Inter-University Research Institute Corporation / Research Organization of Information and Systems
National Institute of Informatics

Speech synthesis workshop
Vienna, Austria, 2019

Harmonic-plus-noise neural source-filter waveform model with trainable maximum-voiced frequency

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Note: Japanese natural waveforms are deleted due to licence reason

contact: wangxin@nii.ac.jp
we welcome critical comments, suggestions, and discussion

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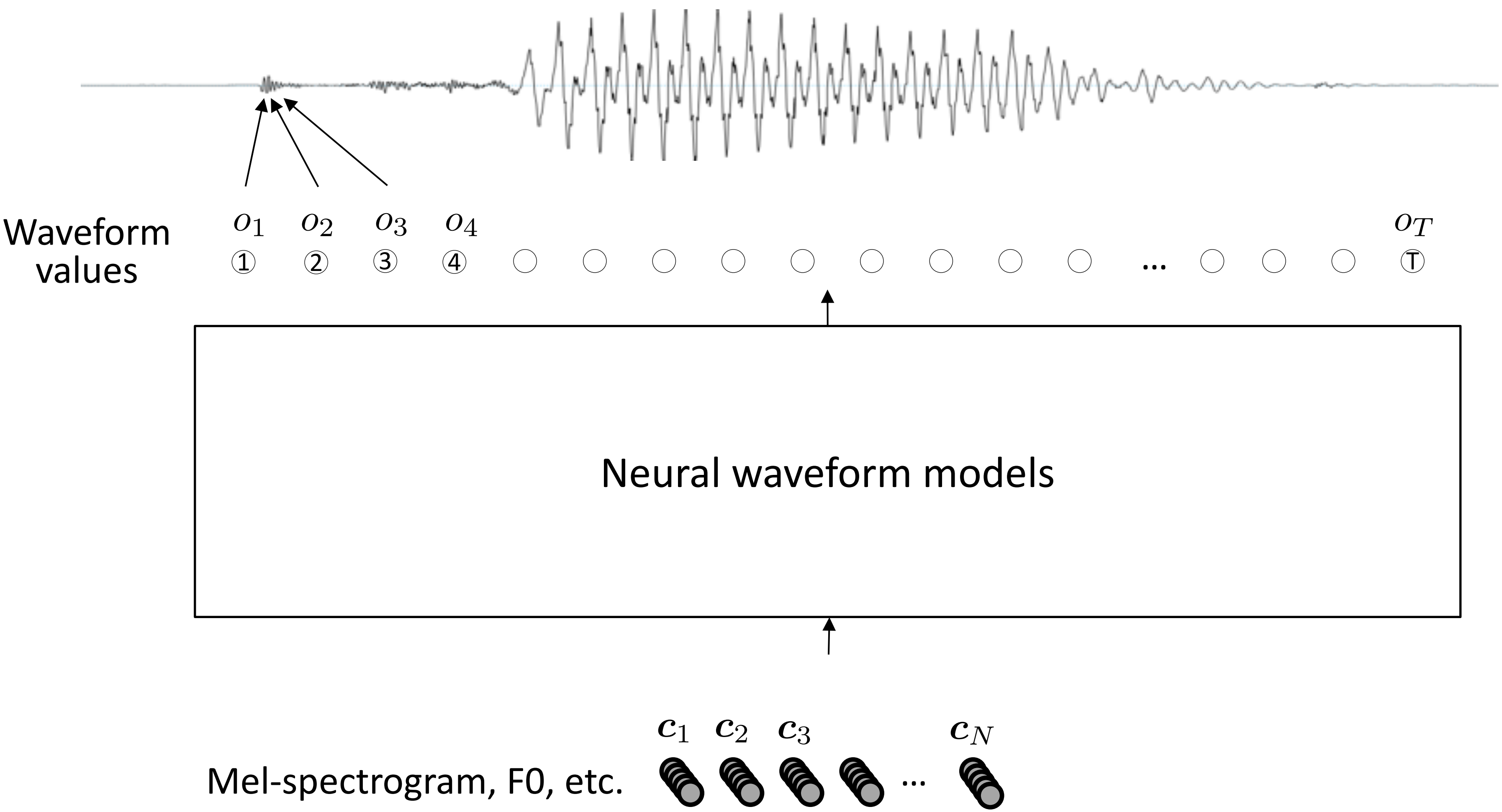
INTRODUCTION

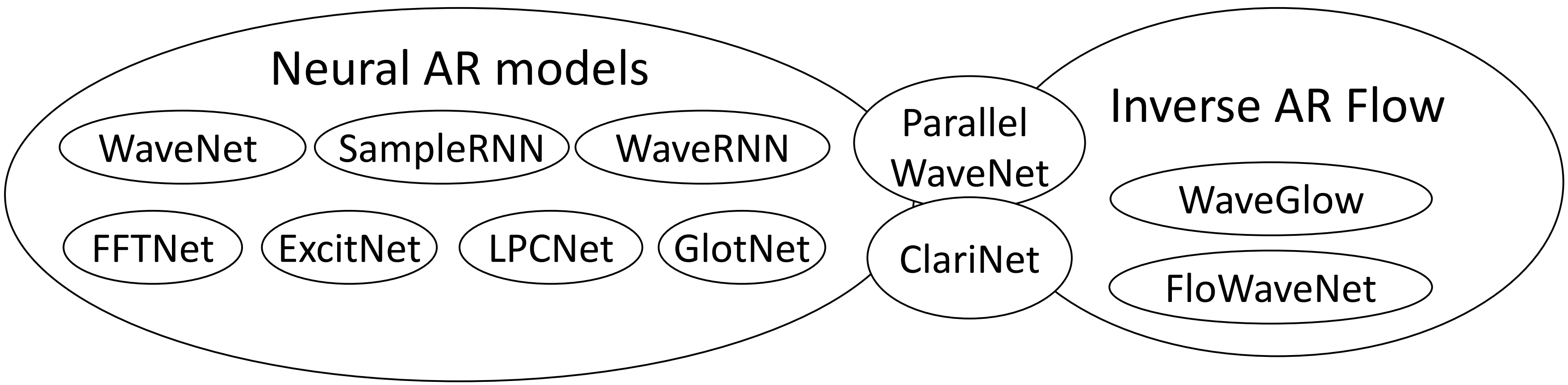
Task



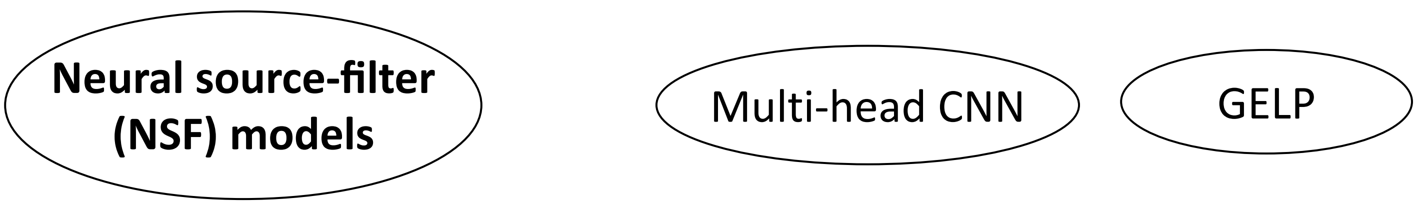
INTRODUCTION

Models

- Neural autoregressive (AR) and inverse AR flow

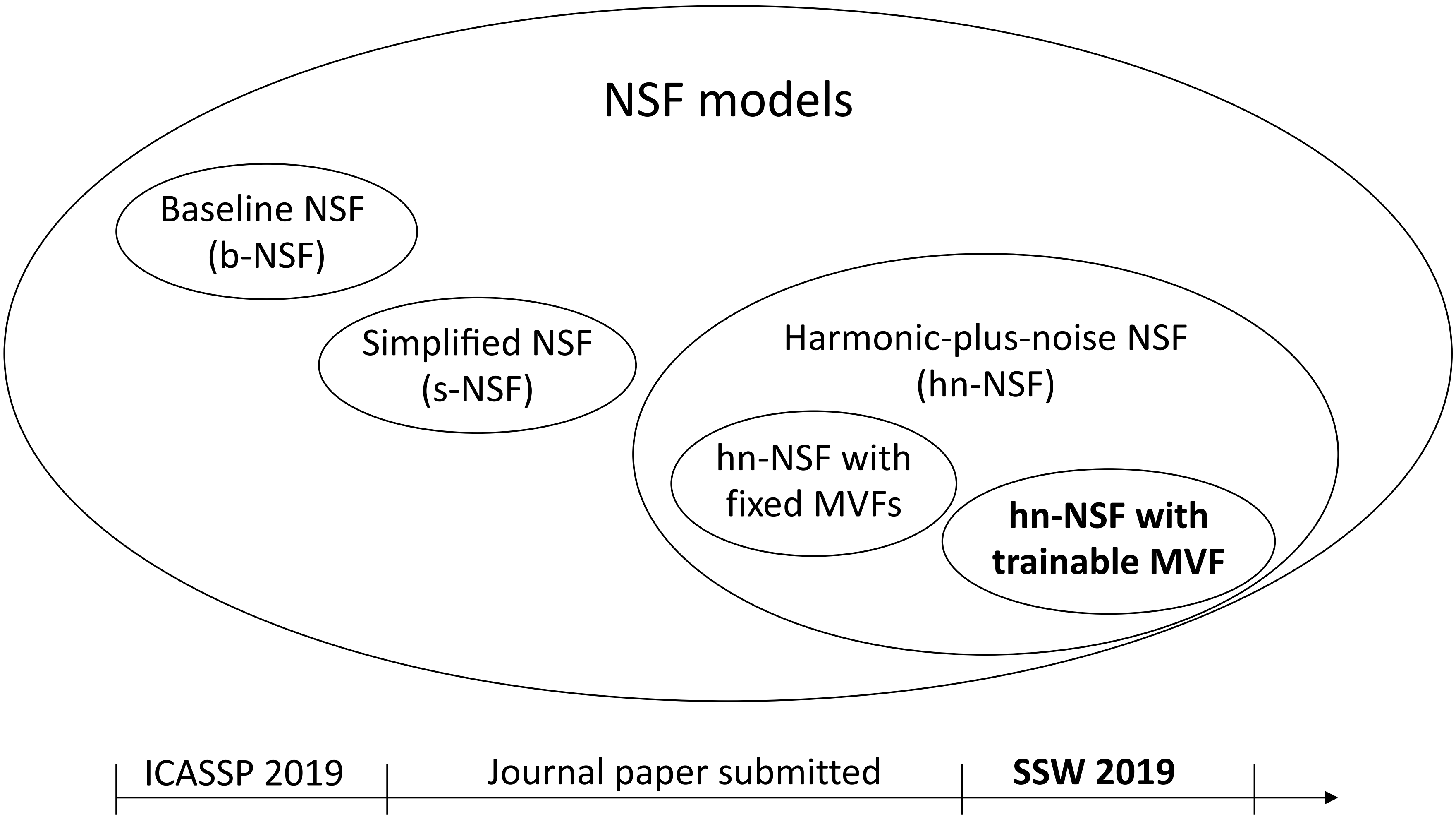


- No AR or inverse AR flow



  - Spectral-domain training criterion
  - Source-filter architecture

INTRODUCTION



❖ MVF: Maximum voiced frequency

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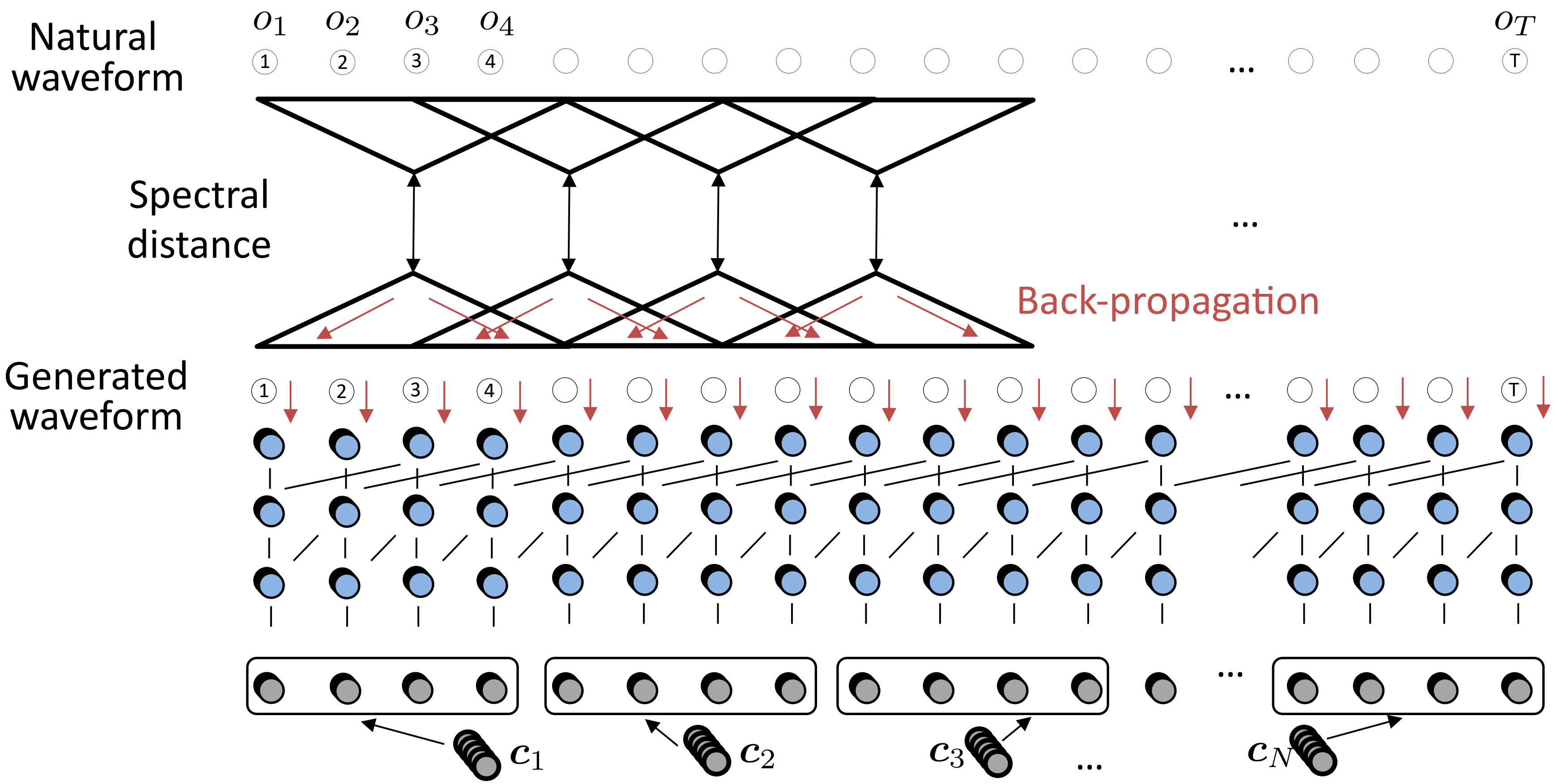
NEURAL SOURCE-FILTER MODEL

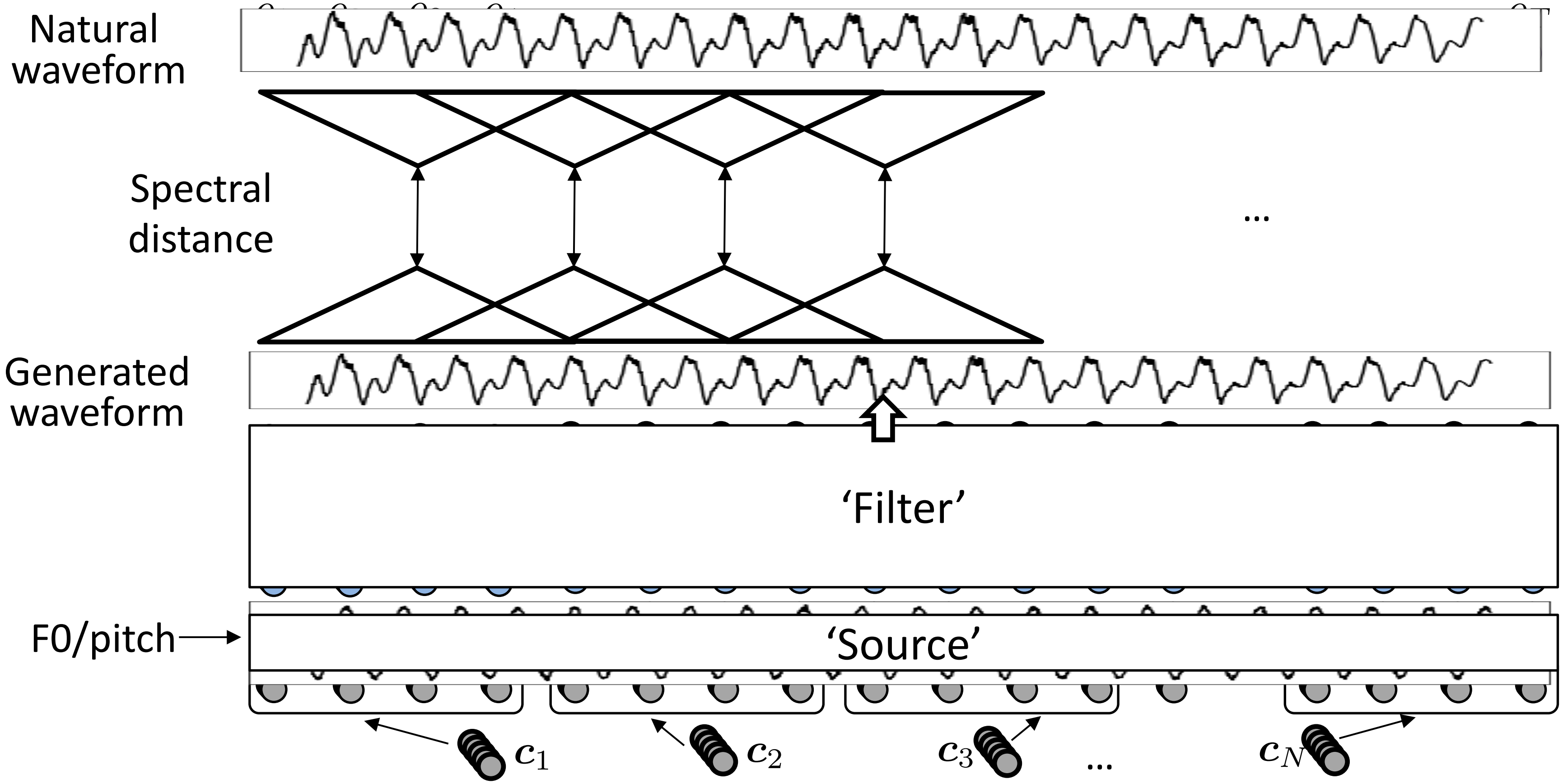
Idea 1: spectral domain criterion



- Based on short time Fourier transform (STFT)

