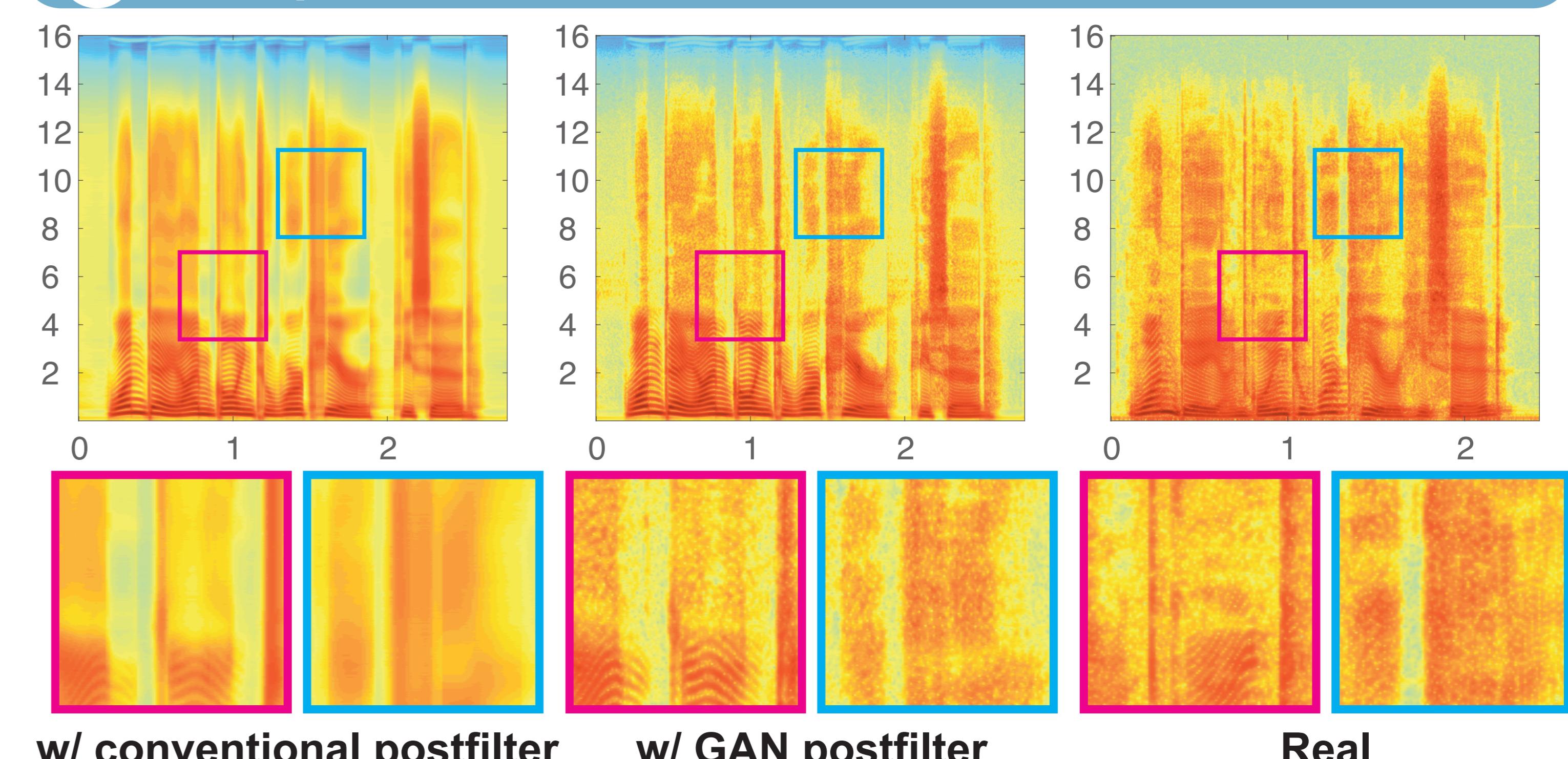
- Predict STFT-spectra directly from text.
- Postfilter predicted STFT spectrograms: [Use GAN-based postfilter here!](#)
- Generate waveform using Griffin and Lim phase recovery.

4 Experiments

i Experimental Conditions

- Dataset**: Blizzard Challenge 2011
- Speaker**: American professional female speaker.
- Data**: 12,085 utterances (17 hours), 200 utterances used for evaluation.
- Sampling rate**: 32 kHz.
- STFT condition**: Frame length: 25 ms. Frame shift: 5 ms. Blackman window function.
- GAN-based Postfilter**
 - Partition**: 4 Bands (0-5 kHz, 4-9 kHz, 8-13 kHz, 12-16 kHz). Overlap: 1 kHz.
 - Concatenation**: Hamming window function.
- Comparison**
 - Baseline**: Speech synthesis without GAN-based postfilter (w/ conventional postfilter)
 - Proposed**: Speech synthesis with GAN-based postfilter (w/ GAN postfilter)

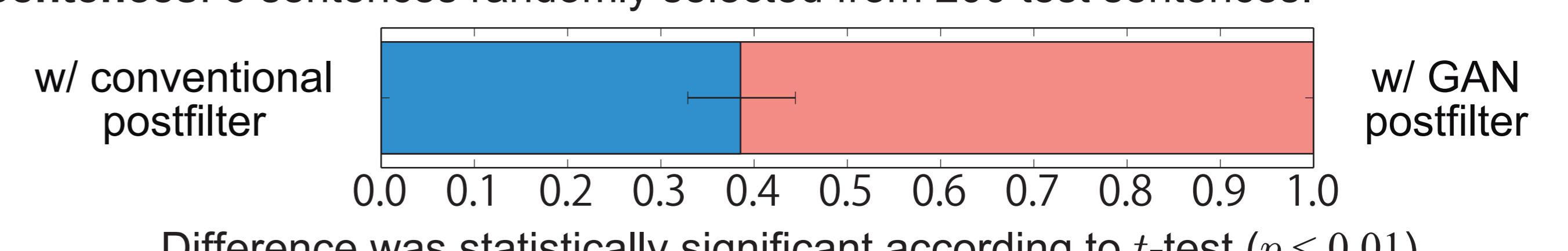
ii Sample Results



iii Subjective Evaluation

AB preference test

- Participants**: 18 native speakers of English.
- Sentences**: 8 sentences randomly selected from 200 test sentences.



5 Related Work