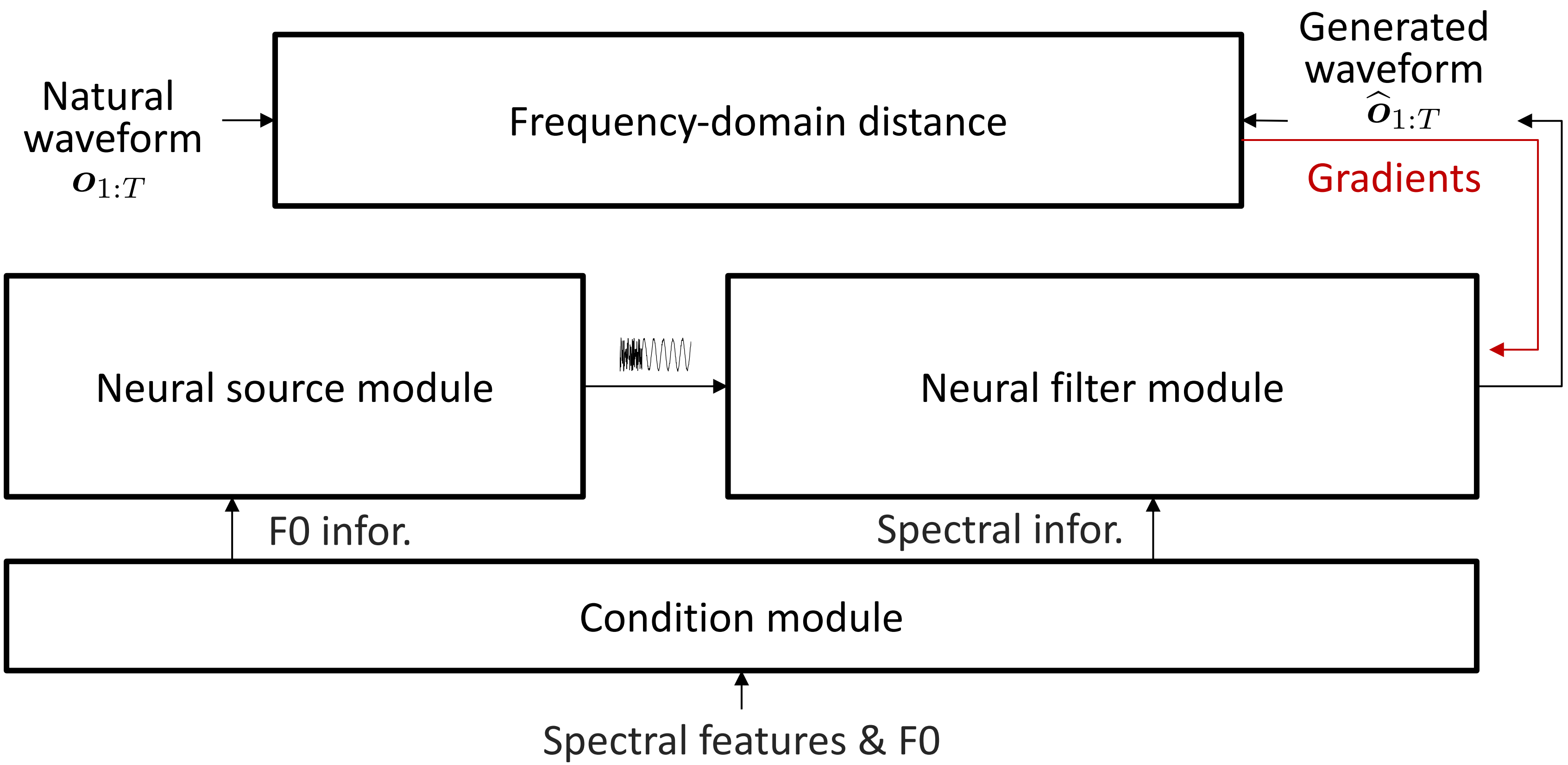
NEURAL SOURCE-FILTER MODEL

Idea 2: source-filter



NEURAL SOURCE-FILTER MODEL

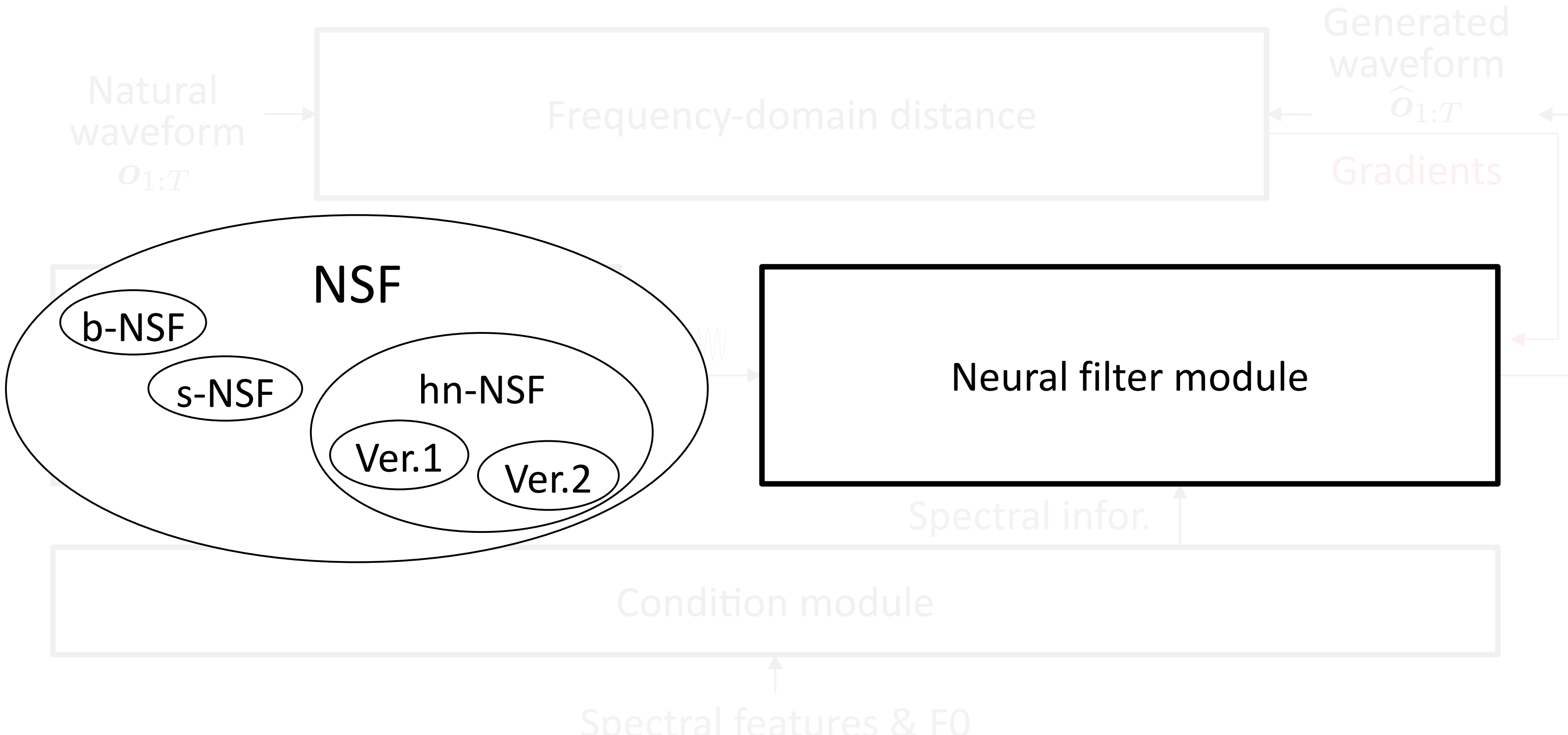
General framework



- No AR or inverse AR flow

NEURAL SOURCE-FILTER MODEL

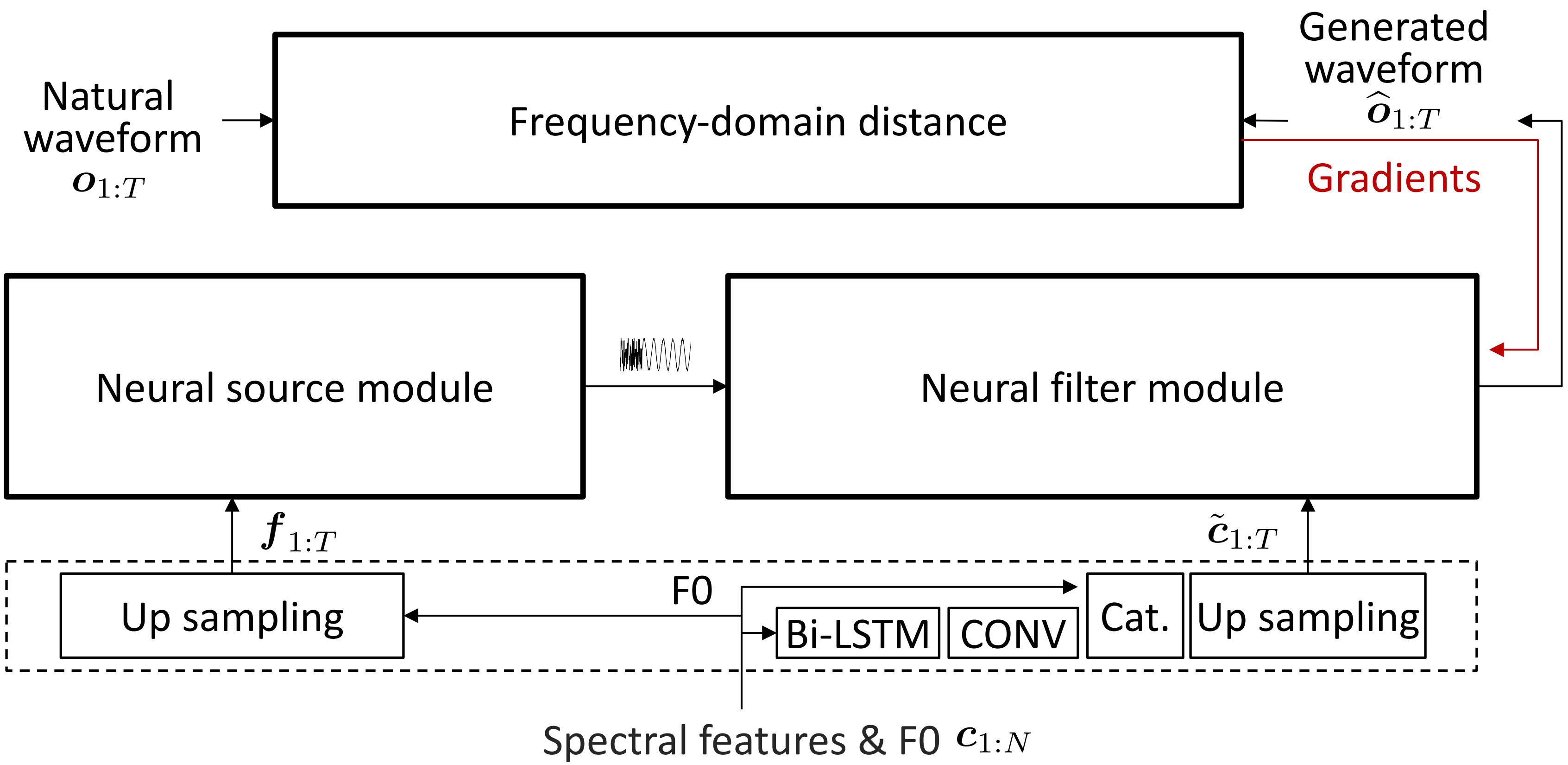
General framework



- Different neural filter modules

NEURAL SOURCE-FILTER MODEL

General framework

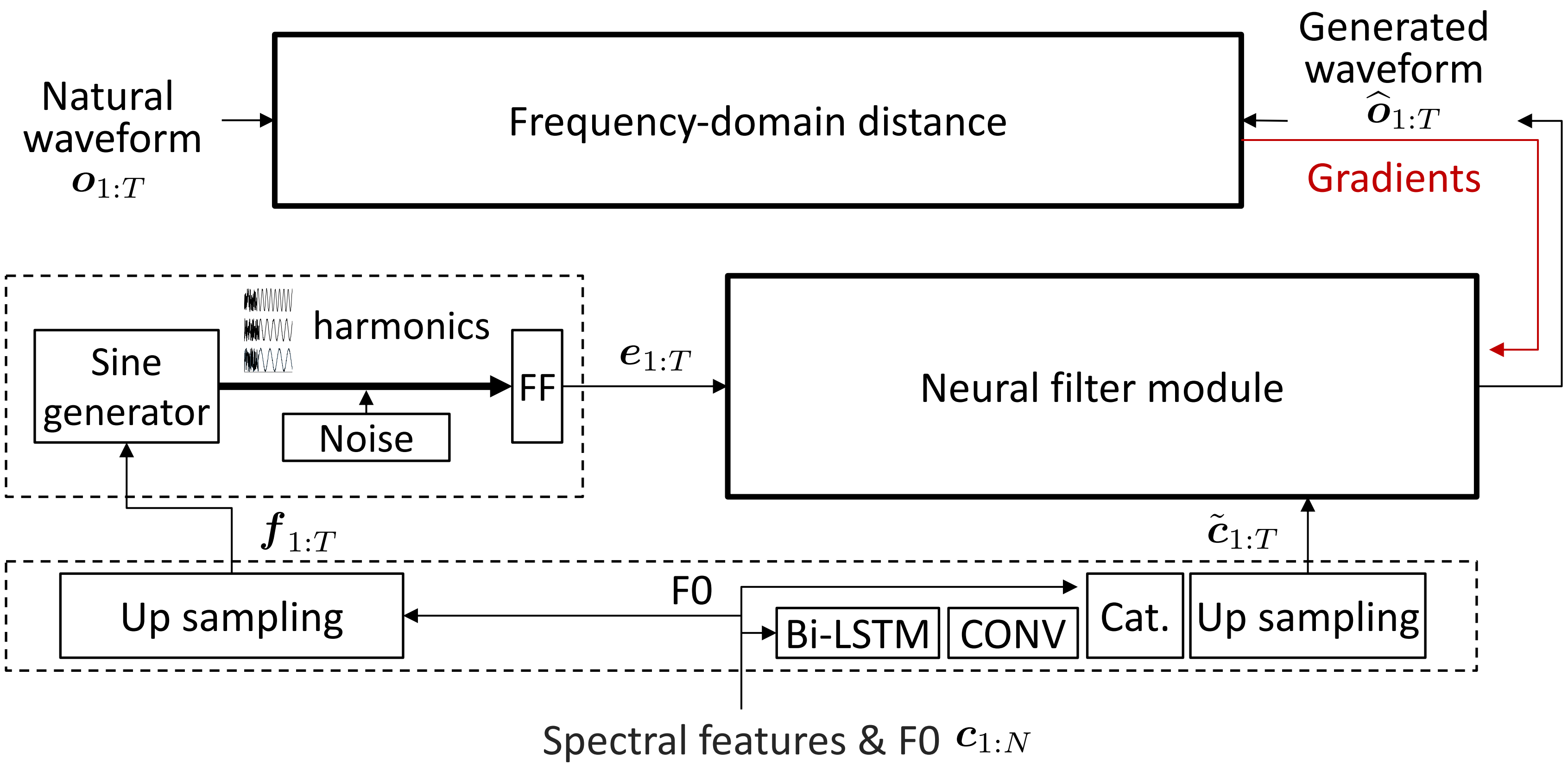


- Condition module: Up sampling / Dimension change

❖ CONV: convolution
❖ Cat.: concatenation

NEURAL SOURCE-FILTER MODEL

General framework



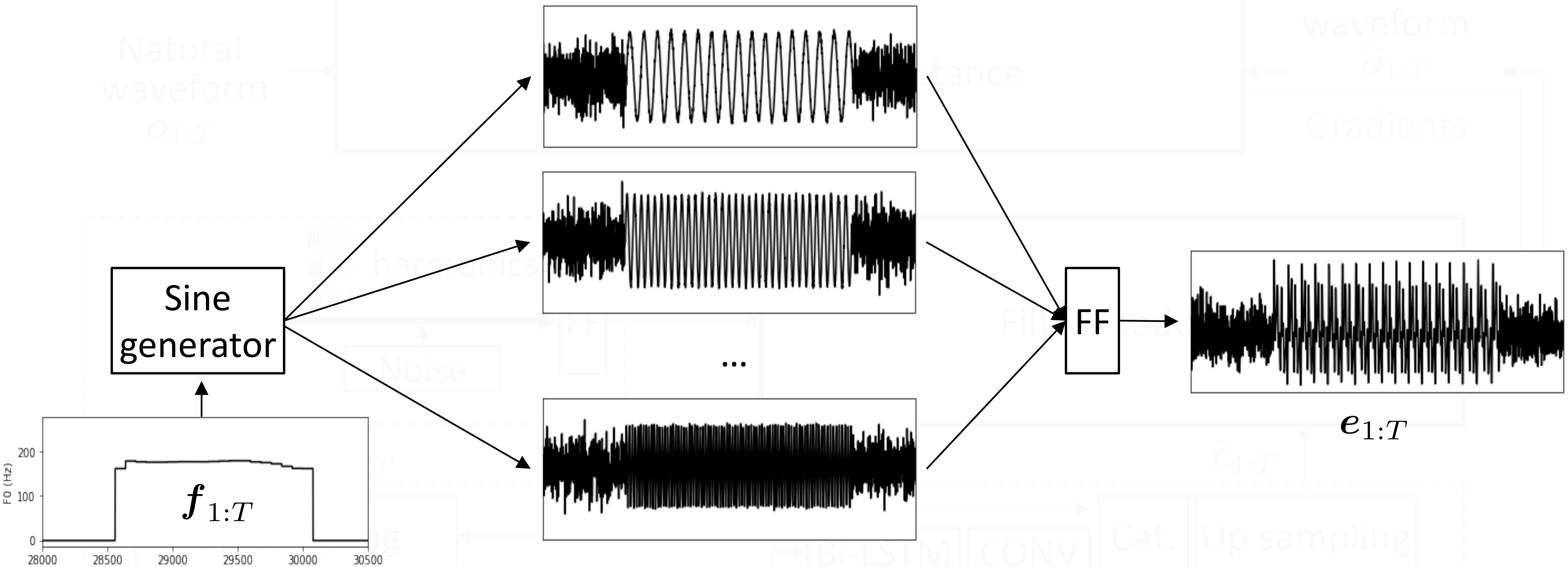
- Source module: generate sine-based excitation given F0

$$f_t \in \{0\} \cup \mathbb{R}^+ \longrightarrow e_t \in \mathbb{R}, \forall t \in \{1, \cdots, T\}$$

❖ FF: feedforward layer with Tanh

NEURAL SOURCE-FILTER MODEL

General framework



Fundamental component

Voiced: $\sin(\sum_{k=1}^{t} 2\pi \underline{\frac{f_k}{N_s}} + \underline{\phi}) + \underline{n_t}$

Noise

Random initial phase

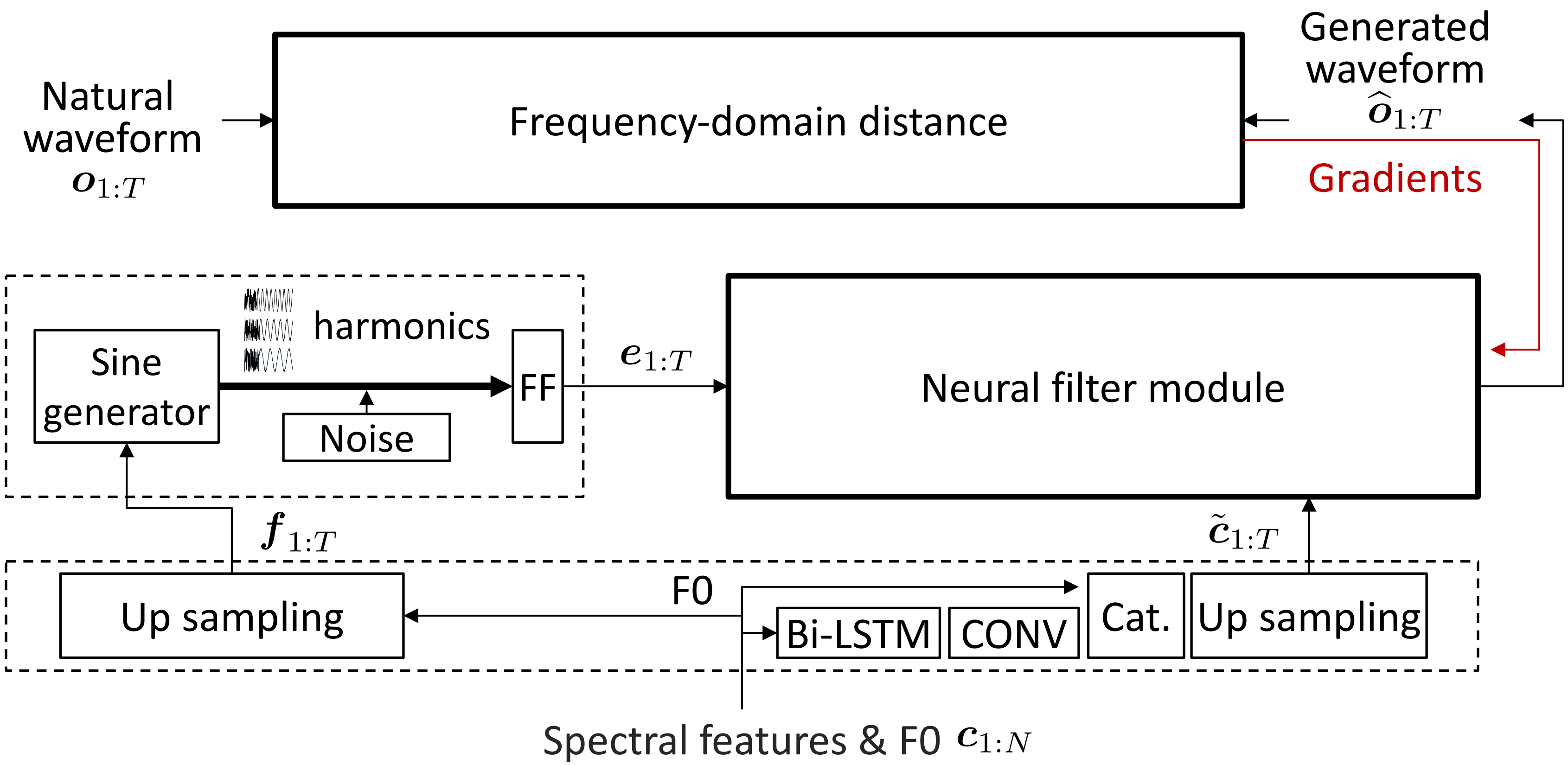
Sampling rate

Unvoiced: noise

- FF: feedforward layer with Tanh

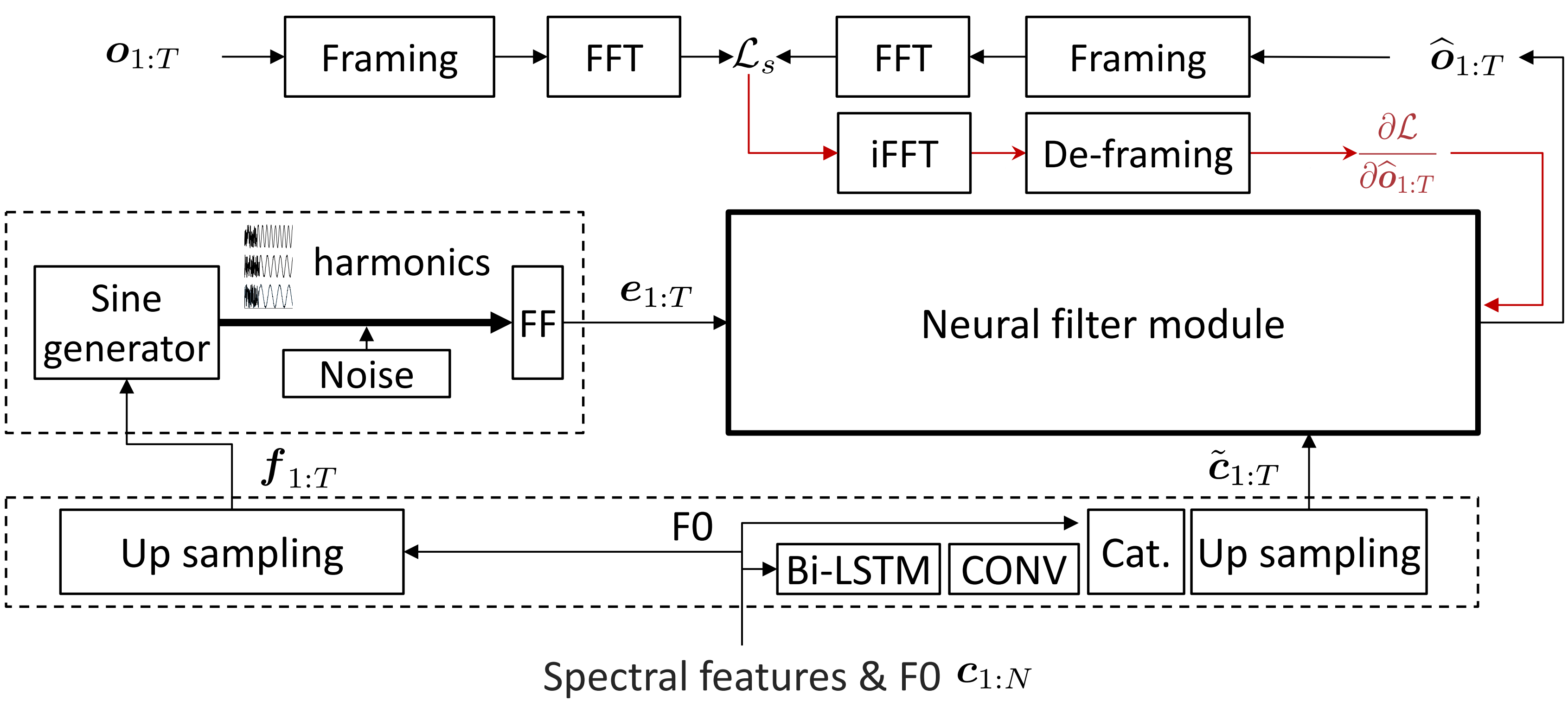
NEURAL SOURCE-FILTER MODEL

General framework



NEURAL SOURCE-FILTER MODEL

General framework

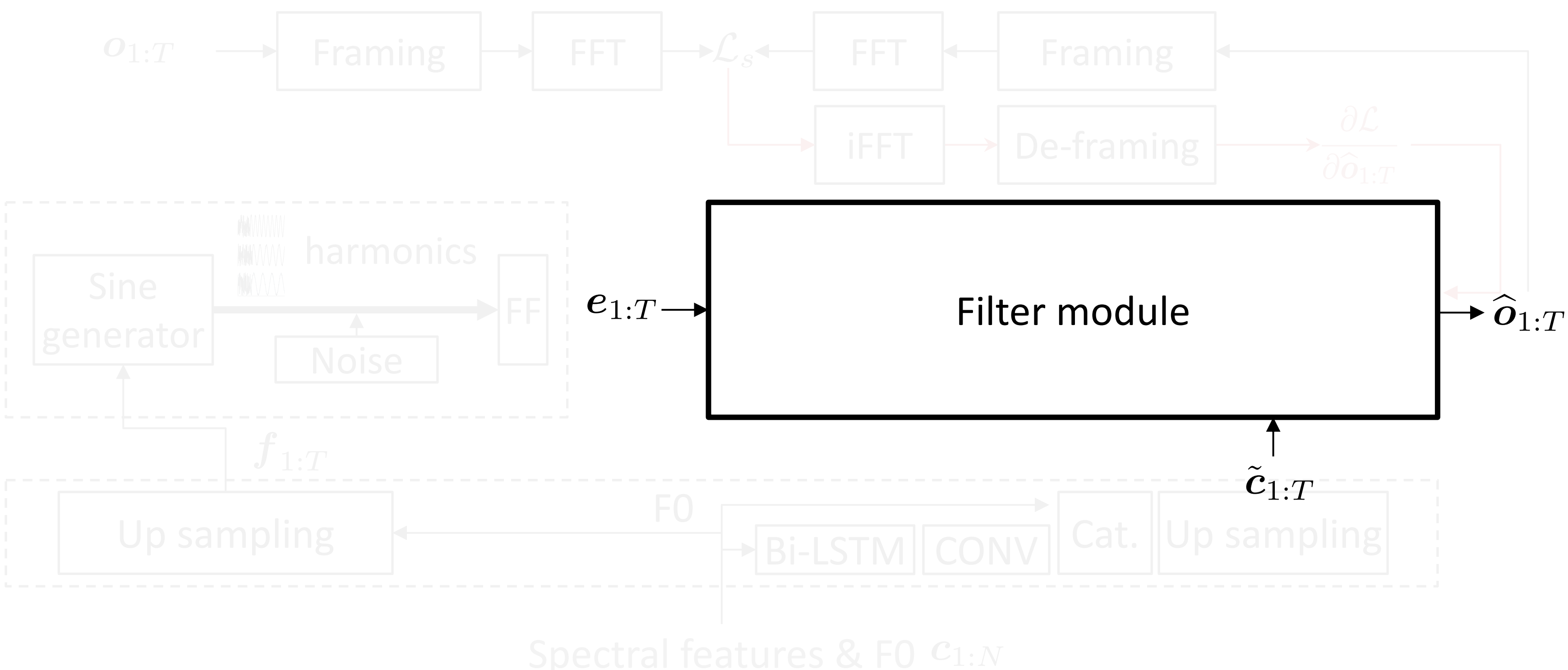


- Multiple L_s : different frame shift & length (☛ ICASSP 2019)

❖ FFT: fast Fourier transform

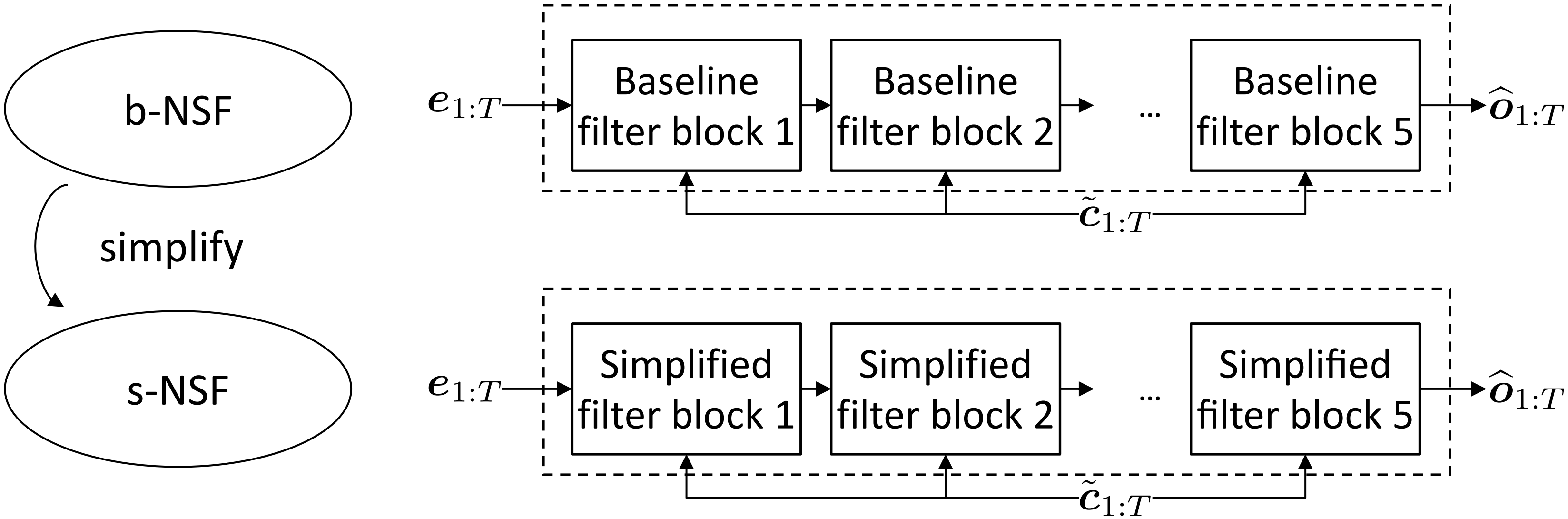
NEURAL SOURCE-FILTER MODEL

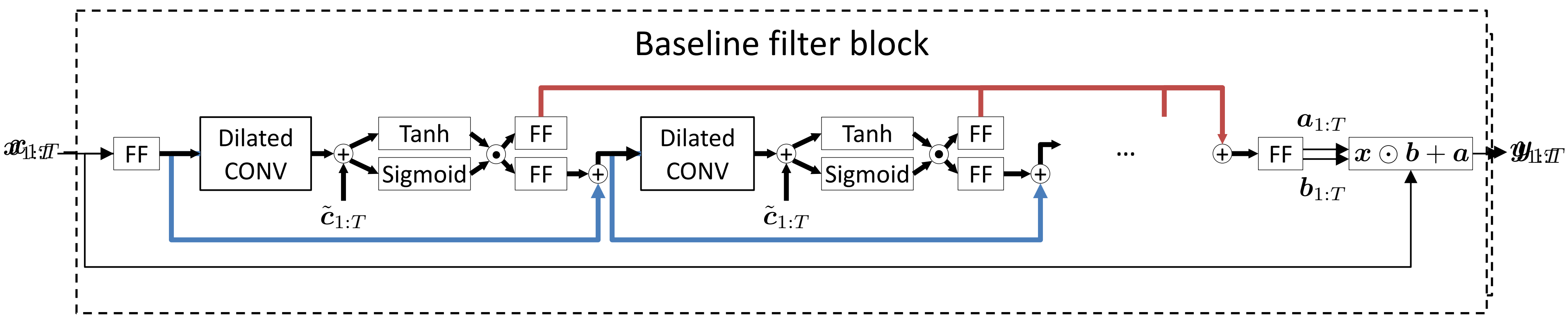
General framework



NEURAL SOURCE-FILTER MODEL

Filter modules in NSF models

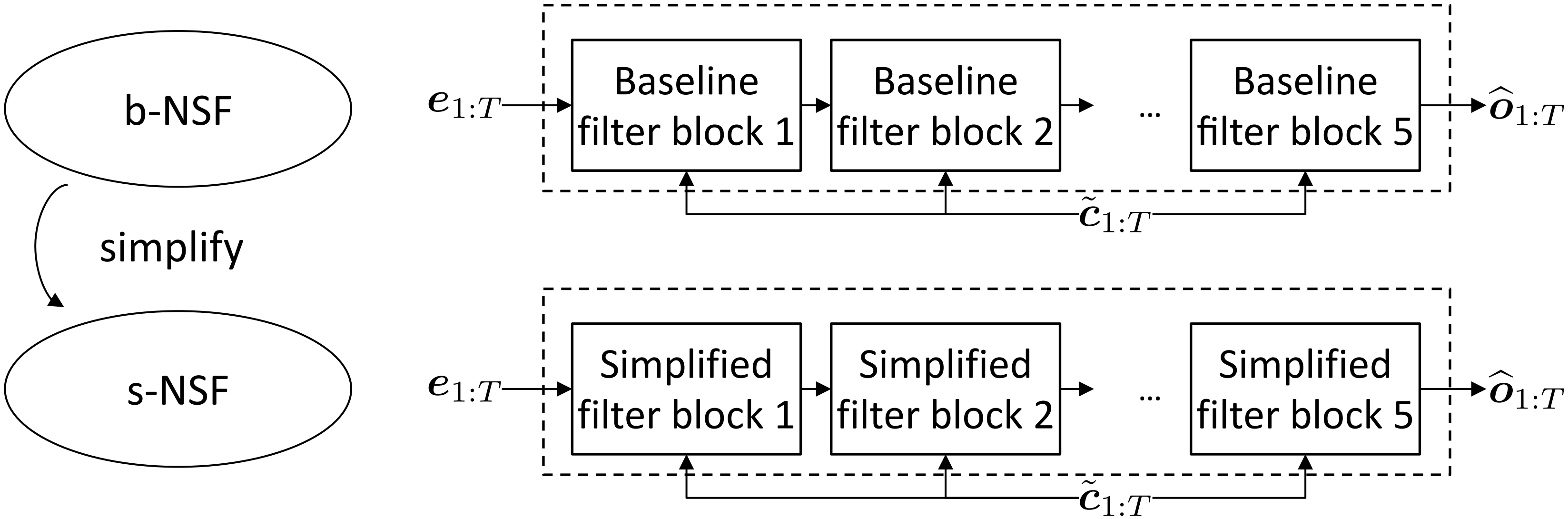




- $x_t, y_t, \hat{o}_t, a_t \in \mathbb{R},\ b_t \in \mathbb{R}^+,\ \tilde{c}_t \in \mathbb{R}^{64},\ \forall t \in \{1, \cdots, T\}$
- Element-wise multiplication $\odot$

NEURAL SOURCE-FILTER MODEL

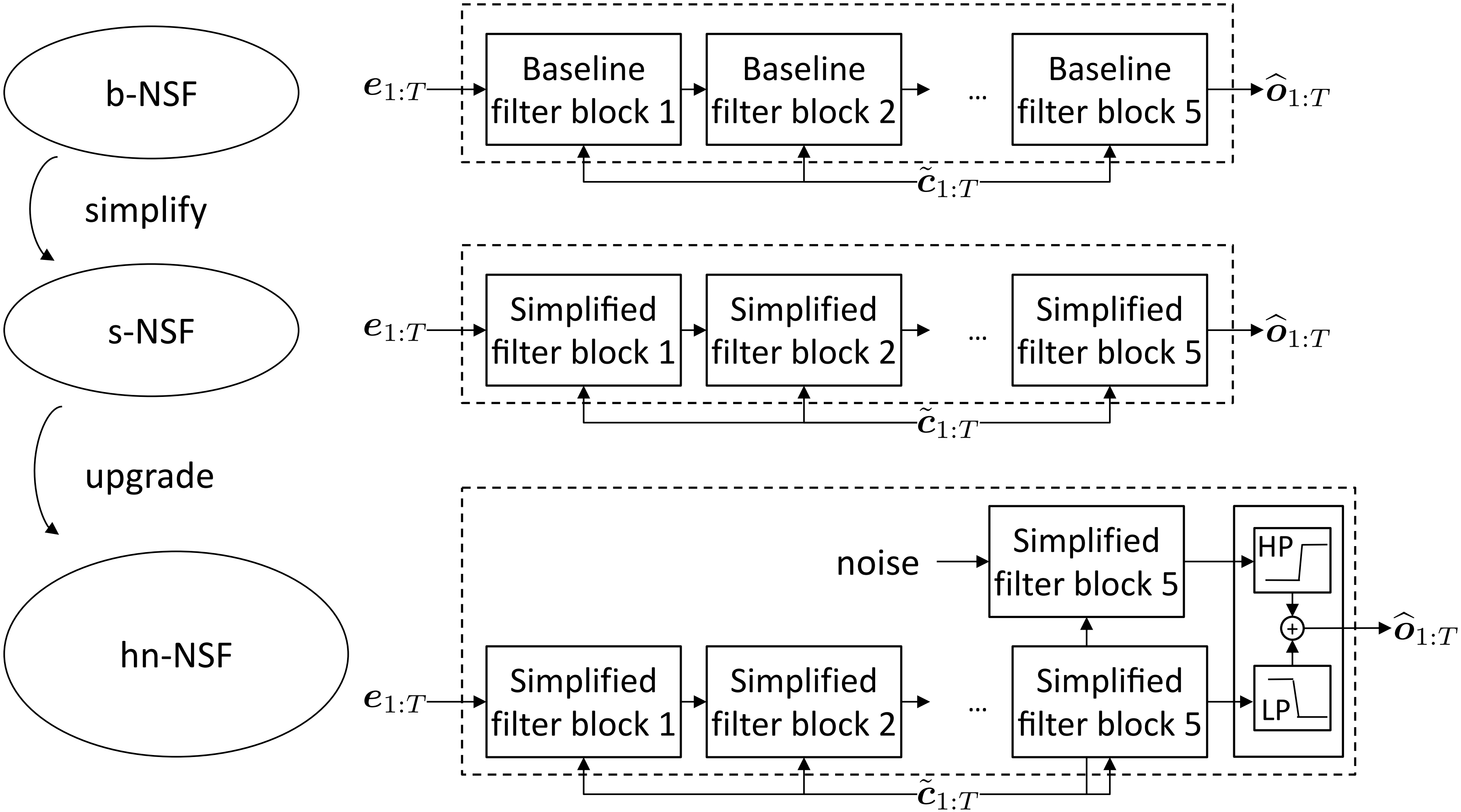
Filter modules in NSF models



- Artifacts in both models (☛ journal paper):
  1. Strong harmonics in high-frequency band
  2. Bad unvoiced sounds
  3. …

NEURAL SOURCE-FILTER MODEL

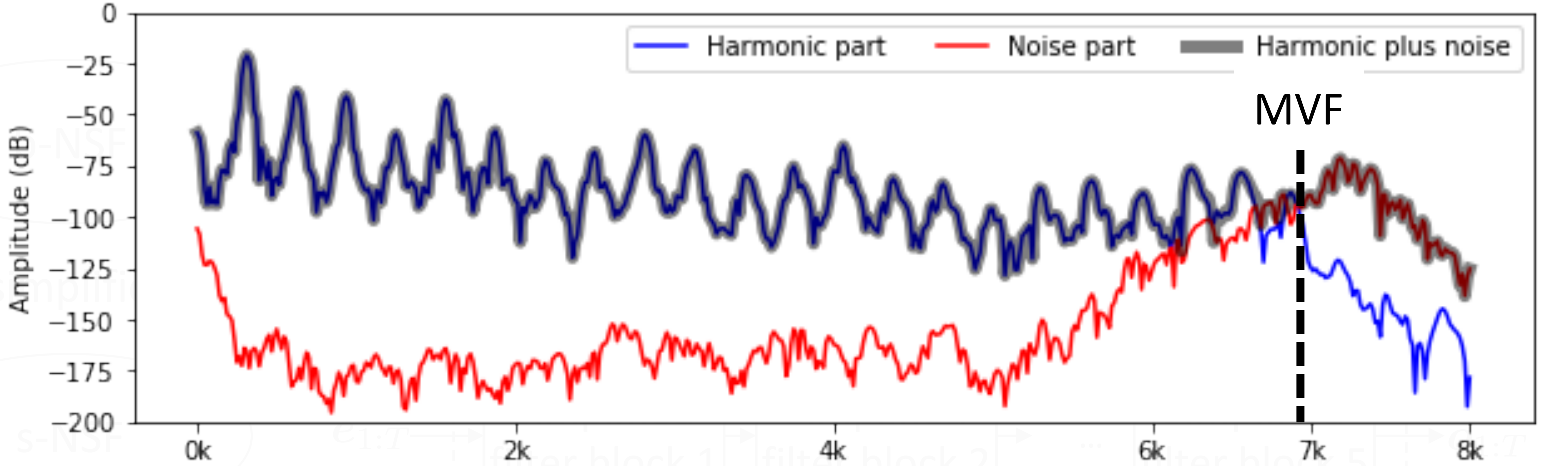
Filter modules in NSF models



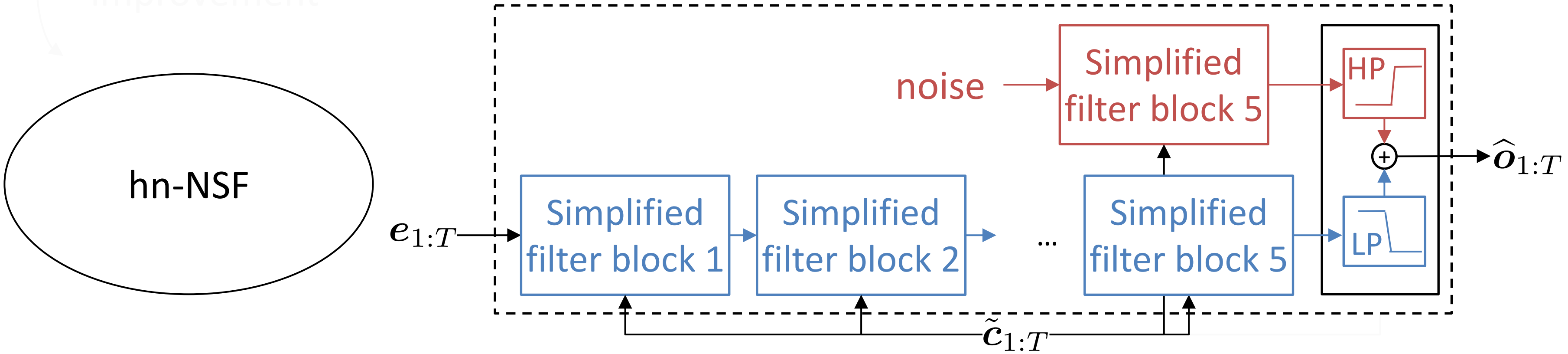
- HP, LP: high- and low-pass finite-impulse-response (FIR) filter

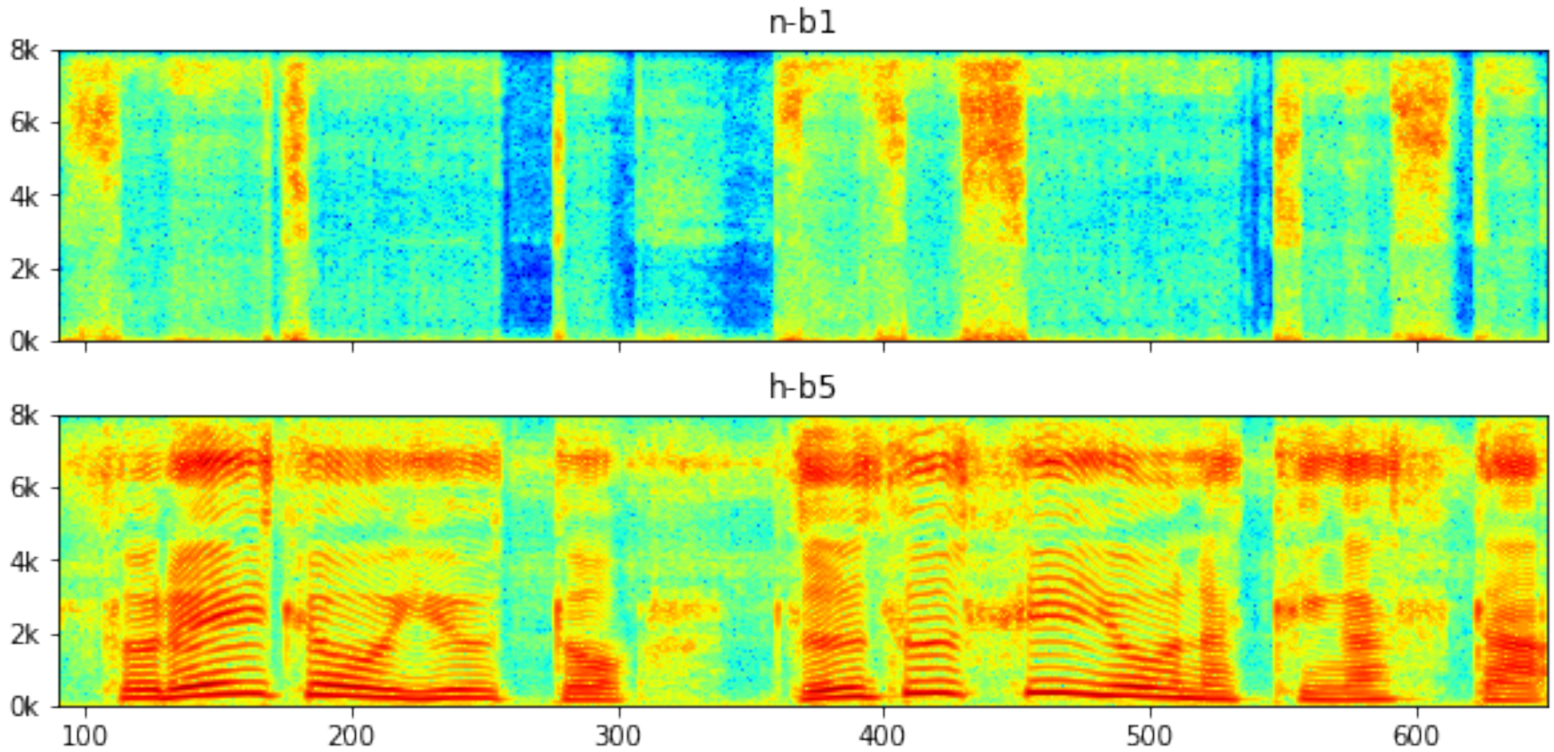
NEURAL SOURCE-FILTER MODEL

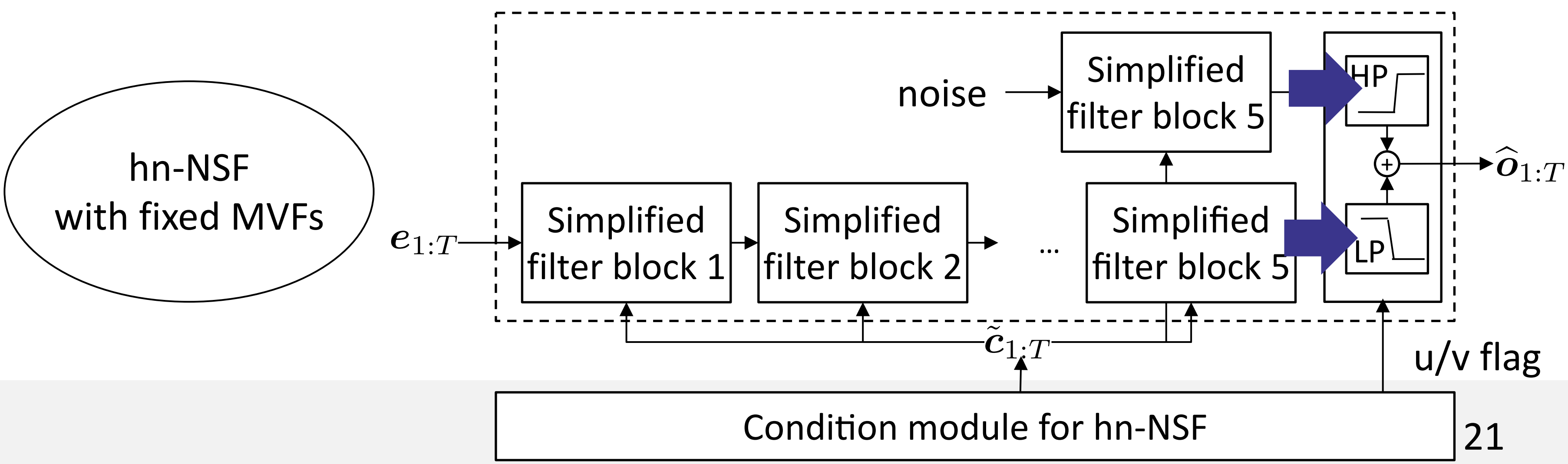
Harmonic-plus-noise NSF

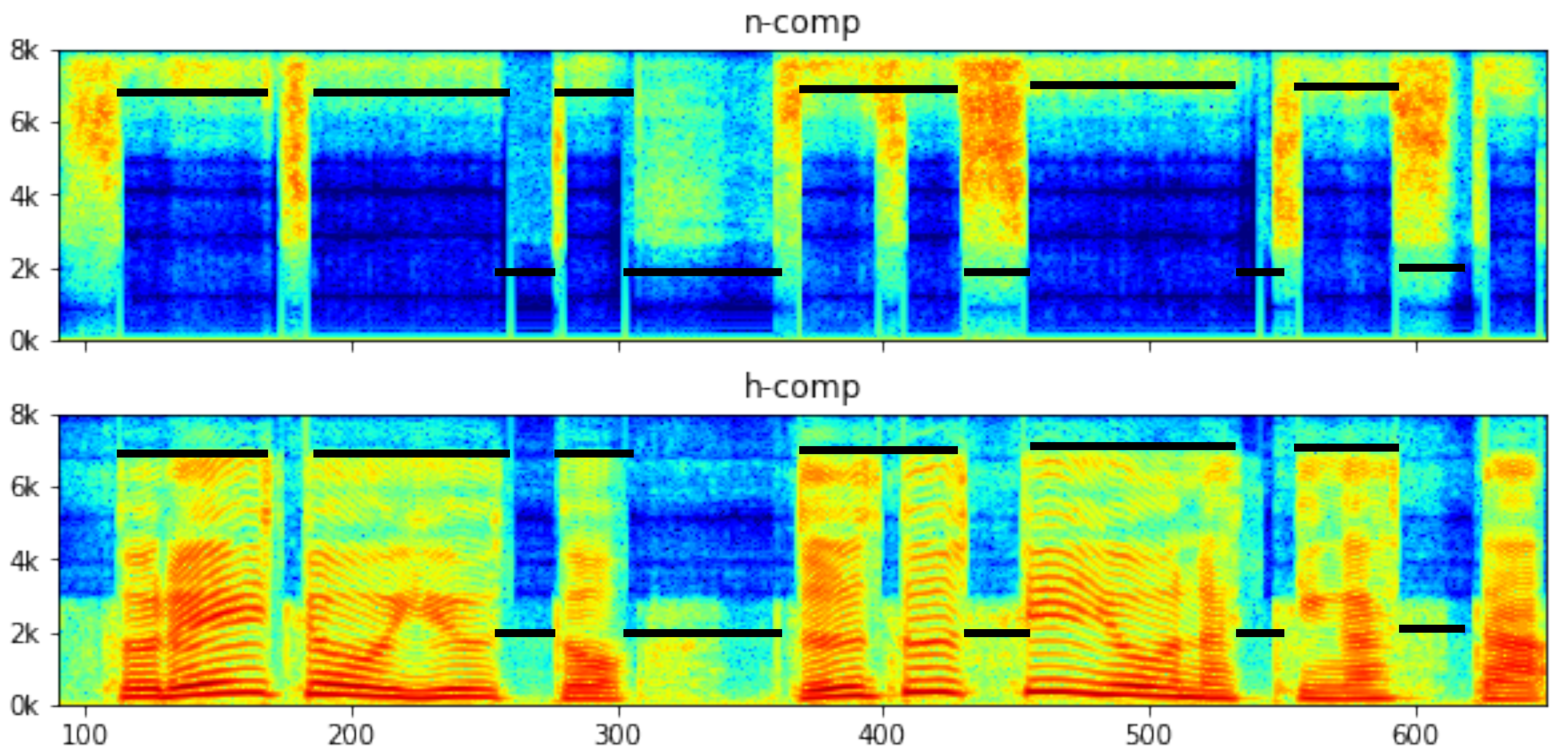


- Filtering in time domain

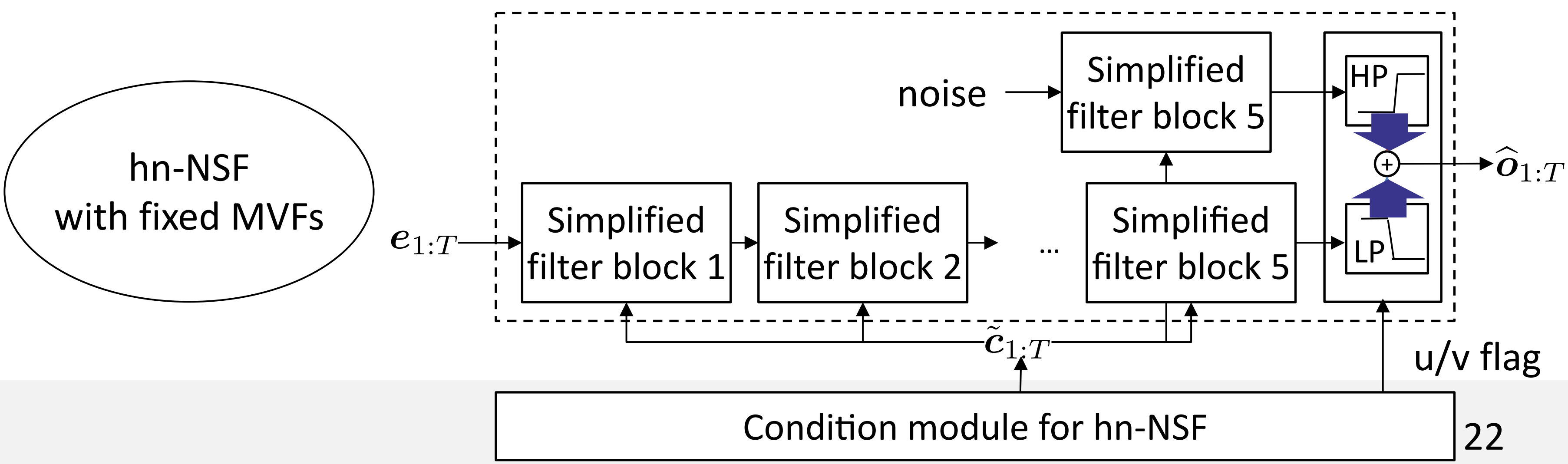



n-b1
8k
6k
4k
2k
0k
h-b5
8k
6k
4k
2k
0k
100
200
300
400
500
600

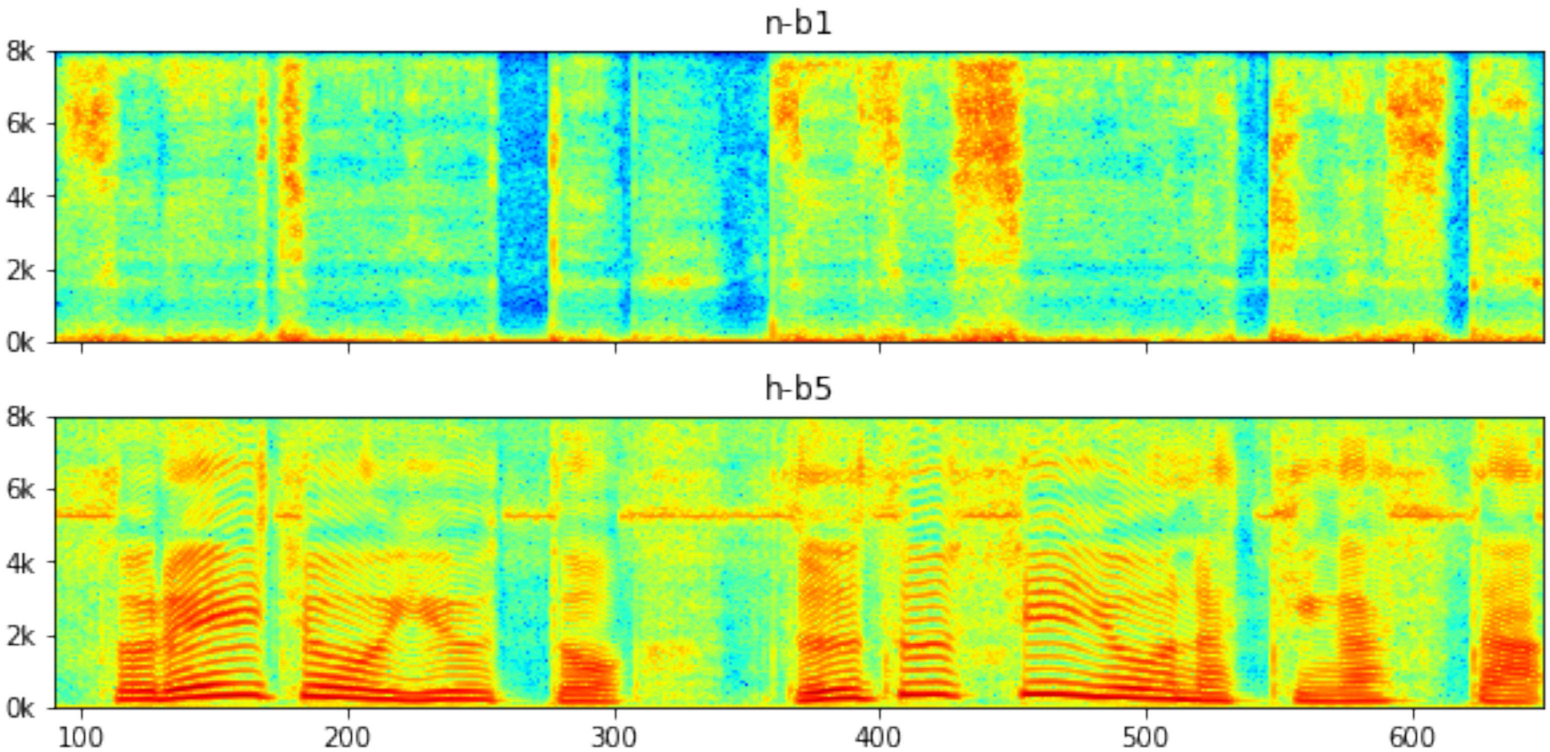

hn-NSF
with fixed MVFs
noise
Simplified filter block 5
HP
$\widehat{\boldsymbol{o}}_{1:T}$
$\boldsymbol{e}_{1:T}$
Simplified filter block 1
Simplified filter block 2
...
Simplified filter block 5
LP
$\tilde{\boldsymbol{c}}_{1:T}$
u/v flag
Condition module for hn-NSF



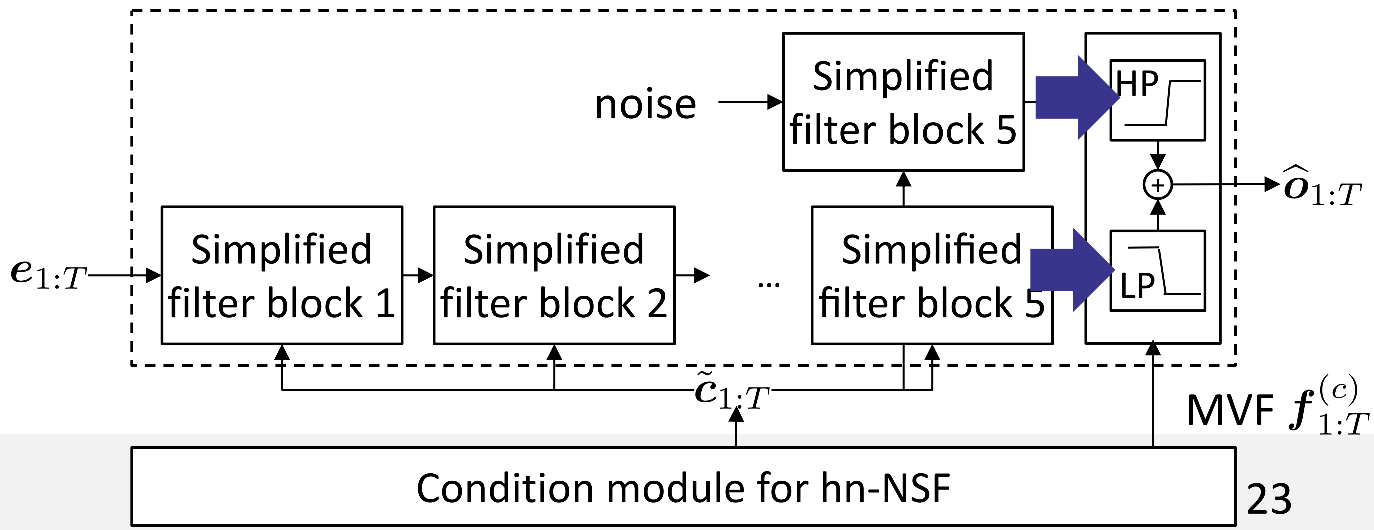
n-comp
h-comp
8k
6k
4k
2k
0k
100
200
300
400
500
600

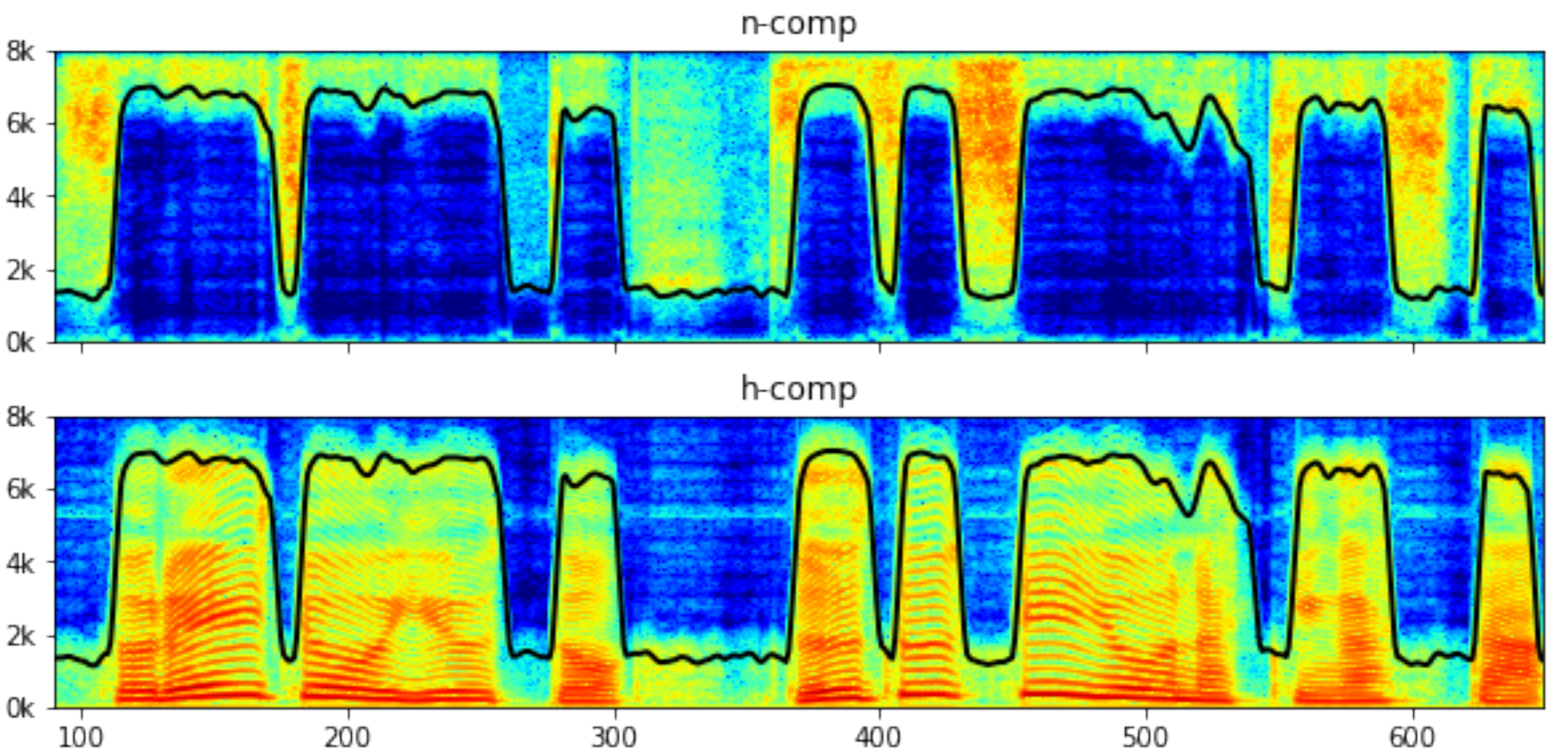


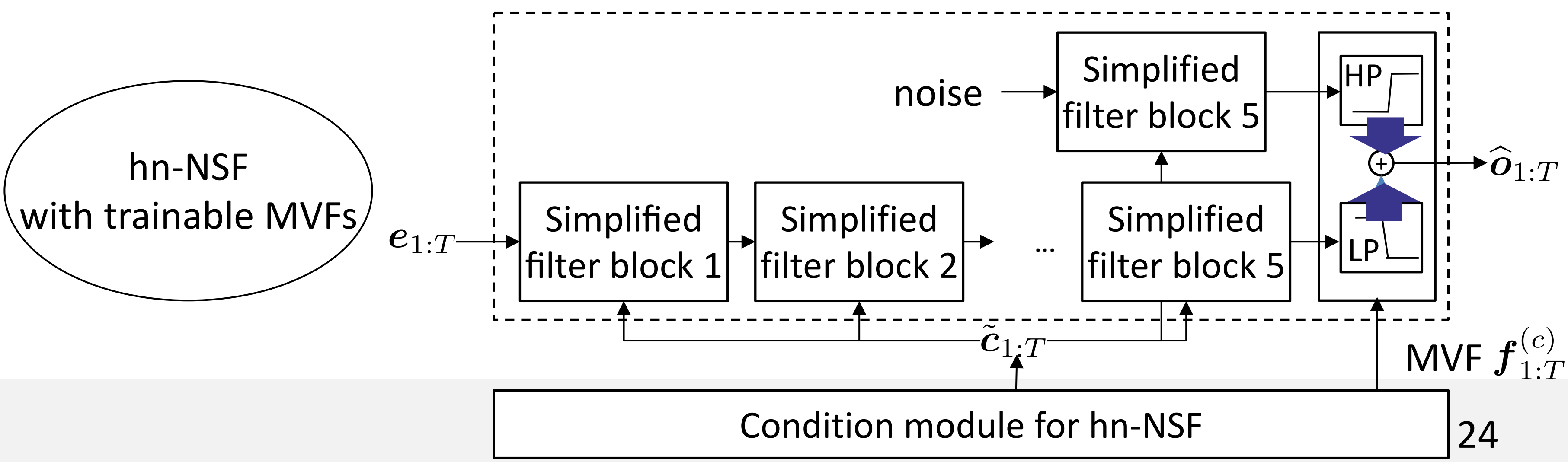
hn-NSF
with fixed MVFs
$e_{1:T}$
Simplified filter block 1
Simplified filter block 2
...
Simplified filter block 5
noise
Simplified filter block 5
HP
LP
$\widehat{o}_{1:T}$
$\tilde{c}_{1:T}$
u/v flag
Condition module for hn-NSF



hn-NSF
with trainable MVFs



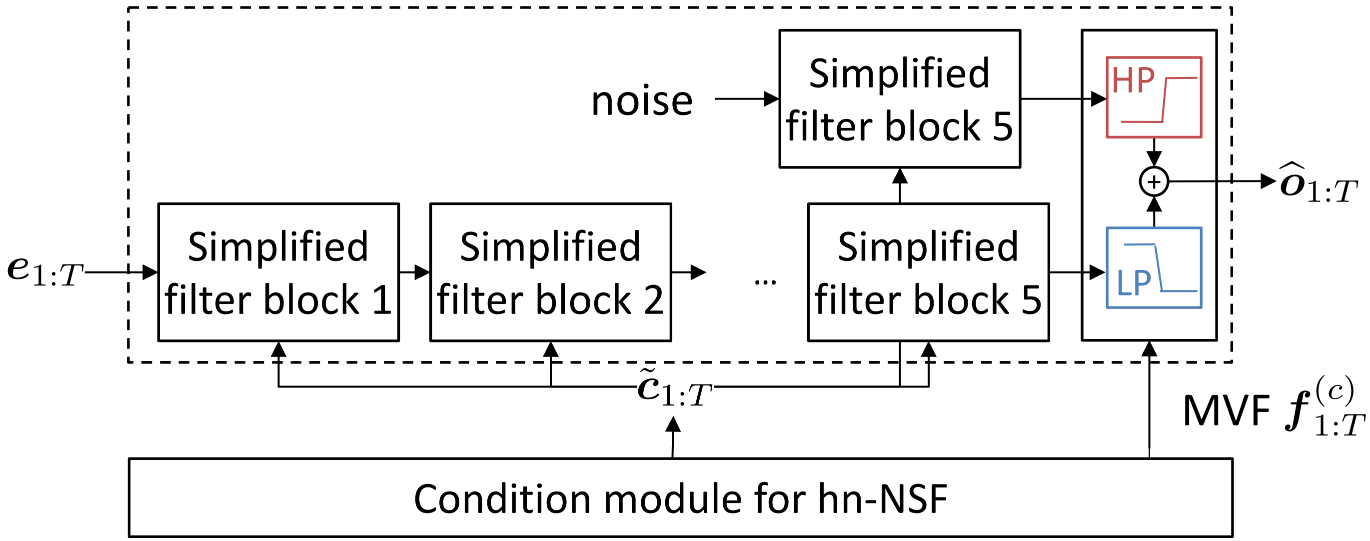

n-comp
h-comp
8k
6k
4k
2k
0k
100
200
300
400
500
600


hn-NSF
with trainable MVFs
noise
Simplified filter block 5
HP
LP
$\boldsymbol{e}_{1:T}$
Simplified filter block 1
Simplified filter block 2
...
Simplified filter block 5
$\widehat{\boldsymbol{o}}_{1:T}$
$\tilde{\boldsymbol{c}}_{1:T}$
MVF $\boldsymbol{f}^{(c)}_{1:T}$
Condition module for hn-NSF

NEURAL SOURCE-FILTER MODEL

Harmonic-plus-noise NSF

❑ Version 2 (☛ ssw paper)

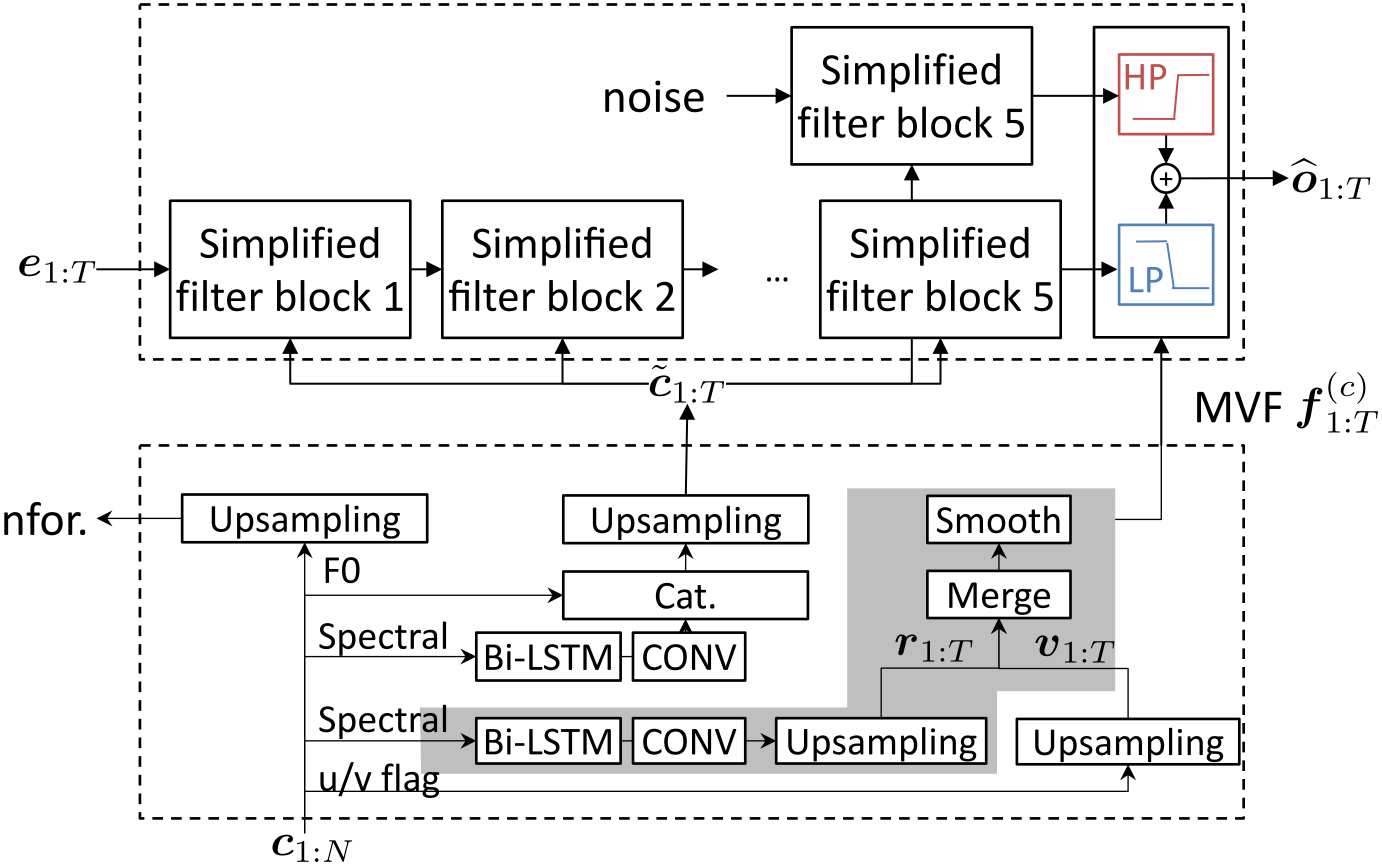


- How to predict MVF?

NEURAL SOURCE-FILTER MODEL

Harmonic-plus-noise NSF

- Version 2 (☛ ssw paper)



- Merge function: $\boldsymbol{f}^{(c)}_{1:T} = \mathcal{F}(a\boldsymbol{v}_{1:T} + b\boldsymbol{r}_{1:T} + c)$
- Use unvoiced / voiced $v_{1:T}$ (u/v flag) as prior knowledge

CONTENTS

EXPERIMENTS

Configuration

- Data and features

Corpus	Size	Note
ATR Ximera F009 [1]	15 hours	16kHz, Japanese, neutral style

	Feature	Dimension
Acoustic	Mel-spectra	80
	F0	1

- Models
  - WaveNet, hn-NSF with fixed (manually optimized) MVF
  - Three hn-NSFs with trainable MVF
    1. u/v + predicted feature $f_t^{(c)} = v_t + 0.2r_t$
    2. Predicted feature $f_t^{(c)} = 0.5r_t + 0.5$
    3. Fully trainable $f_t^{(c)} = \text{sigmoid}(av_t + br_t + c)$

$$v_t = \begin{cases} 0.7 & voiced \\ 0.3 & unvoiced \end{cases}$$

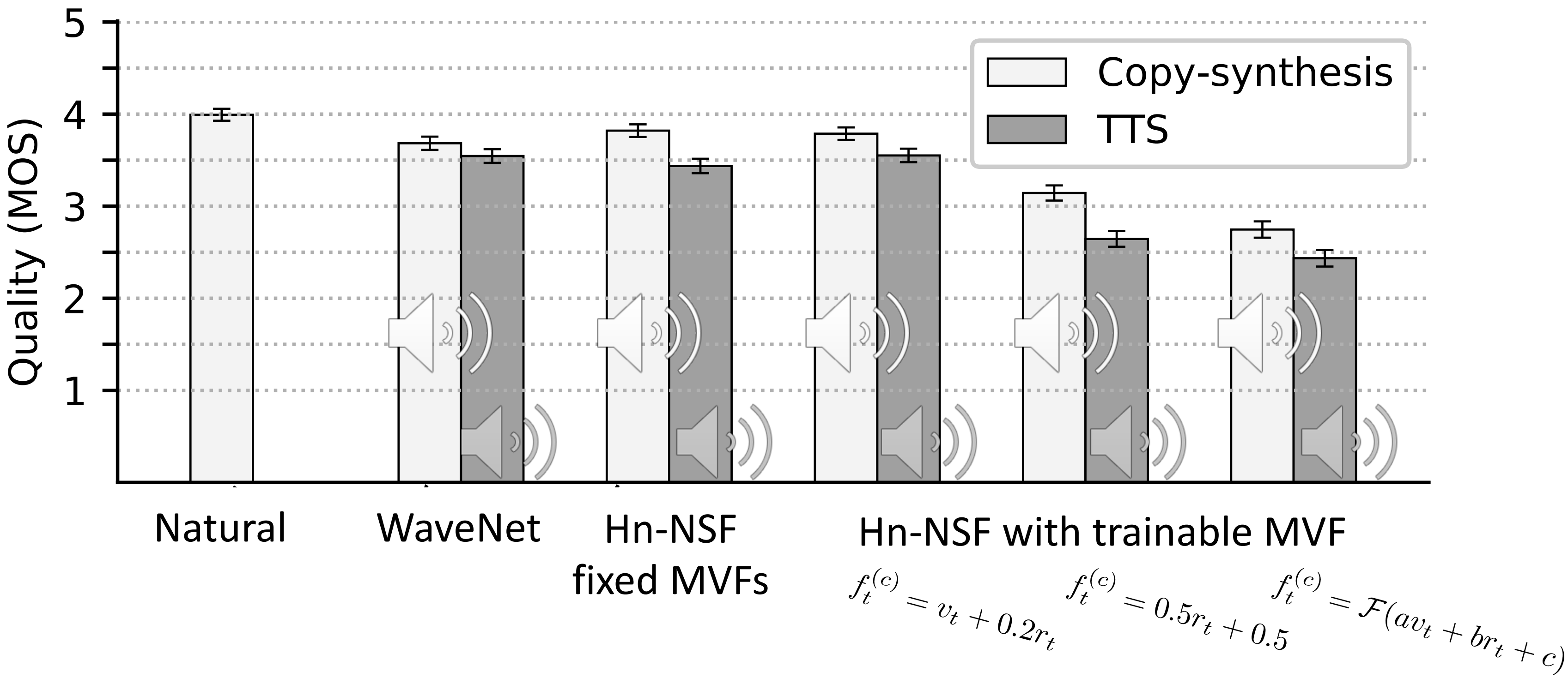
$$r_t \in (0, 1)$$

[1] Kawai, H., Toda, T., Ni, J., Tsuzaki, M., and Tokuda, K. (2004). Ximera: A new TTS from ATR based on corpus-based technologies. In Proc. SSW5, pages 179–184..

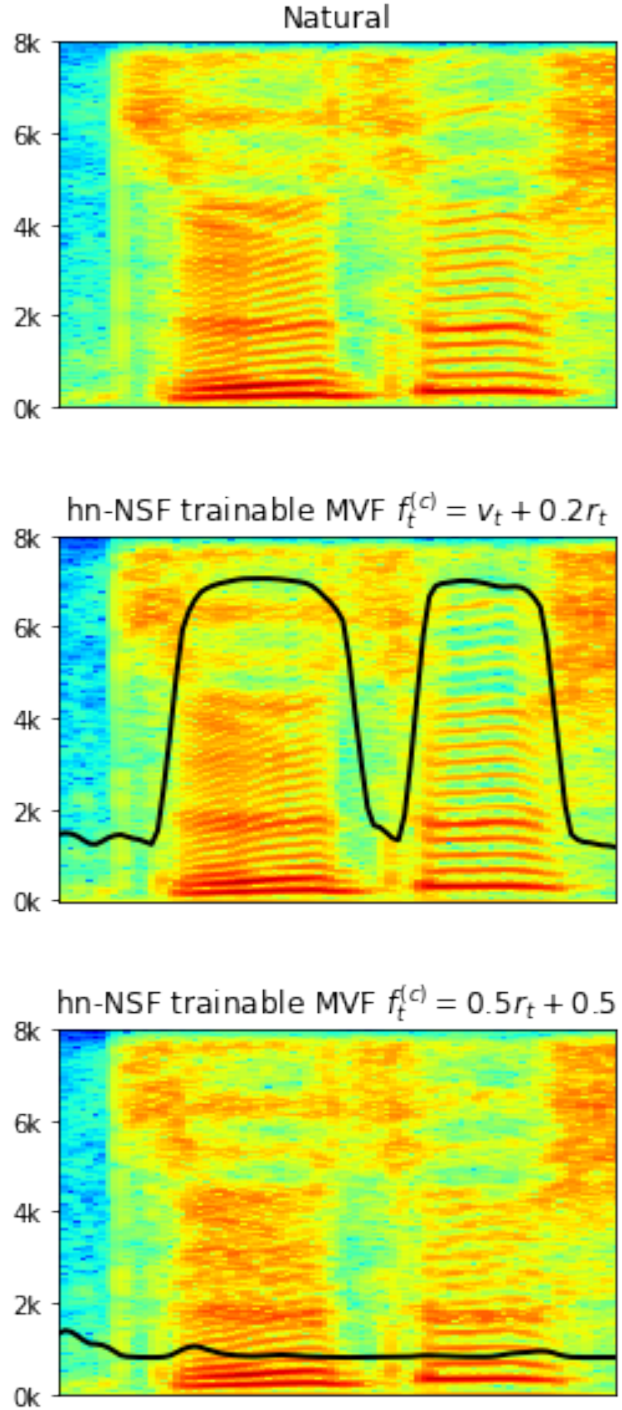
EXPERIMENTS

Results

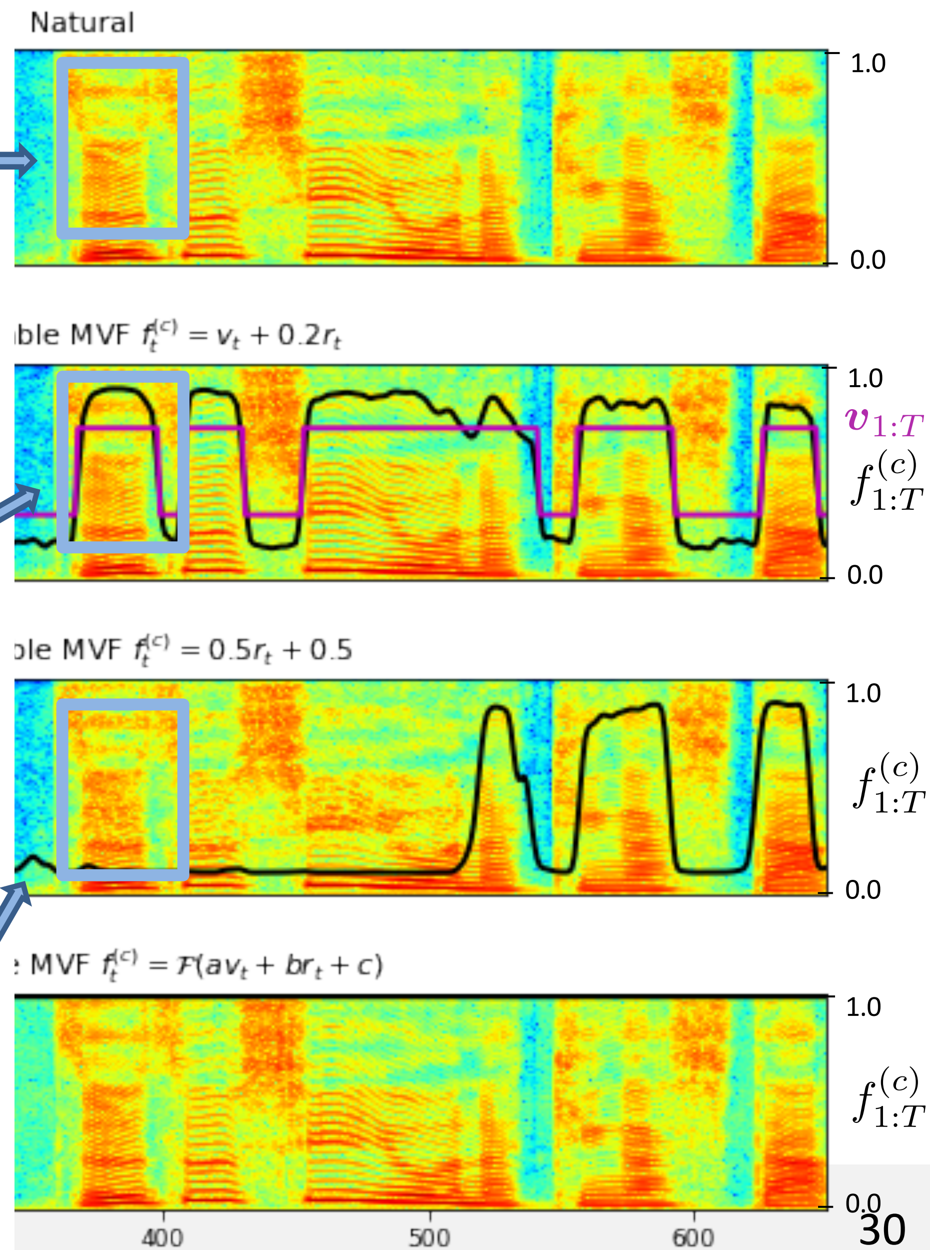
- Speech quality
  - ~150 paid evaluators, 1604 evaluation sets
    - **Copy-synthesis**: given natural Mel-spec/F0
    - **TTS**: given generated Mel-spec/F0 from acoustic models



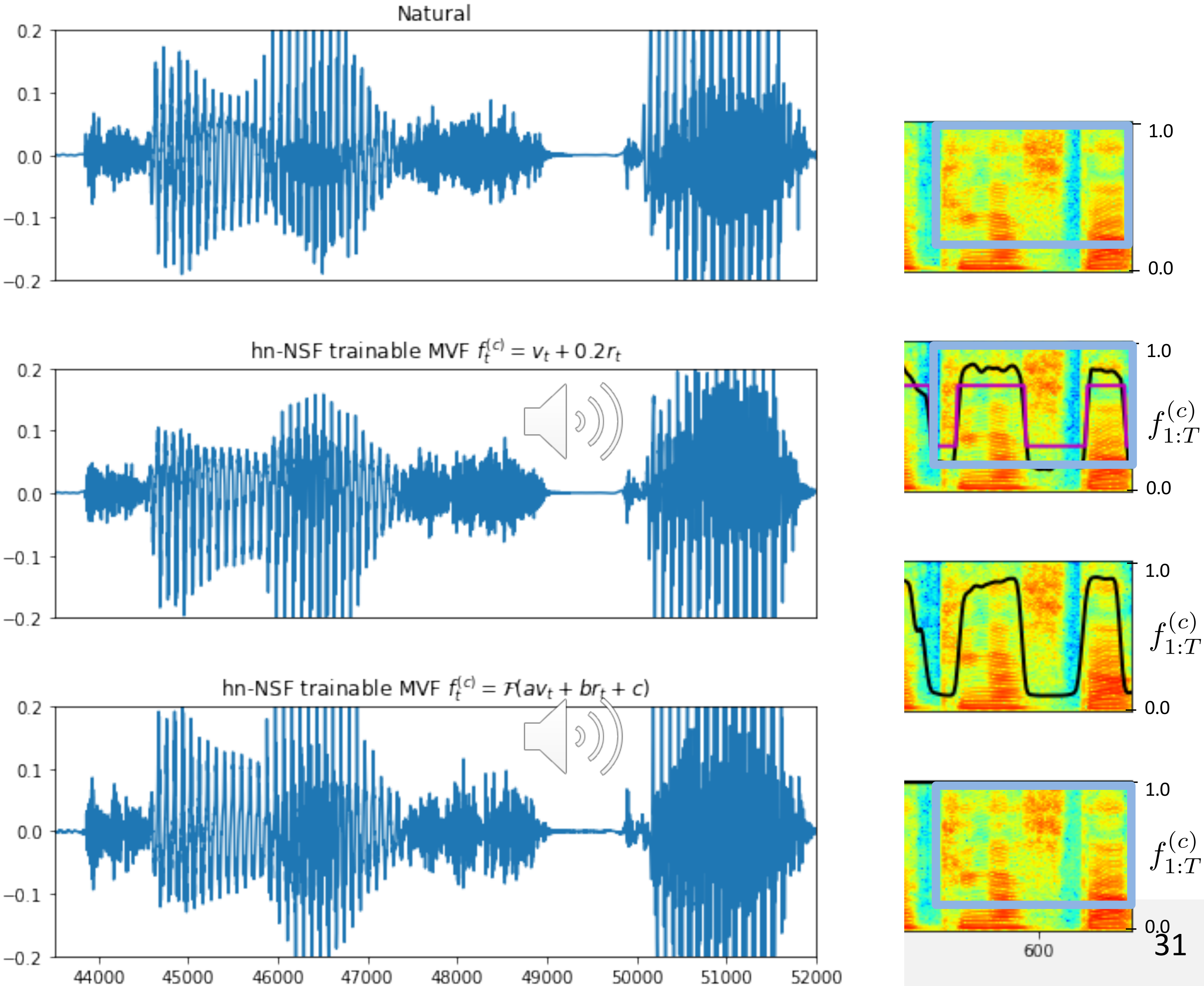
RIMENTS



Natural
8k
6k
4k
2k
0k
hn-NSF trainable MVF $f_t^{(c)} = v_t + 0.2r_t$
hn-NSF trainable MVF $f_t^{(c)} = 0.5r_t + 0.5$



Natural
1.0
0.0
ble MVF $f_t^{(c)} = v_t + 0.2r_t$
$v_{1:T}$
$f_{1:T}^{(c)}$
ble MVF $f_t^{(c)} = 0.5r_t + 0.5$
MVF $f_t^{(c)} = \mathcal{F}(av_t + br_t + c)$
400
500
600



Natural
hn-NSF trainable MVF $f_t^{(c)} = v_t + 0.2r_t$
hn-NSF trainable MVF $f_t^{(c)} = \mathcal{F}(av_t + br_t + c)$
0.2
0.1
0.0
−0.1
−0.2
44000
45000
46000
47000
48000
49000
50000
51000
52000
1.0
0.0
$f_{1:T}^{(c)}$
600

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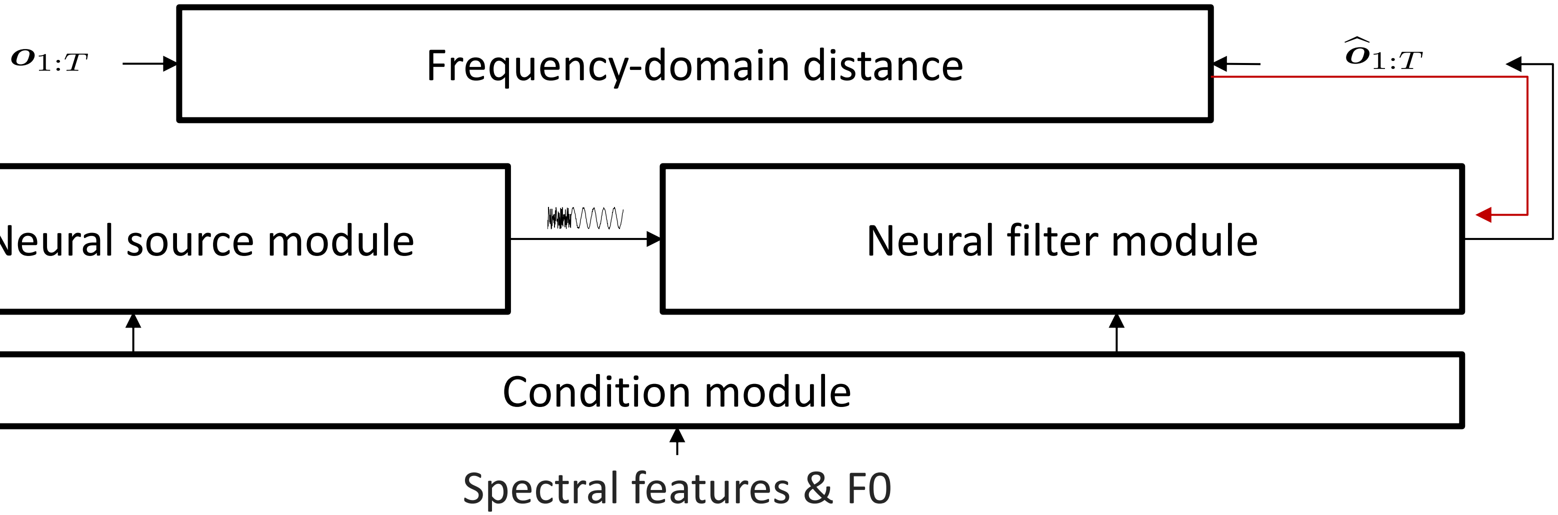
SUMMARY

NSF framework



- No AR nor inverse AR flow
- Easy training & fast generation (☛ appendix)
- hn-NSF is recommended

Questions & Comments are always Welcome!

https://nii-yamagishilab.github.io/samples-nsf/index.html

Home page: neural source-filter waveform models

Authors: Xin Wang, Shinji Takaki, Junichi Yamagishi

This is the home page for our recent work on neural source-filter (NSF) models.
If you have any comment and question, please send email to wangxin ~a~t~ nii ~dot~ ac ~dot~ jp.

Harmonic-plus-noise NSF model with trainable Maximum Voice Frequency

This new model is developed on the basis of Harmonic-plus-noise NSF model. The differences include:

1. the new model uses sinc-based high/low pass FIR filters
2. the cut-off frequency is predicted from input acoustic features, rather than pre-defined

- Date: Sep 2019
- Publication: to be presented in Speech Synthesis Workshop 10, 2019
- Webpage: nsf-v3.html hosts the manuscript paper, samples, and codes.

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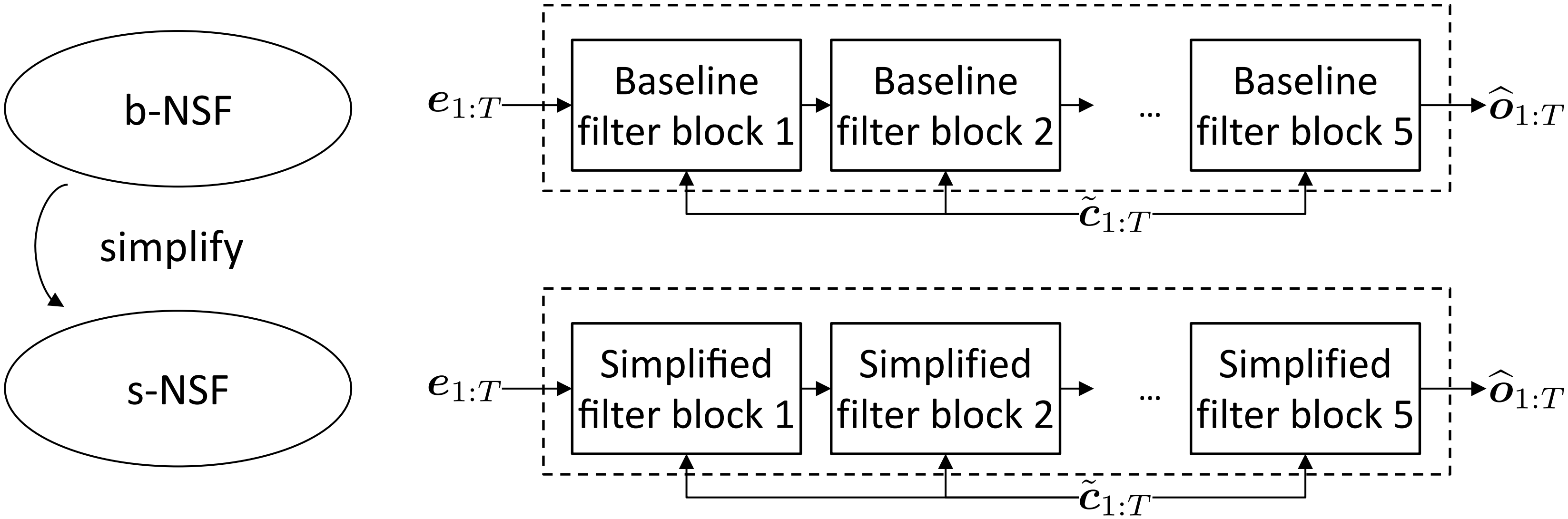
NEURAL SOURCE-FILTER MODEL

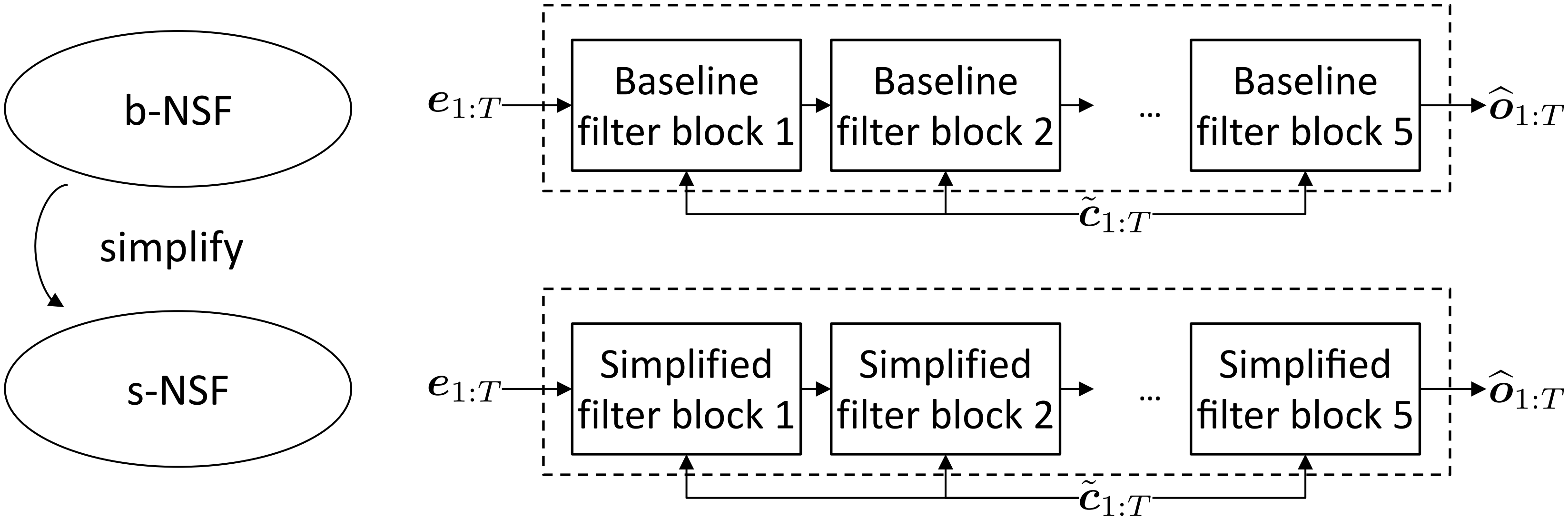
Baseline and simplified NSF

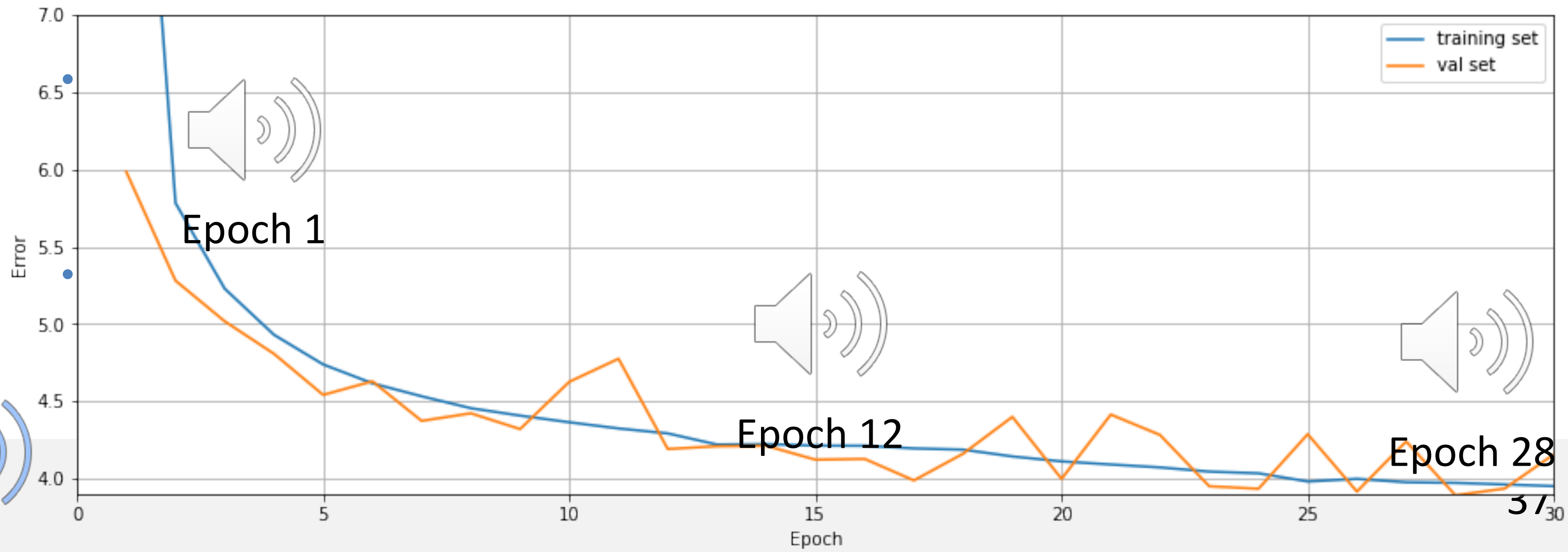


- Both models:
  1. Strong harmonics in high-frequency bands
  2. Awful unvoiced (fricative) sounds

NEURAL SOURCE-FILTER MODEL

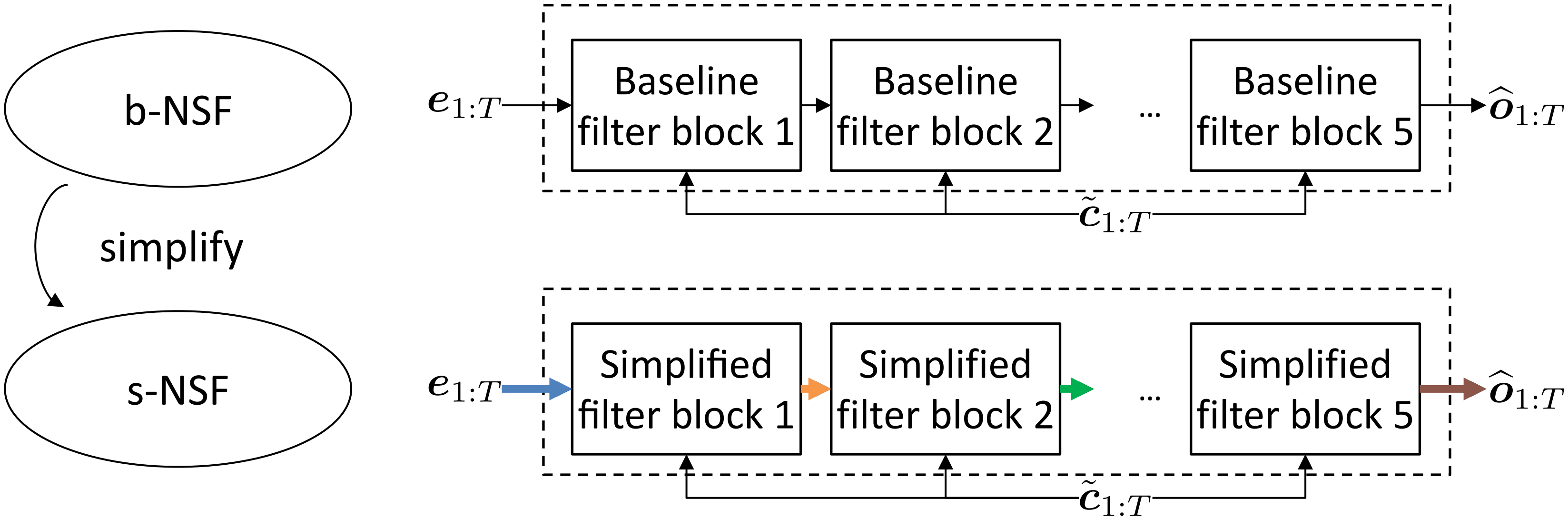
Baseline and simplified NSF

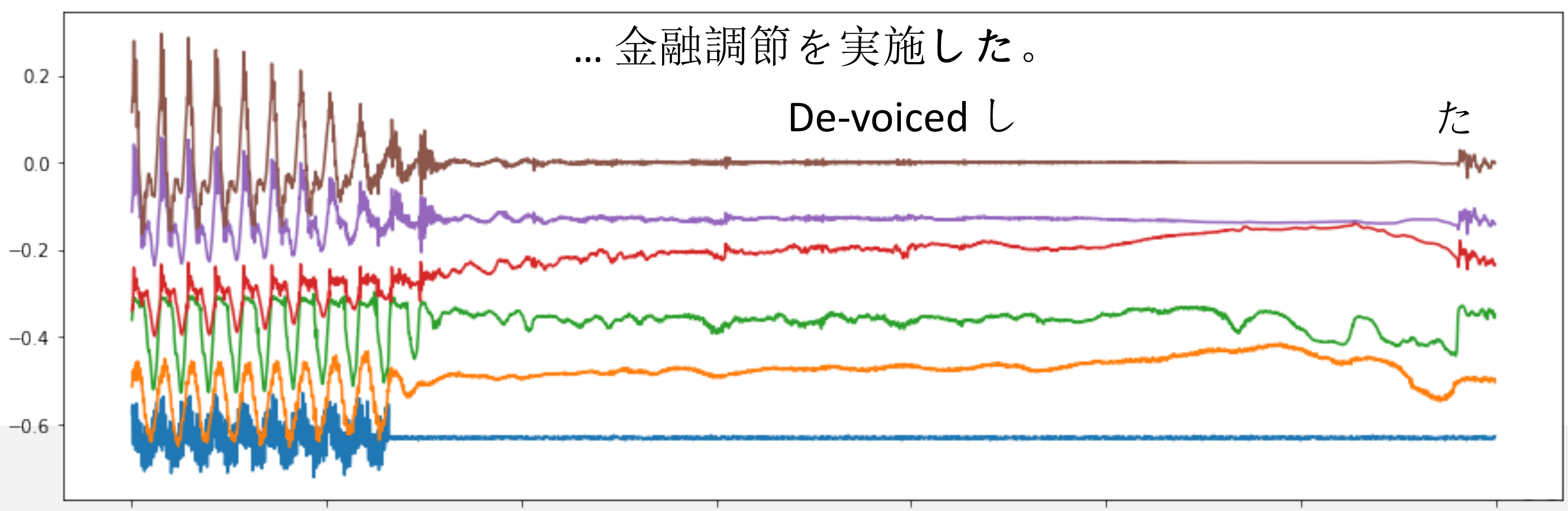




NEURAL SOURCE-FILTER MODEL

Baseline and simplified NSF

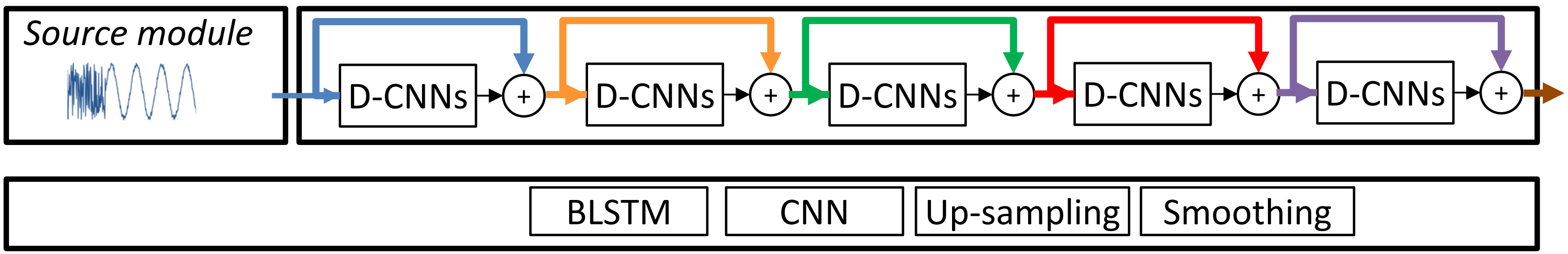


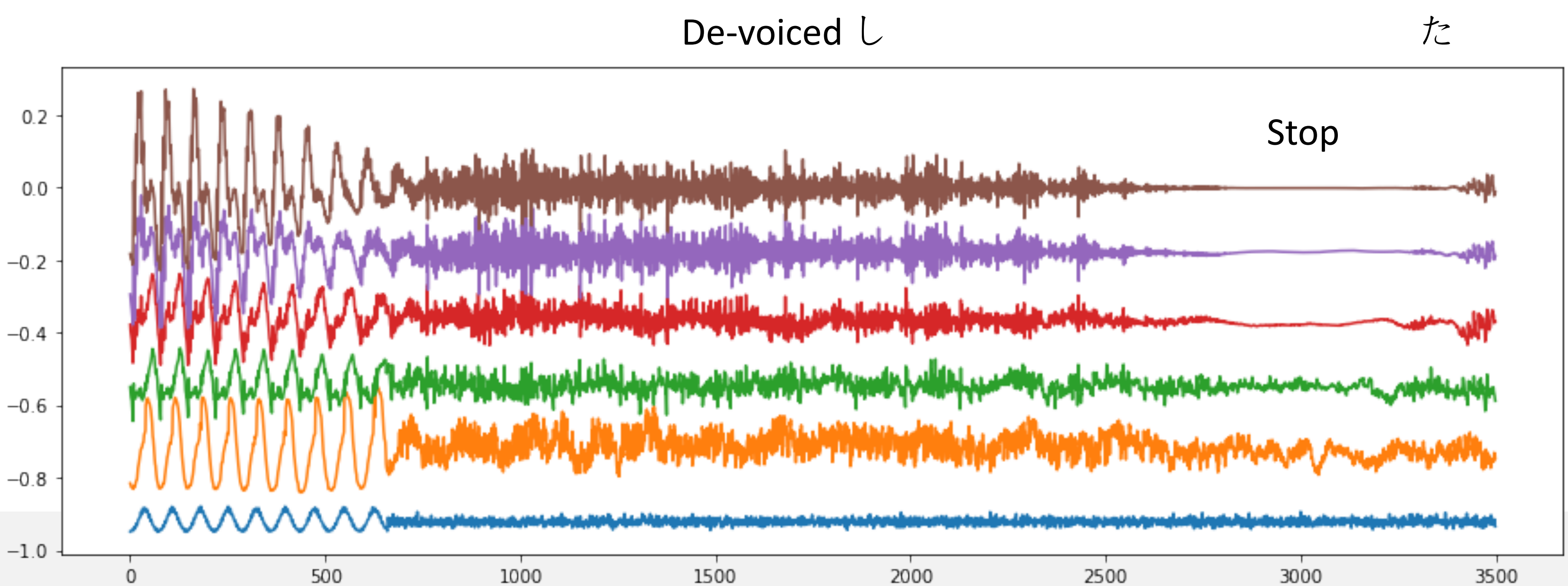


WAVEFORM MODELING

Simplified NSF

- F009 15 hour's data

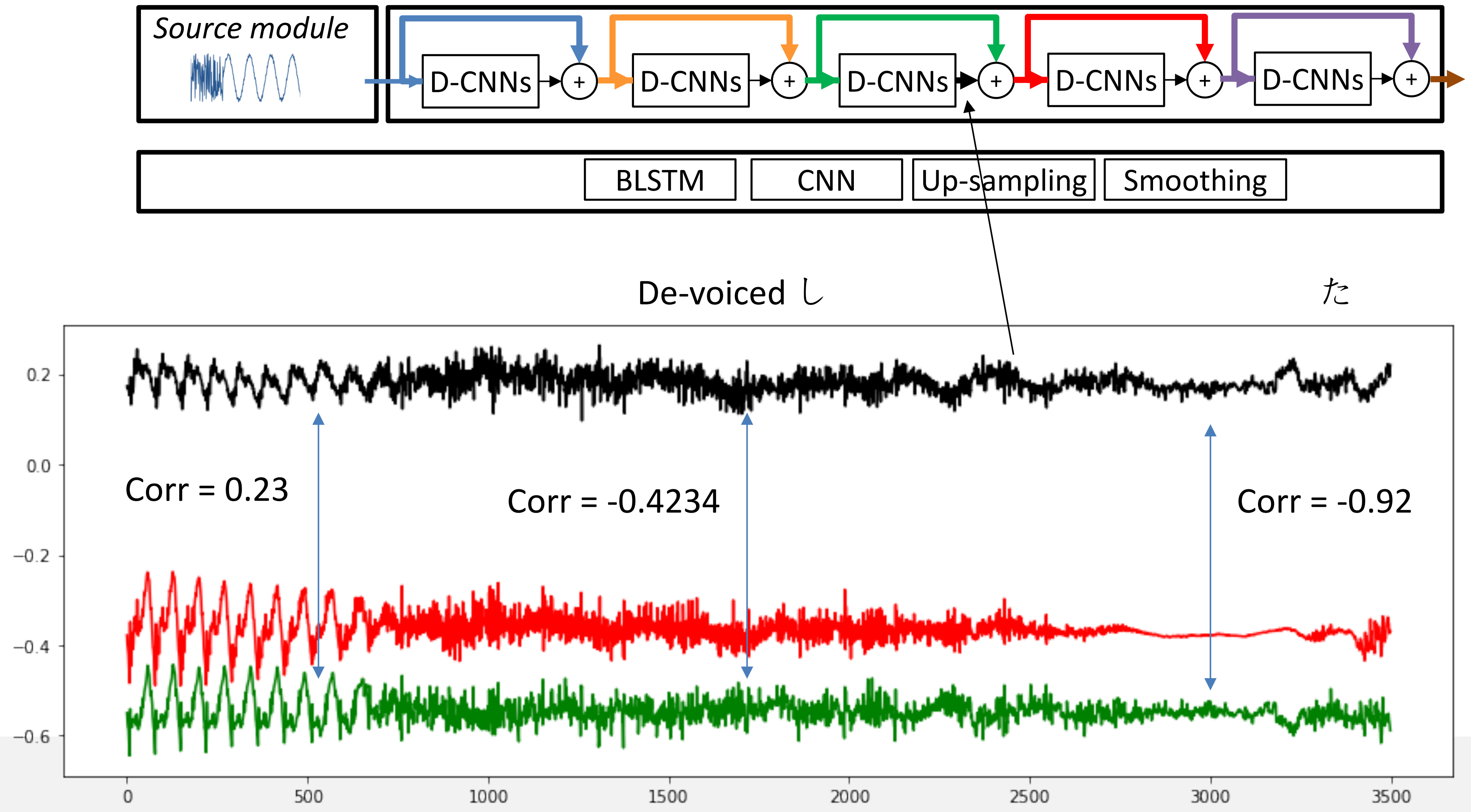




WAVEFORM MODELING

Simplified NSF

- F009 15 hour's data

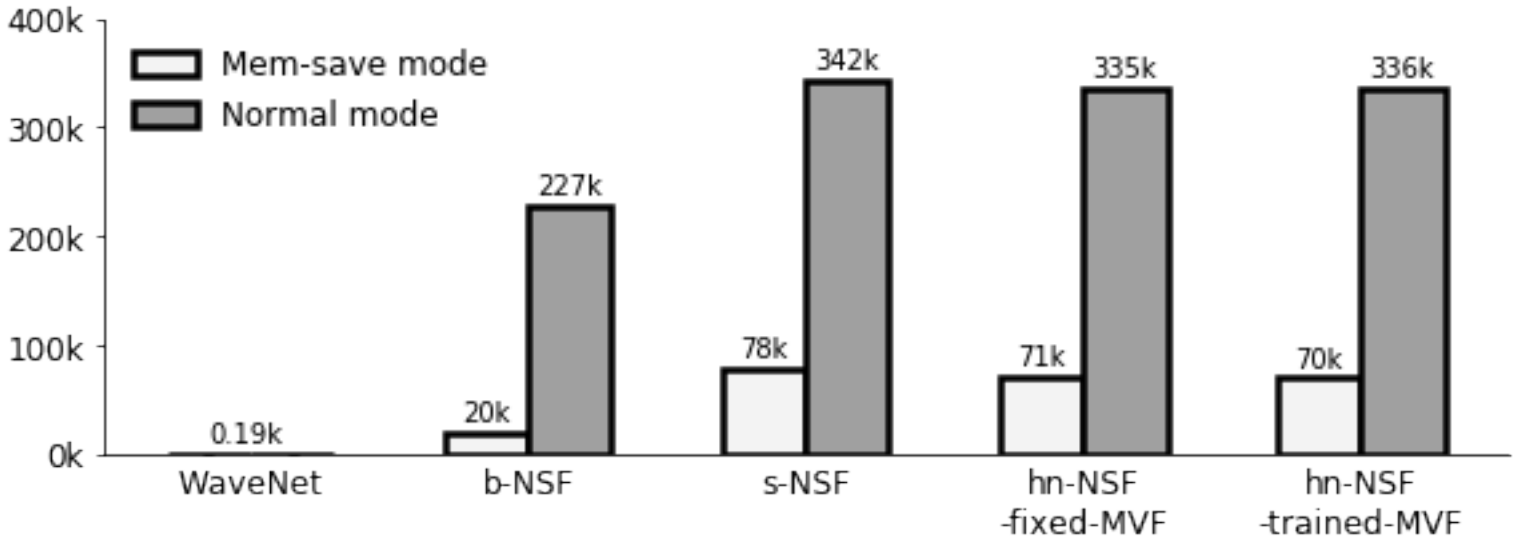


EXPERIMENTS

Analysis

- Generation speed

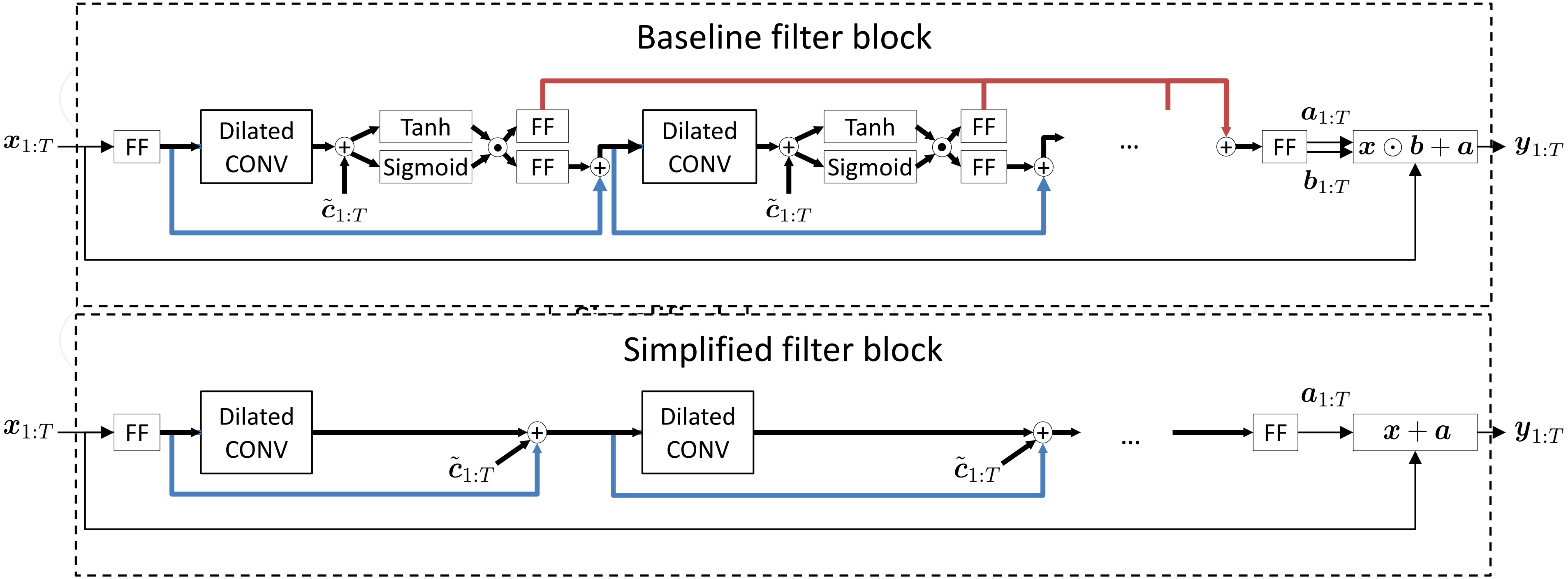
How many waveform points can be generated in 1s (Tesla p100)?



- Mem-save mode: release and allocate GPU memory layer by layer (limited by our CUDA implemetation)
- Normal mode: allocate GPU memory once

NEURAL SOURCE-FILTER MODEL

Filter modules in NSF models

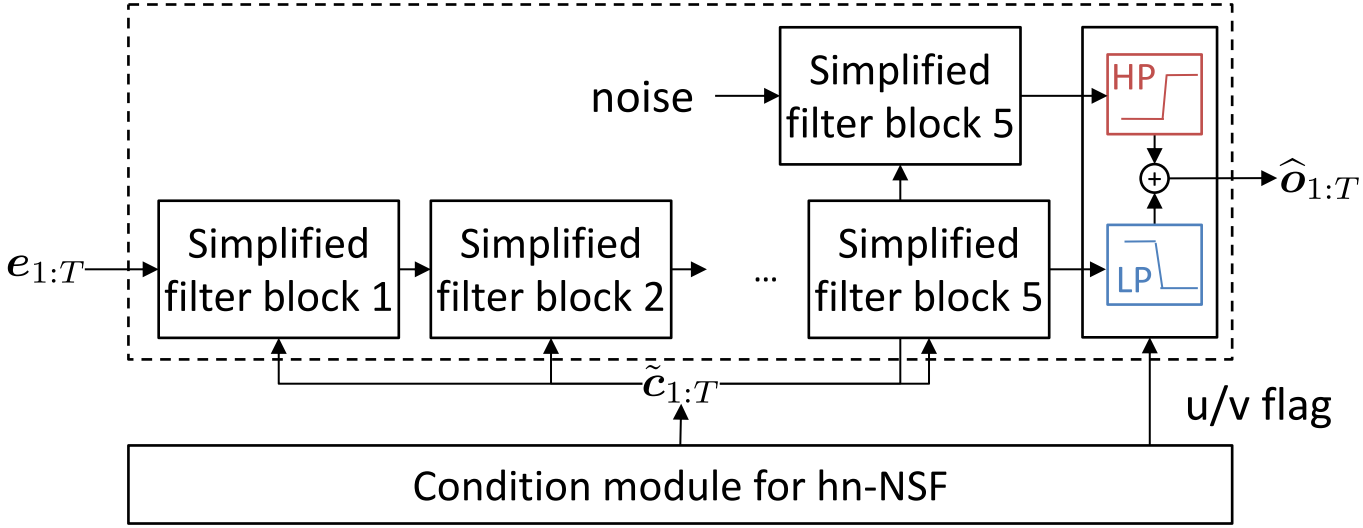


- $x_t, y_t, \widehat{o}_t, a_t \in \mathbb{R},\ b_t \in \mathbb{R}^+,\ \tilde{\boldsymbol{c}}_t \in \mathbb{R}^{64},\ \forall t \in \{1, \cdots, T\}$
- Element-wise multiplication $\odot$

NEURAL SOURCE-FILTER MODEL

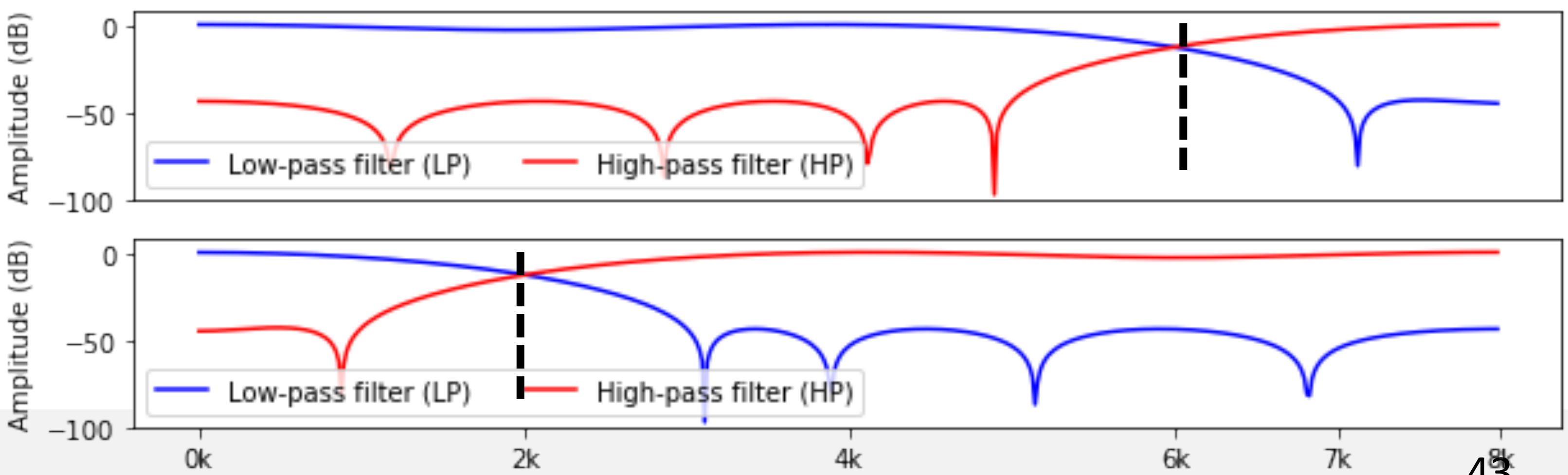
Harmonic-plus-noise NSF

- Version I: choose MVF based on u/v



Voiced sounds

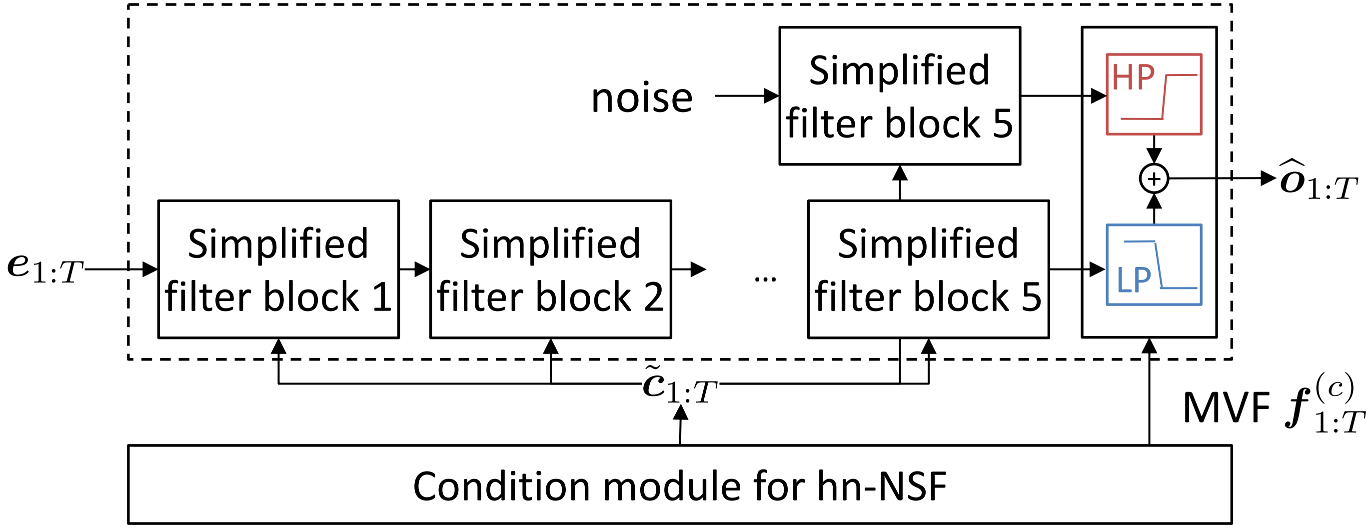
Unvoiced sounds



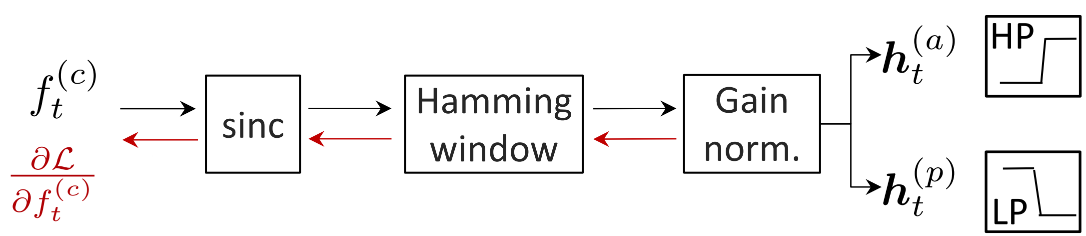
NEURAL SOURCE-FILTER MODEL

Harmonic-plus-noise NSF

- Version II: predict MVF from input features



- Forward and backward propagation (SSW paper section 3)



NEURAL SOURCE-FILTER MODEL

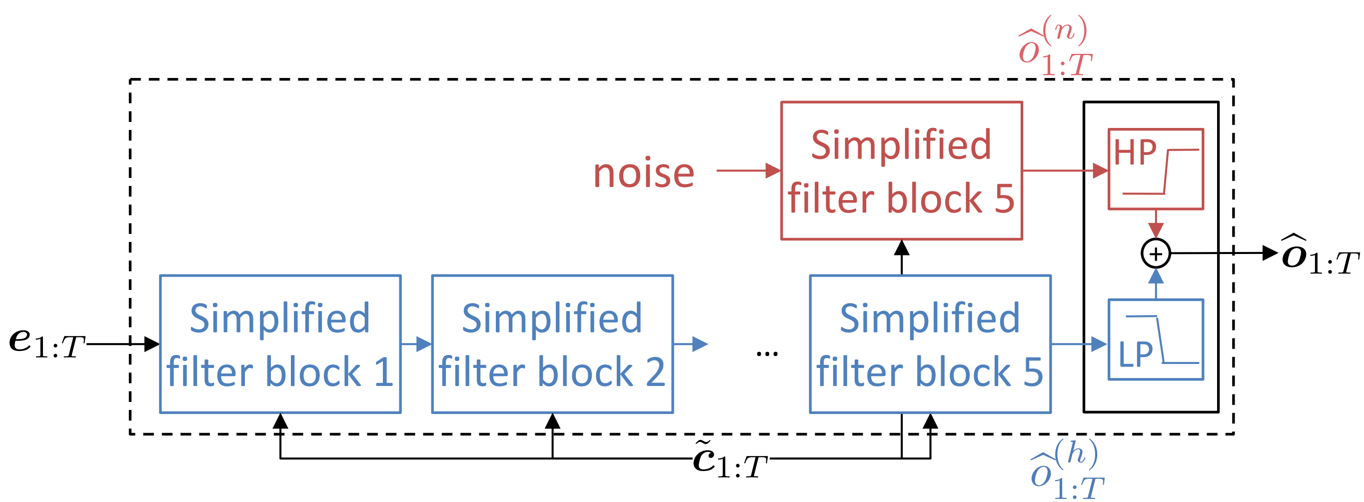
Harmonic-plus-noise NSF

- Time domain filtering

$$\widehat{o}_t = \overbrace{a_{t,0}\widehat{o}_t^{(n)} + a_{t,1}\widehat{o}_{t-1}^{(n)} + \cdots + a_{t,M}\widehat{o}_{t-M}^{(n)}}^{\text{Noise component}} + \overbrace{b_{t,0}\widehat{o}_t^{(h)} + b_{t,1}\widehat{o}_{t-1}^{(h)} + \cdots + b_{t,N}\widehat{o}_{t-N}^{(h)}}^{\text{Harmonic component}}$$

High-pass filter coefficients

Low-pass filter coefficients

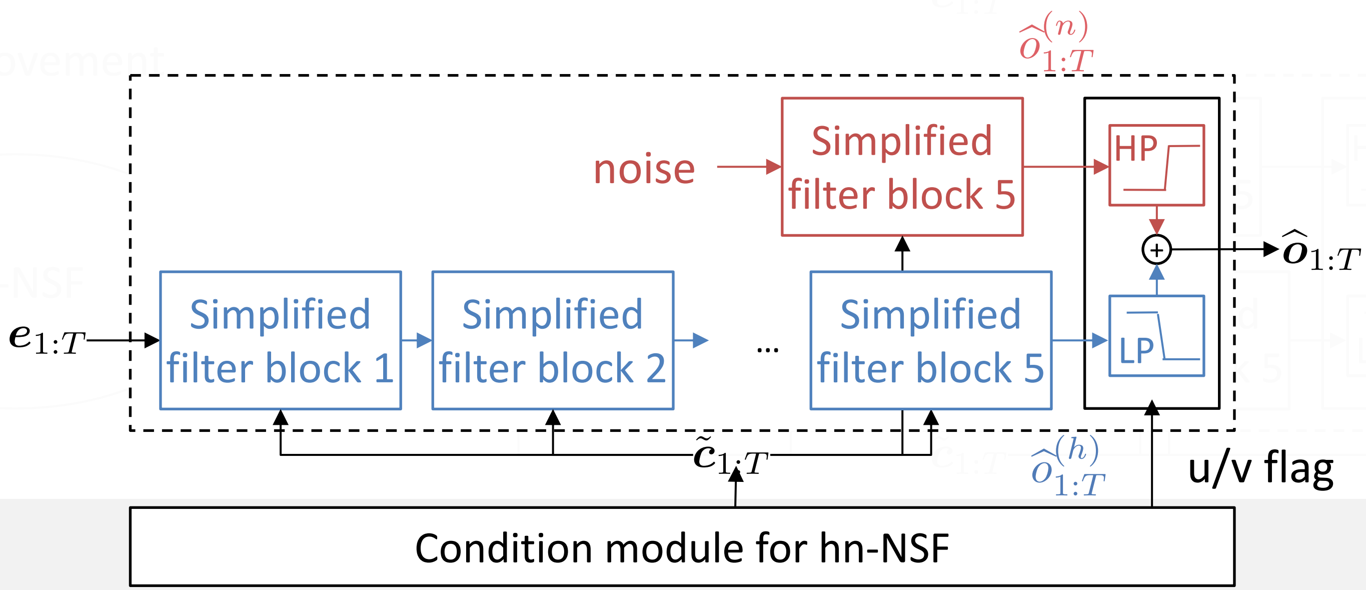


Neural source-filter model

Harmonic-plus-noise NSF

- Version I: pre-defined filters coefficients
  - Select one pair of HP-LP filters based on u/v flag

$$\widehat{o}_t = \begin{cases} \underbrace{a_0\widehat{o}_t^{(n)} + a_1\widehat{o}_{t-1}^{(n)} + \cdots + a_M\widehat{o}_{t-M}^{(n)}}_{\text{Noise component}} + \underbrace{b_0\widehat{o}_t^{(h)} + b_1\widehat{o}_{t-1}^{(h)} + \cdots + b_N\widehat{o}_{t-N}^{(h)}}_{\text{Harmonic component}}, & t \text{ is voiced} \\ c_0\widehat{o}_t^{(n)} + c_1\widehat{o}_{t-1}^{(n)} + \cdots + c_M\widehat{o}_{t-M}^{(n)} + d_0\widehat{o}_t^{(h)} + d_1\widehat{o}_{t-1}^{(h)} + \cdots + d_N\widehat{o}_{t-N}^{(h)}, & t \text{ is unvoiced} \end{cases}$$



NEURAL SOURCE-FILTER MODEL

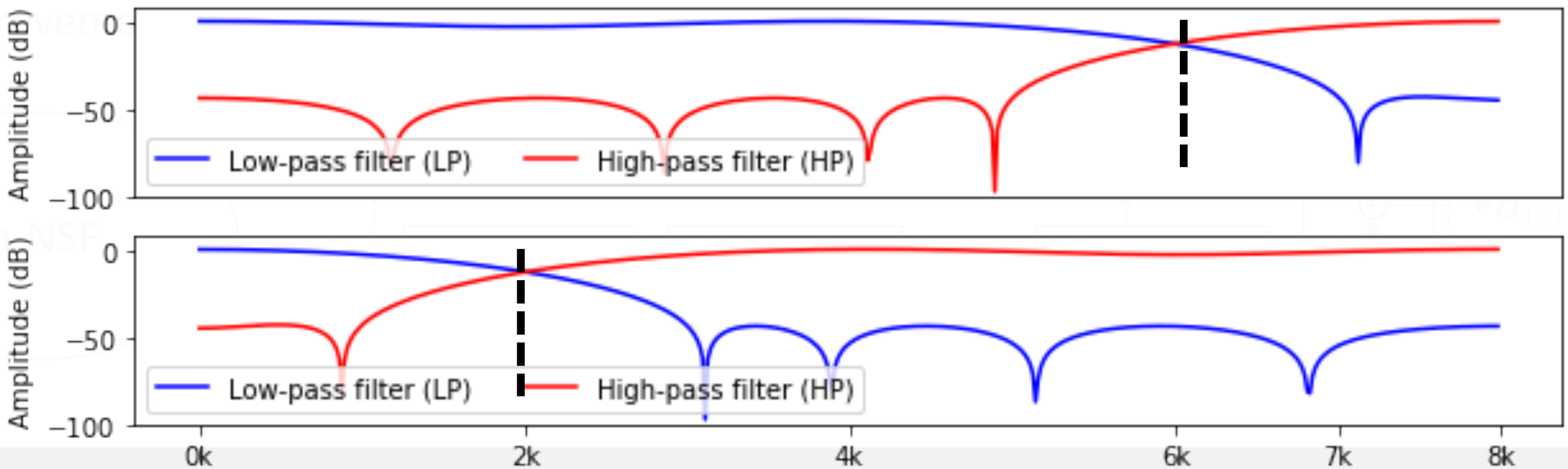
Harmonic-plus-noise NSF

- Version I: pre-defined filters coefficients
  - Select one pair of HP-LP filters based on u/v flag

$$\widehat{o}_t = \begin{cases} \underbrace{a_0\widehat{o}_t^{(n)} + a_1\widehat{o}_{t-1}^{(n)} + \cdots + a_M\widehat{o}_{t-M}^{(n)}}_{\text{Noise component}} + \underbrace{b_0\widehat{o}_t^{(h)} + b_1\widehat{o}_{t-1}^{(h)} + \cdots + b_N\widehat{o}_{t-N}^{(h)}}_{\text{Harmonic component}}, & t \text{ is voiced} \\ c_0\widehat{o}_t^{(n)} + c_1\widehat{o}_{t-1}^{(n)} + \cdots + c_M\widehat{o}_{t-M}^{(n)} + d_0\widehat{o}_t^{(h)} + d_1\widehat{o}_{t-1}^{(h)} + \cdots + d_N\widehat{o}_{t-N}^{(h)}, & t \text{ is unvoiced} \end{cases}$$

Voiced sounds

Unvoiced sounds

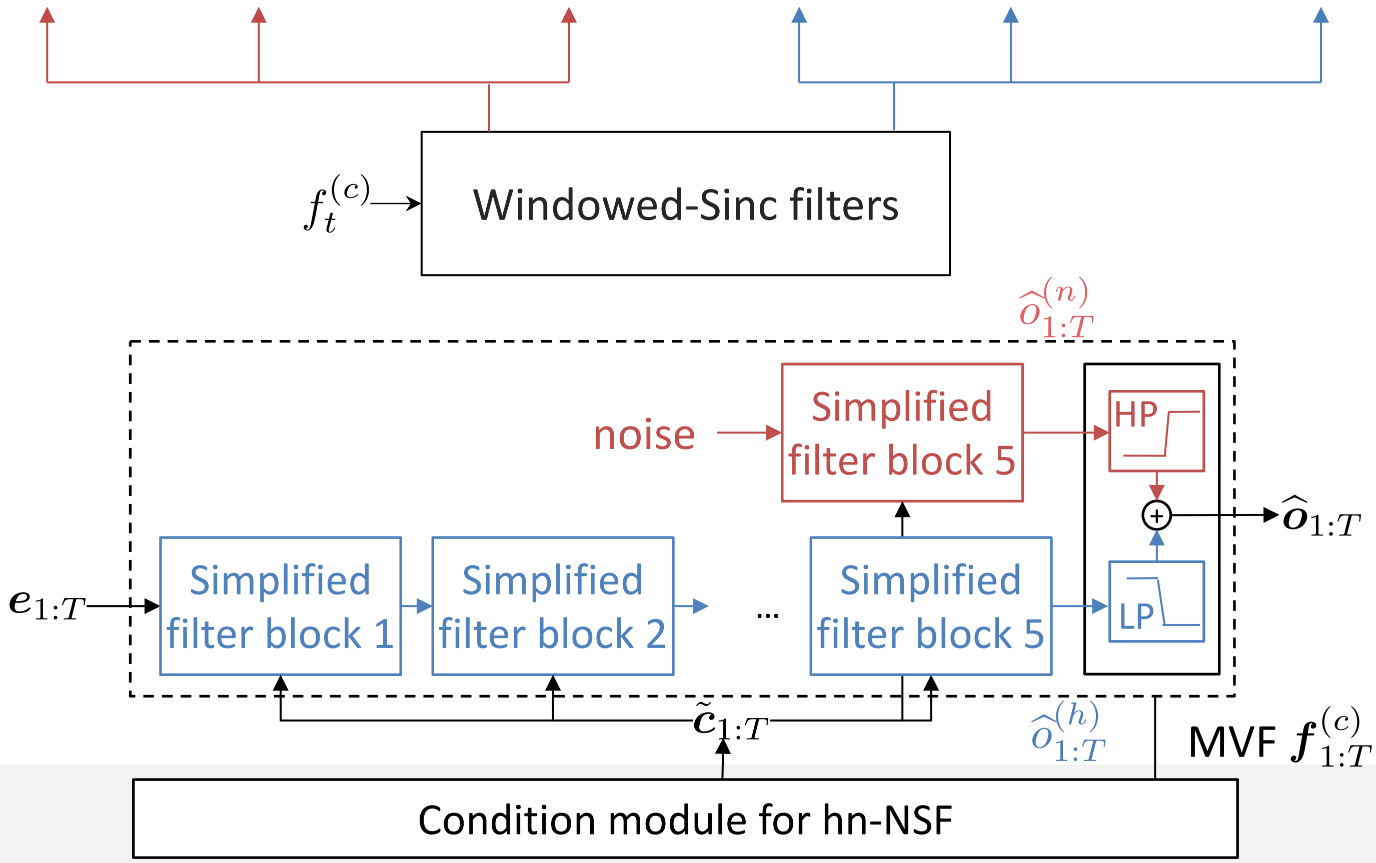


Neural source-filter model

Harmonic-plus-noise NSF

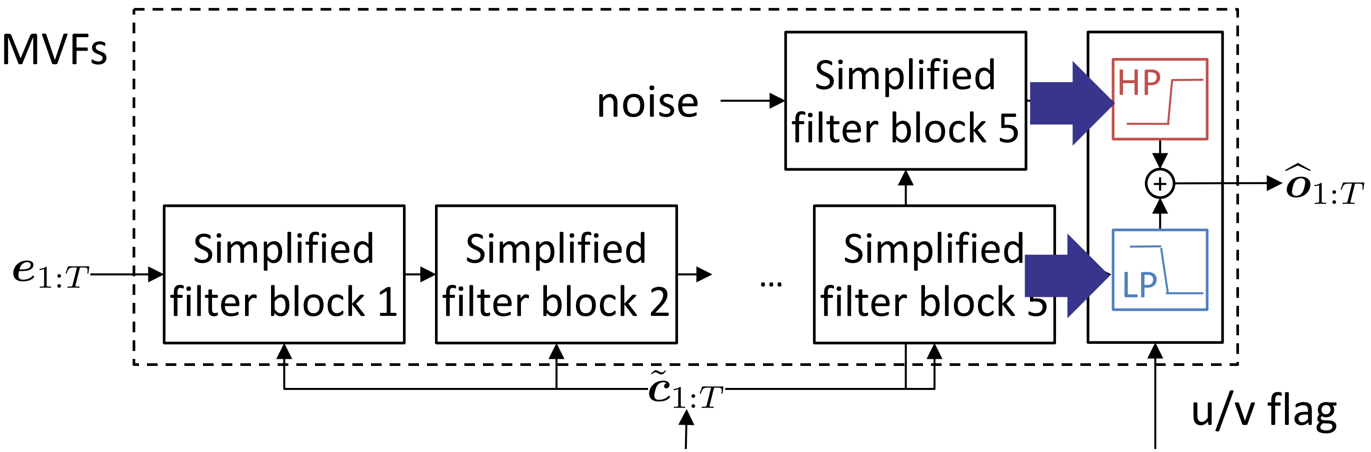
- Version II: predicted filter coefficients

$$\widehat{o}_t = \underbrace{a_{t,0}\widehat{o}_t^{(n)} + a_{t,1}\widehat{o}_{t-1}^{(n)} + \cdots + a_{t,M}\widehat{o}_{t-M}^{(n)}}_{\text{Noise component}} + \underbrace{b_{t,0}\widehat{o}_t^{(h)} + b_{t,1}\widehat{o}_{t-1}^{(h)} + \cdots + b_{t,N}\widehat{o}_{t-N}^{(h)}}_{\text{Harmonic component}}$$

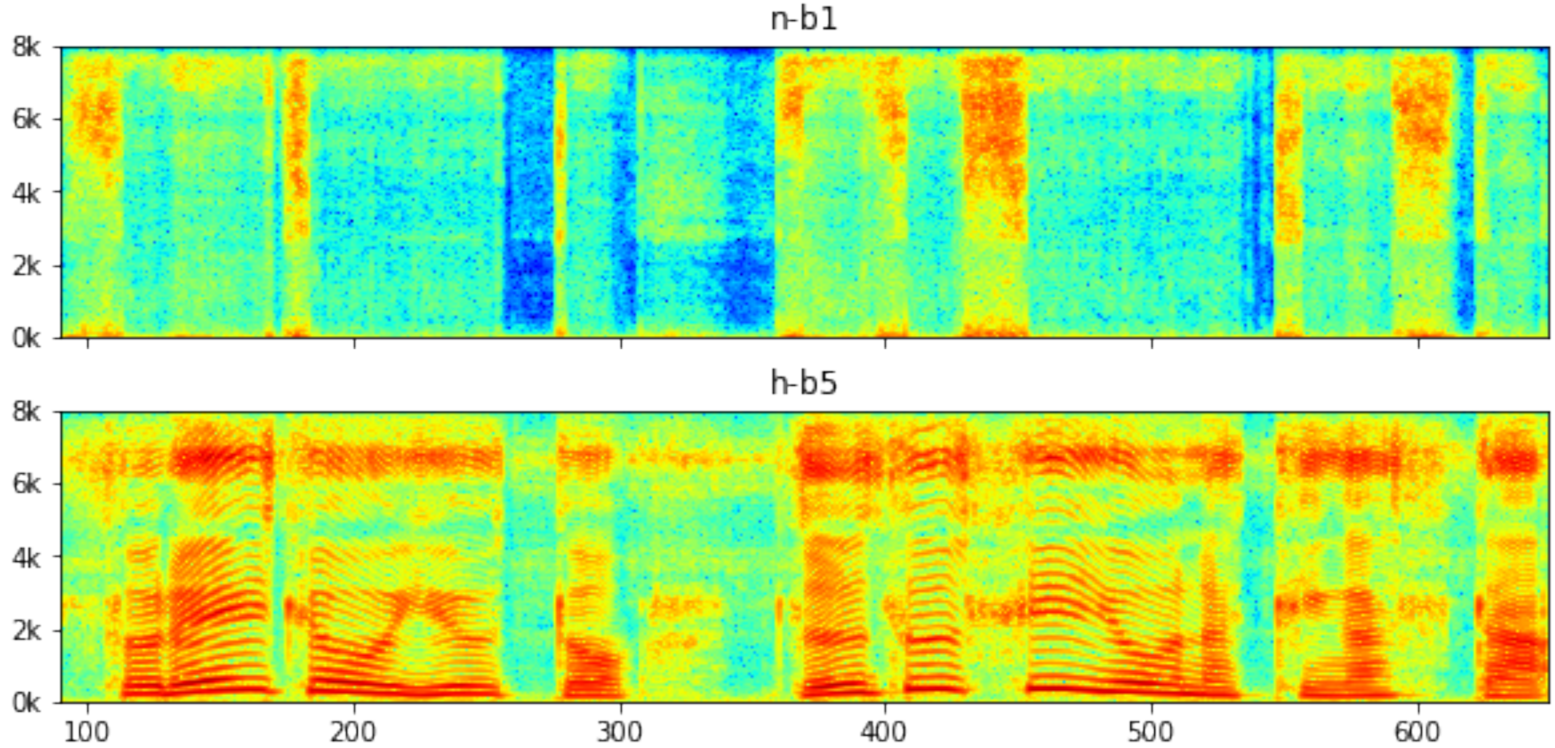


NEURAL SOURCE-FILTER MODEL

Pre-defined MVFs

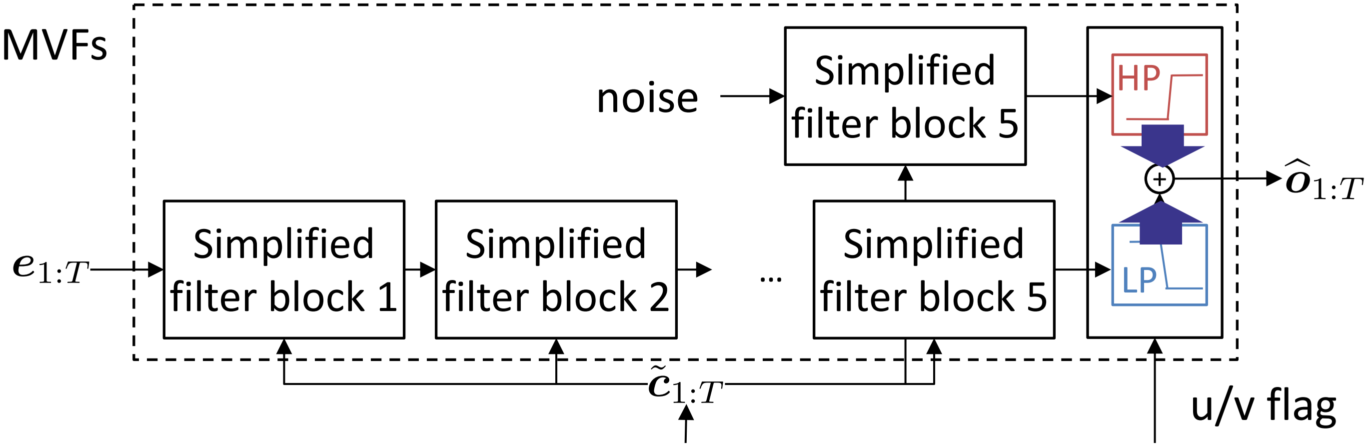


Predi

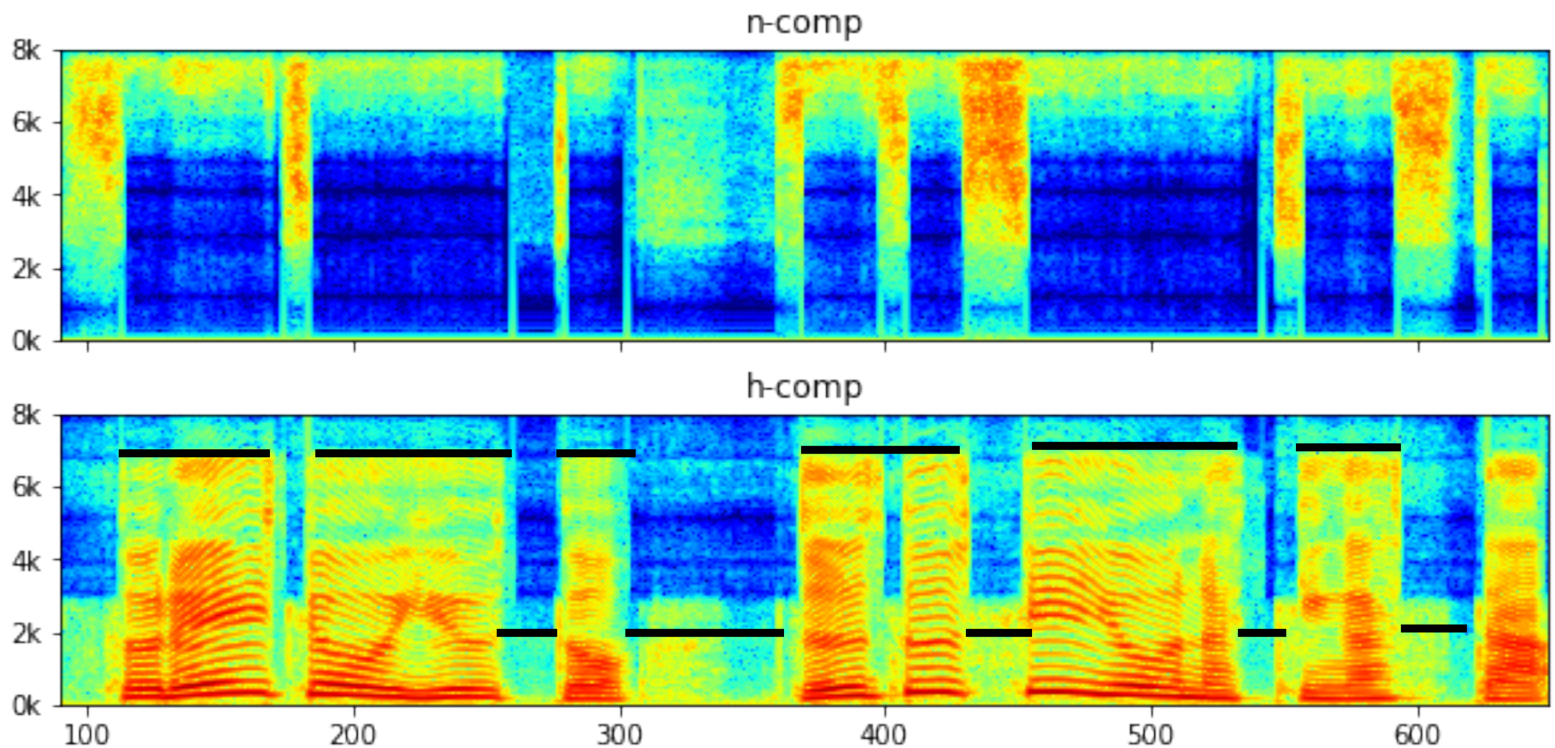


NEURAL SOURCE-FILTER MODEL

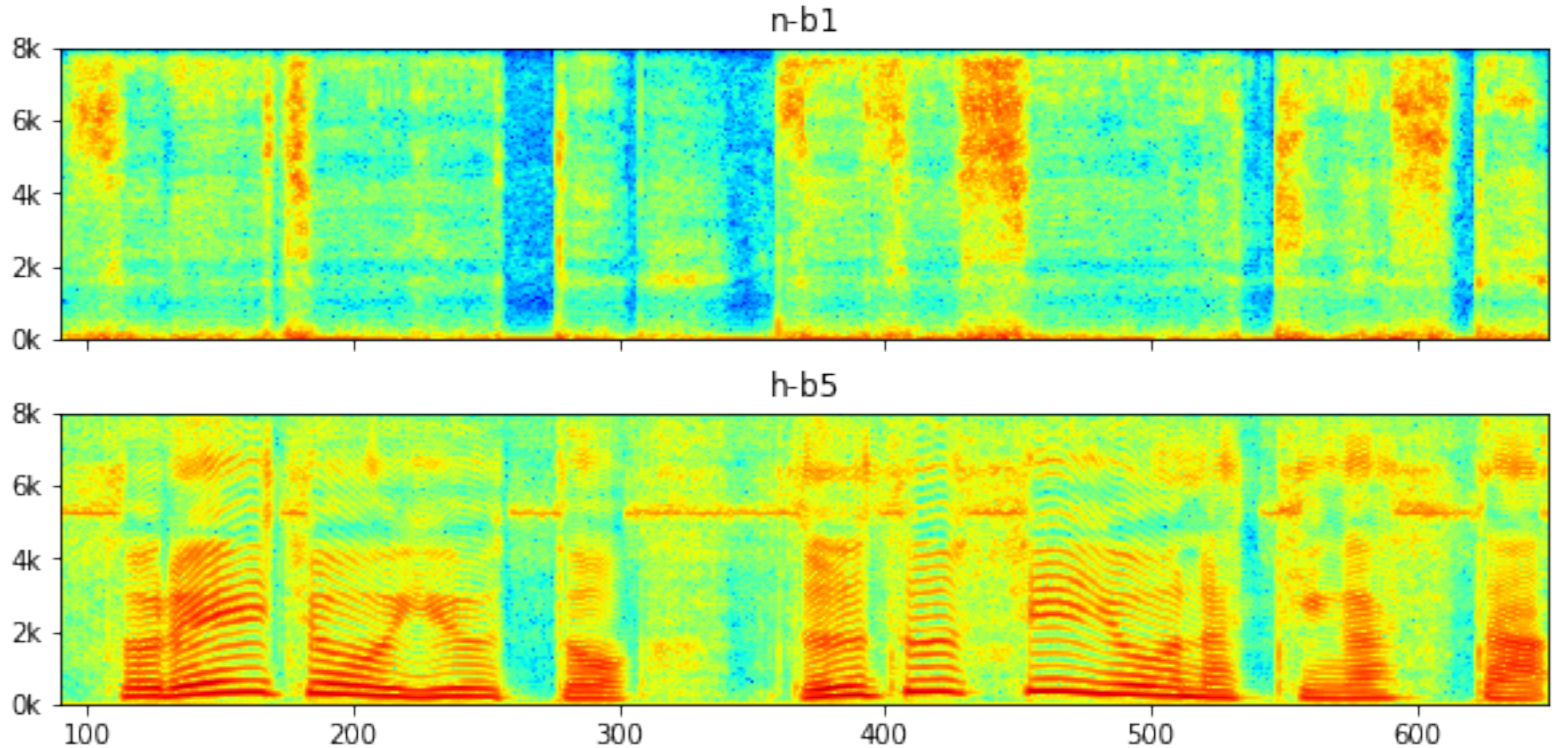
Pre-defined MVFs



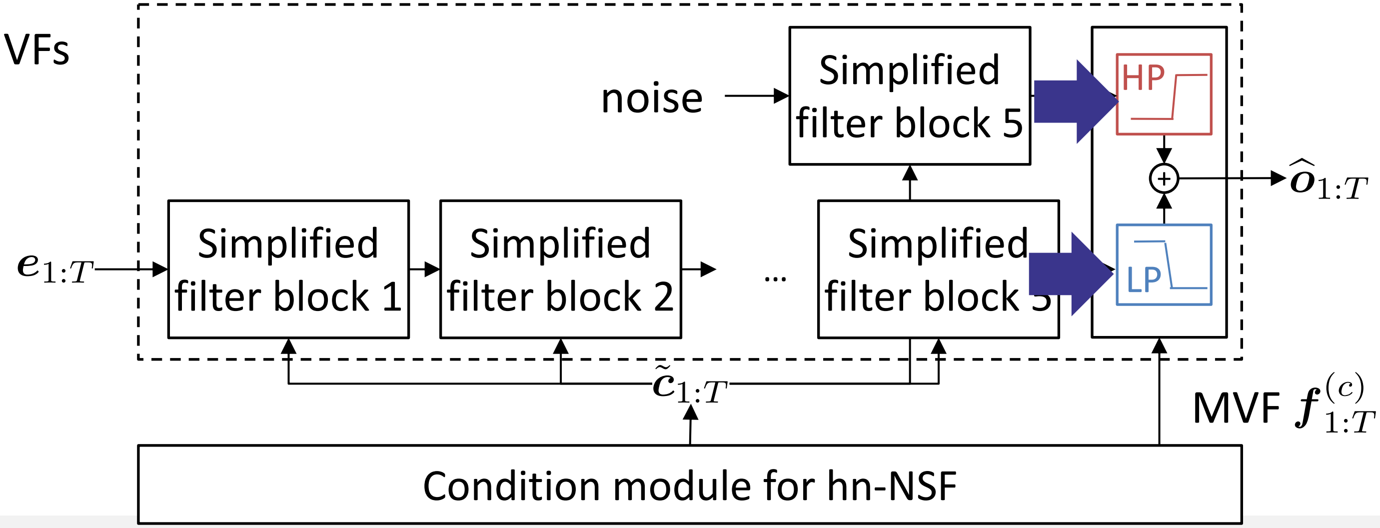
Predi



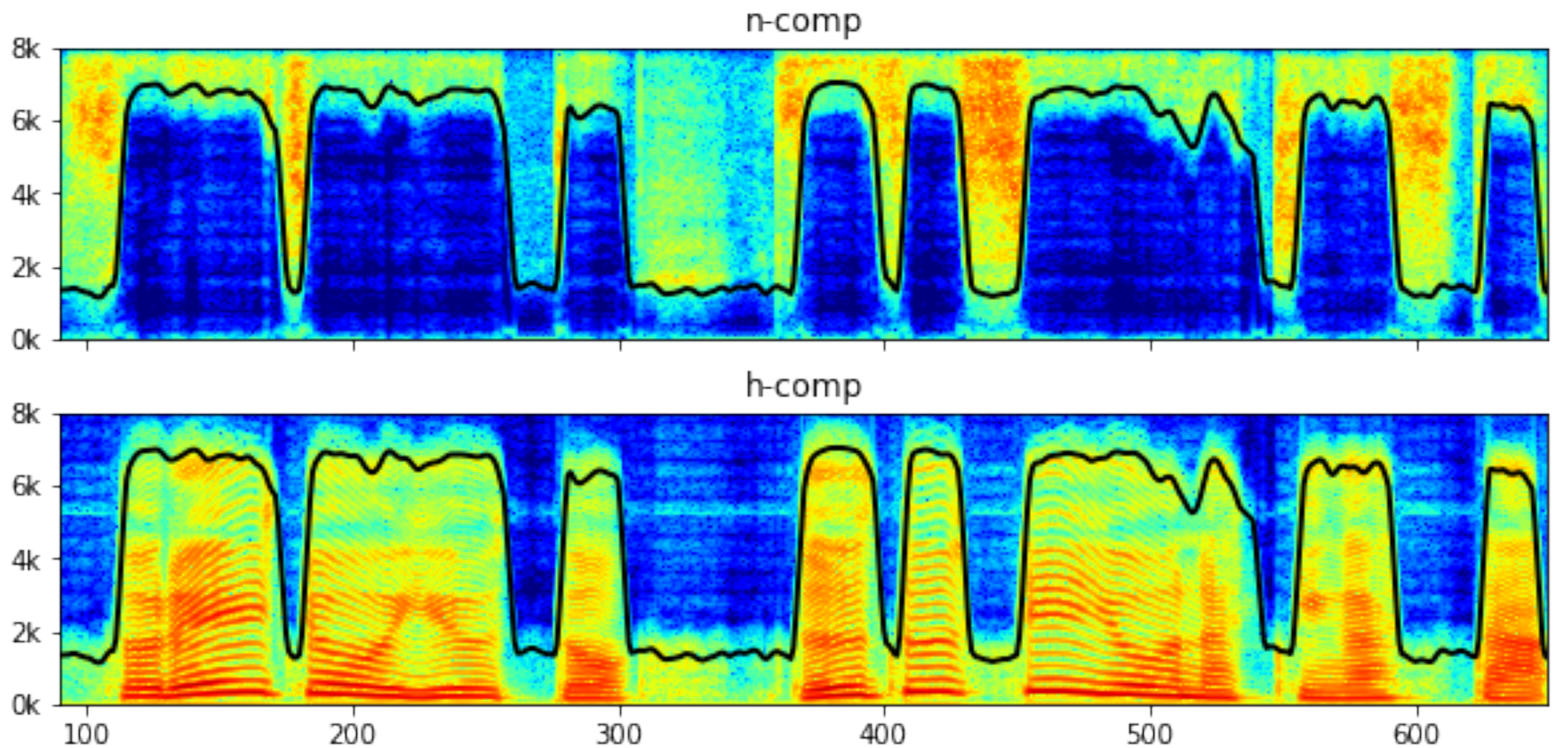
Pre-c



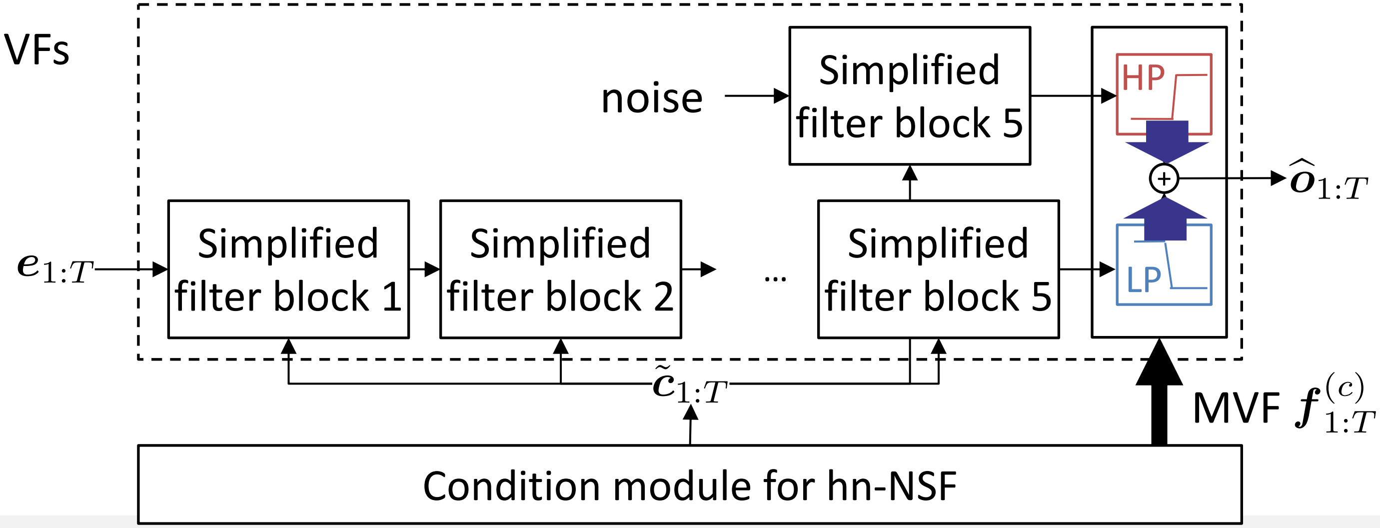
Predicted MVFs



Pre-c



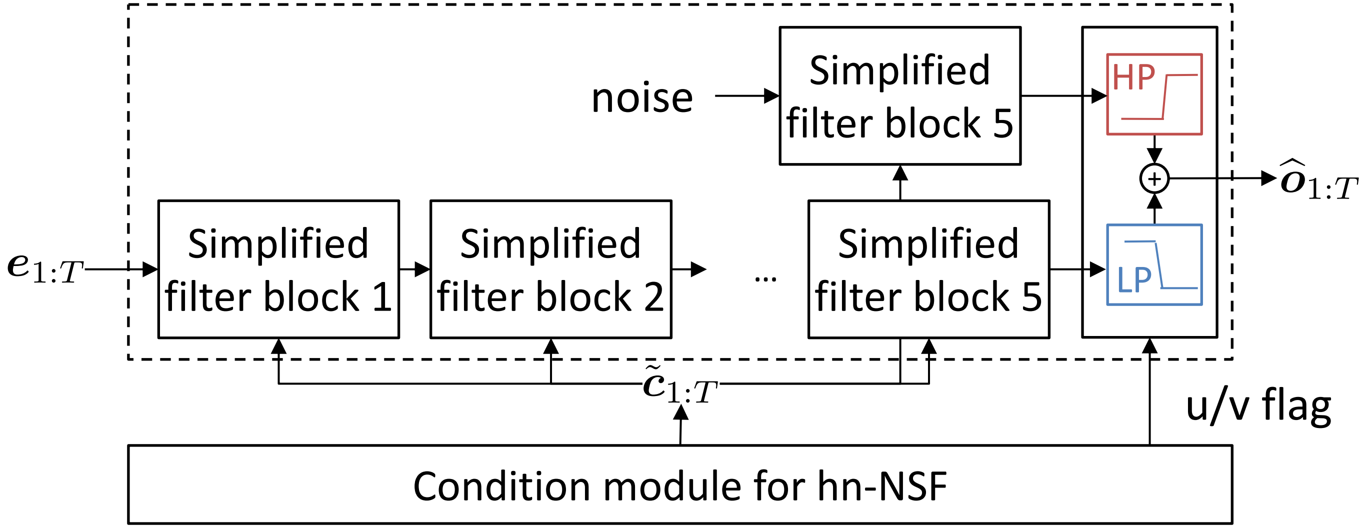
Predicted MVFs



NEURAL SOURCE-FILTER MODEL

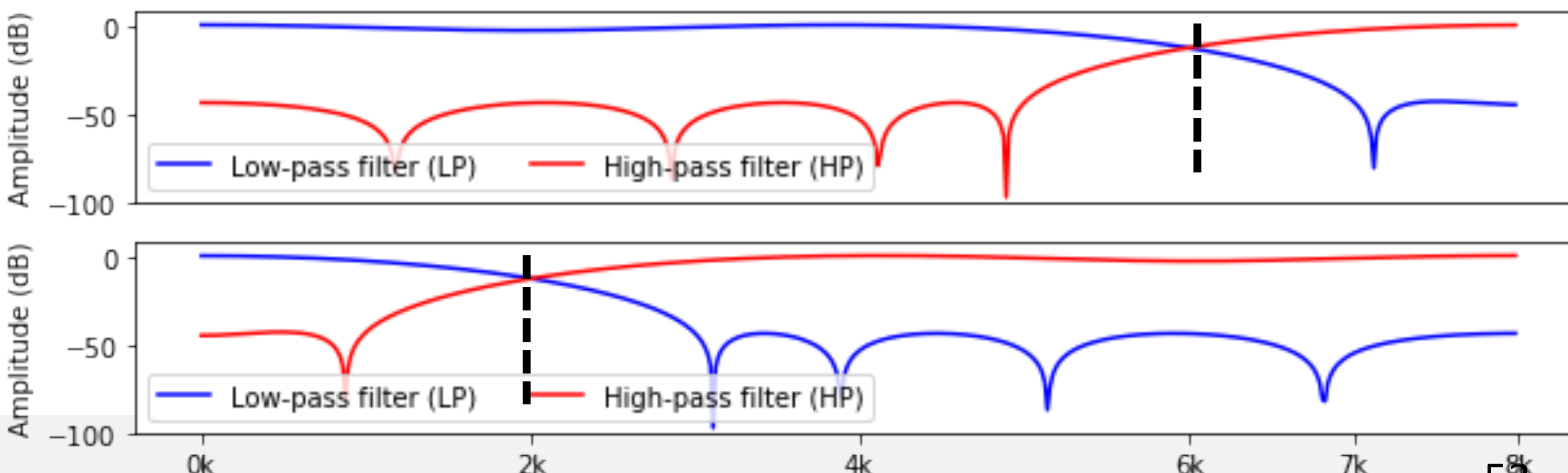
Harmonic-plus-noise NSF

- Version I: choose MVF based on u/v



Voiced sounds

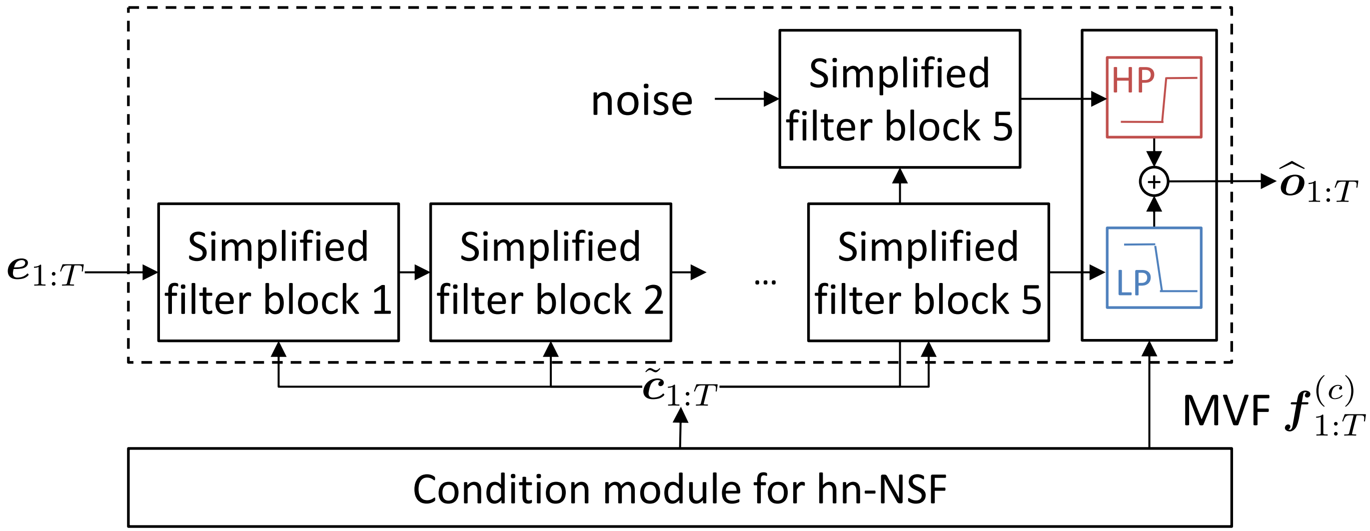
Unvoiced sounds



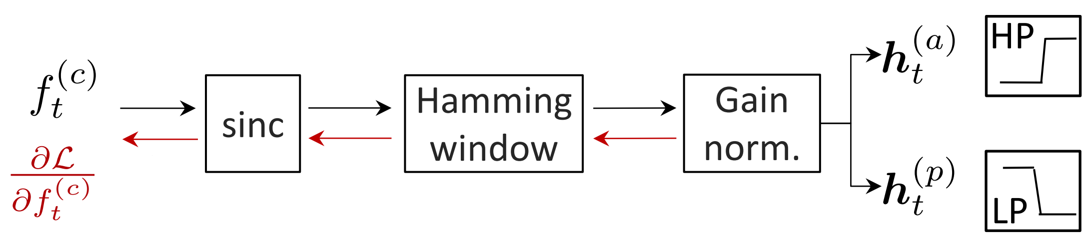
NEURAL SOURCE-FILTER MODEL

Harmonic-plus-noise NSF

- Version II: predict MVF from input features



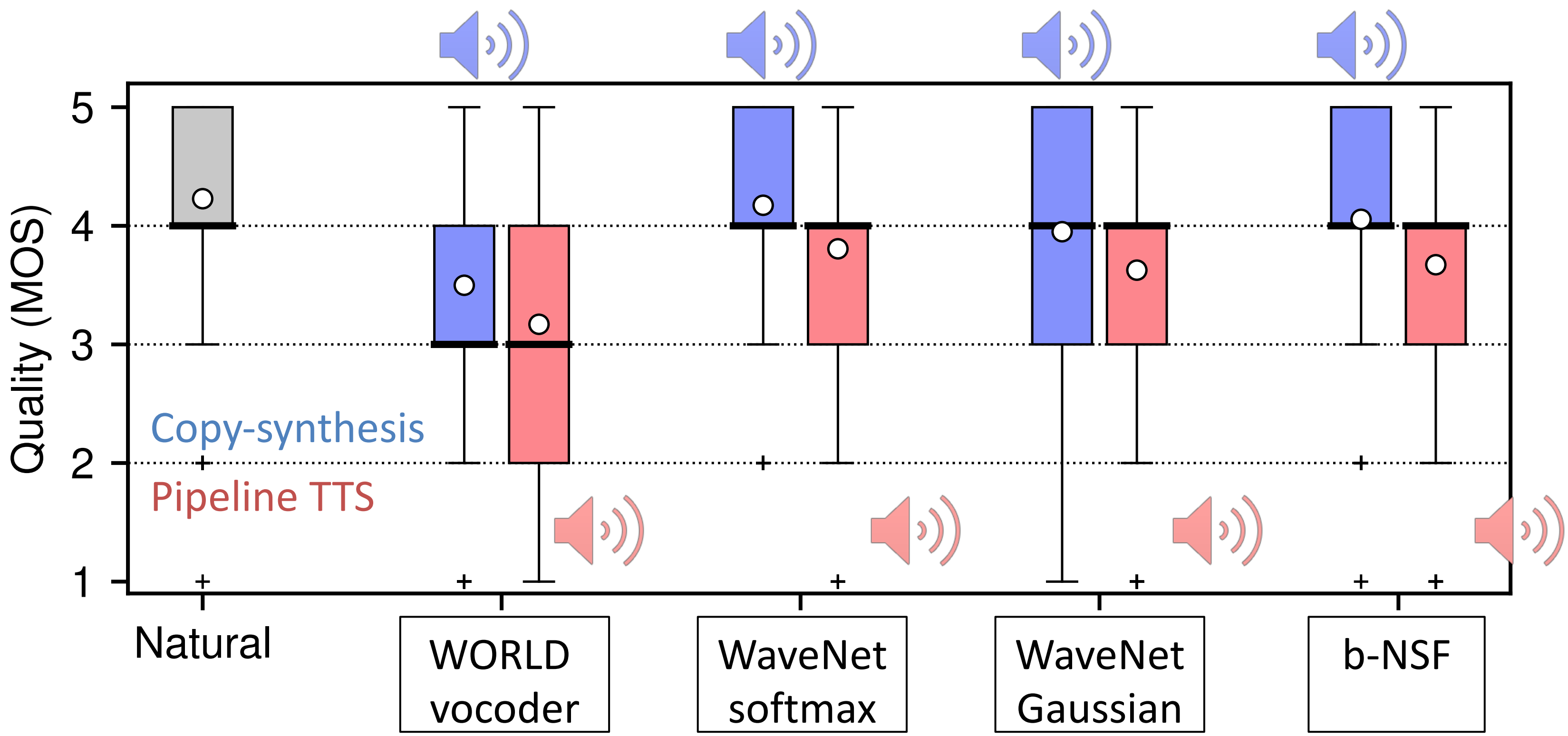
- Forward and backward propagation (SSW paper section 3)



PRACTICE: COMPARISON

Speech quality (ICASSP)

WORLD vocoder	WaveNet softmax	WaveNet Gaussian	b-NSF	s-NSF	hn-NSF fixed MVF	hn-NSF trainable MVF

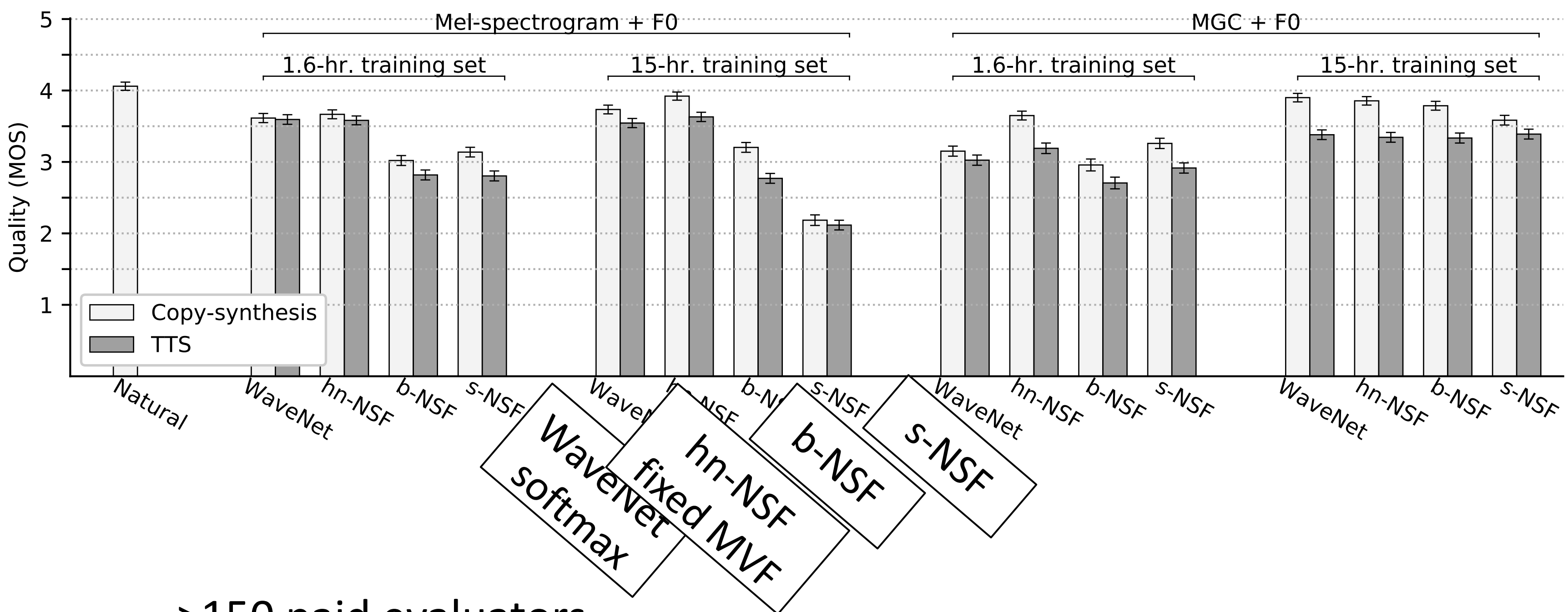


- 245 paid evaluators, 1450 evaluation sets

PRACTICE: COMPARISON

Speech quality (Journal paper submitted)

WORLD vocoder	WaveNet softmax	WaveNet Gaussian	b-NSF	s-NSF	hn-NSF fixed MVF	hn-NSF trainable MVF



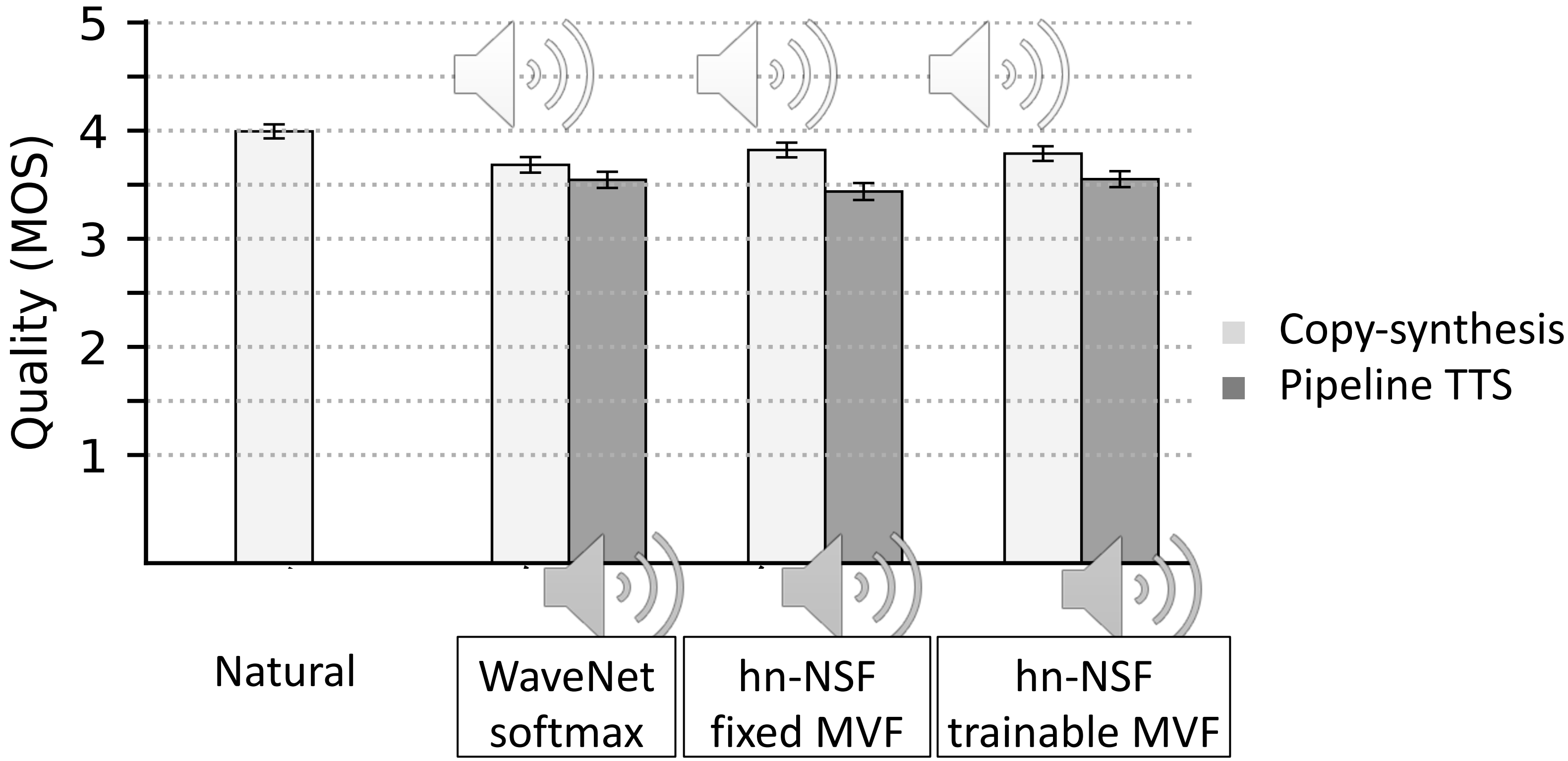
- >150 paid evaluators
- s-NSF did badly on unvoiced sounds

☛ Samples, models, codes: https://nii-yamagishilab.github.io/samples-nsf/nsf-v2.html

Practice: comparison

Speech quality (SSW 2019)

WORLD vocoder	WaveNet softmax	WaveNet Gaussian	b-NSF	s-NSF	hn-NSF fixed MVF	hn-NSF trainable MVF

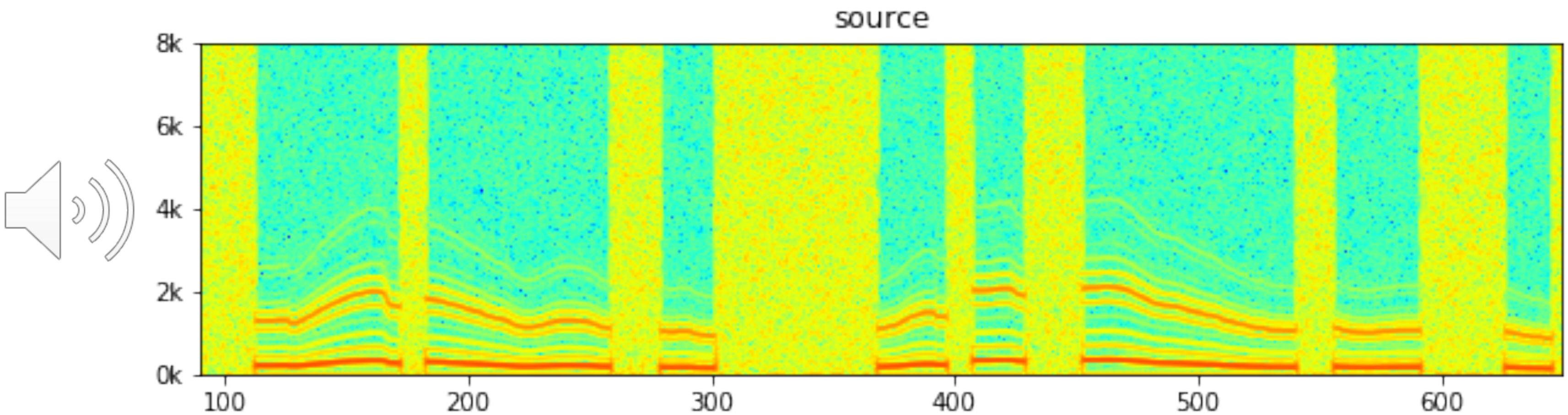


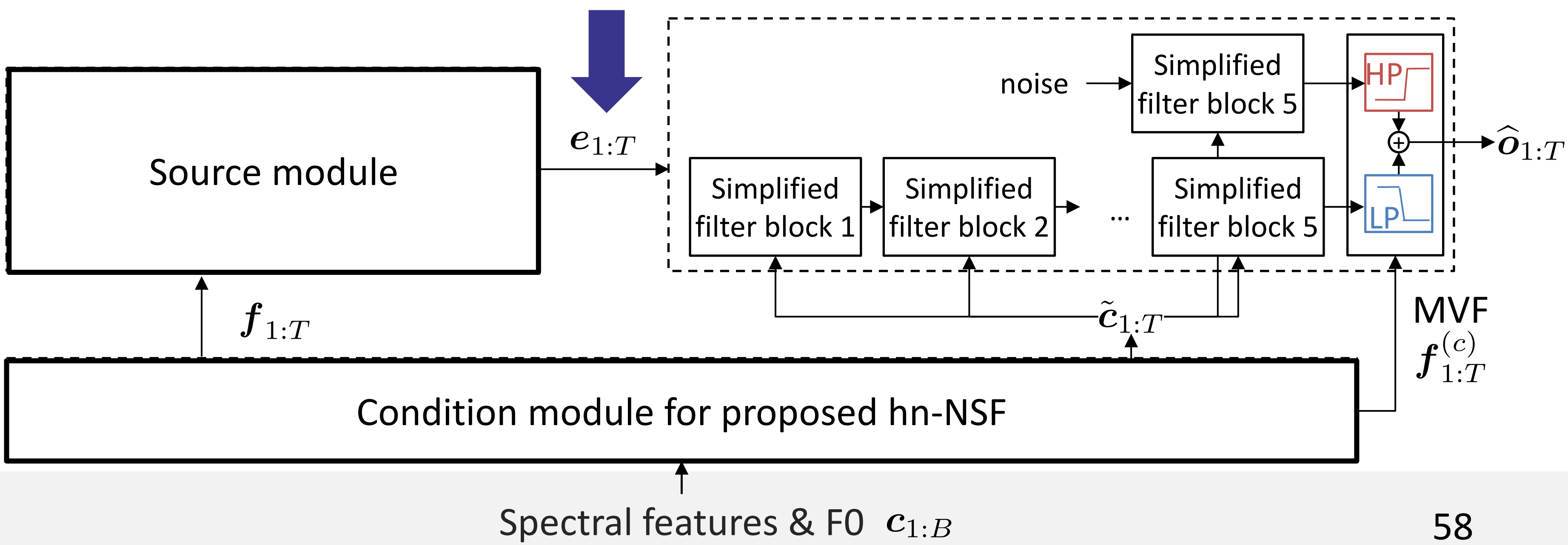
- >150 paid evaluators

☛ Samples, models, codes: https://nii-yamagishilab.github.io/samples-nsf/nsf-v3.html

EXPERIMENTS

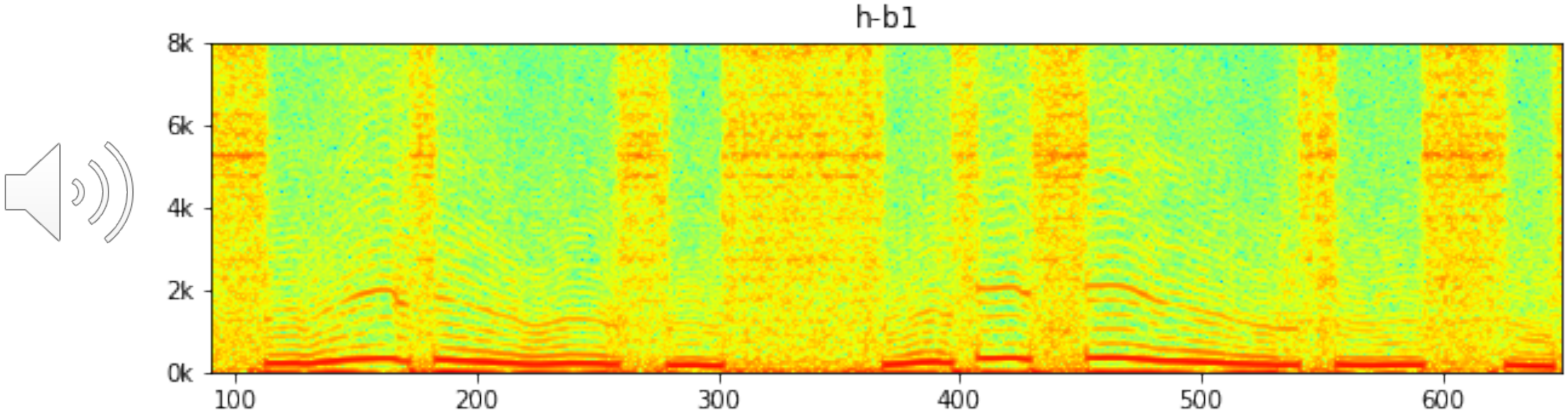
Waveform generation: step by step

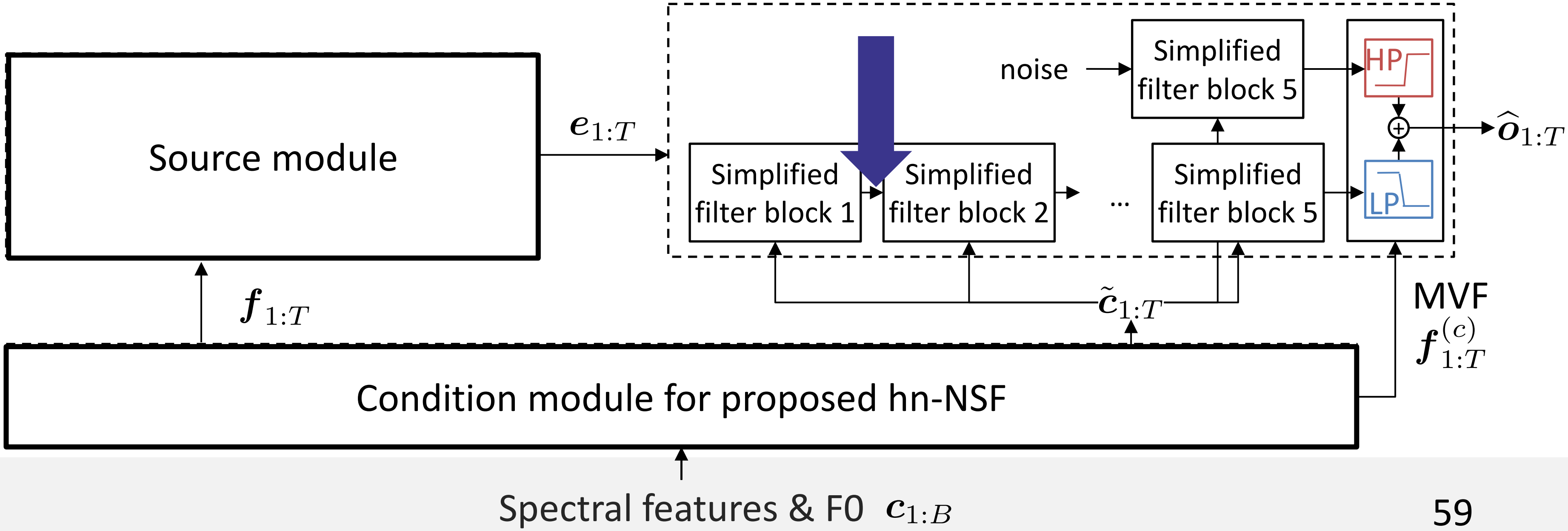




EXPERIMENTS

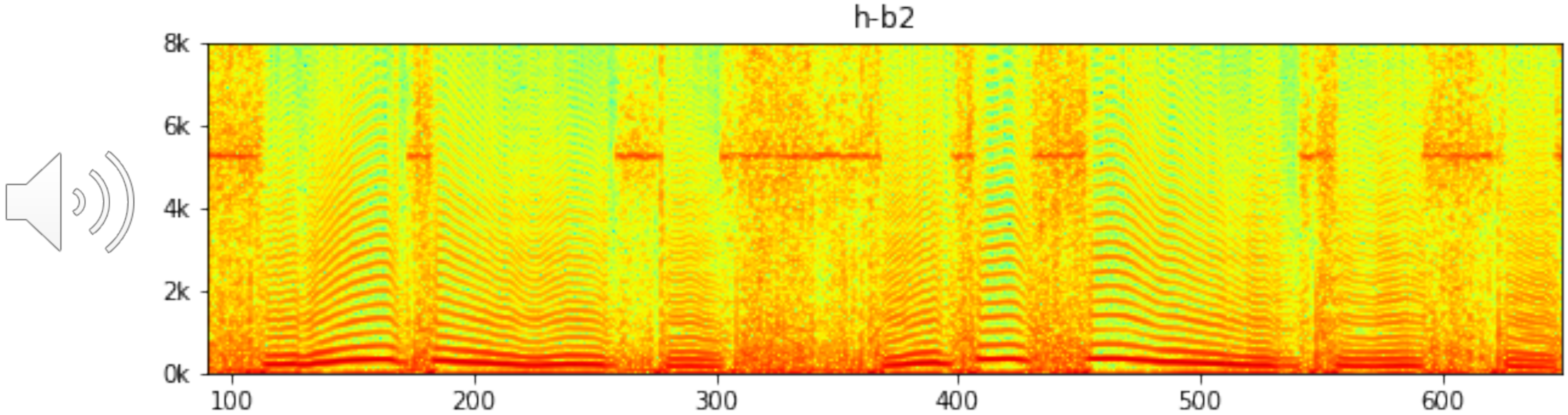
Waveform generation: step by step

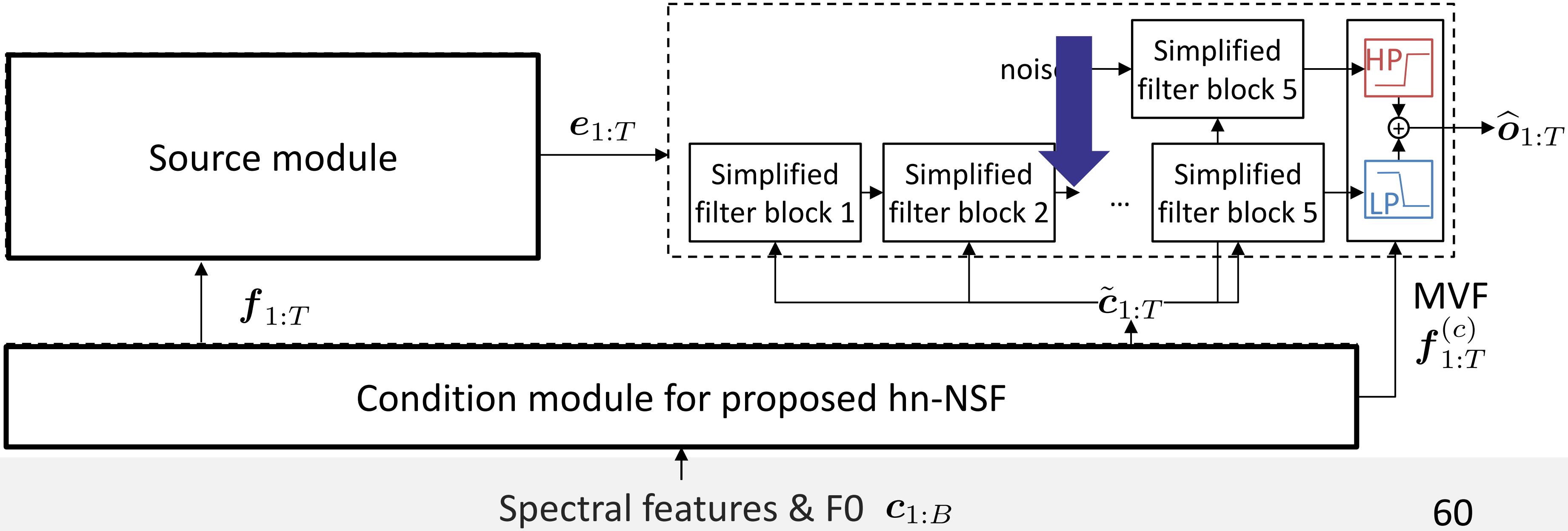




EXPERIMENTS

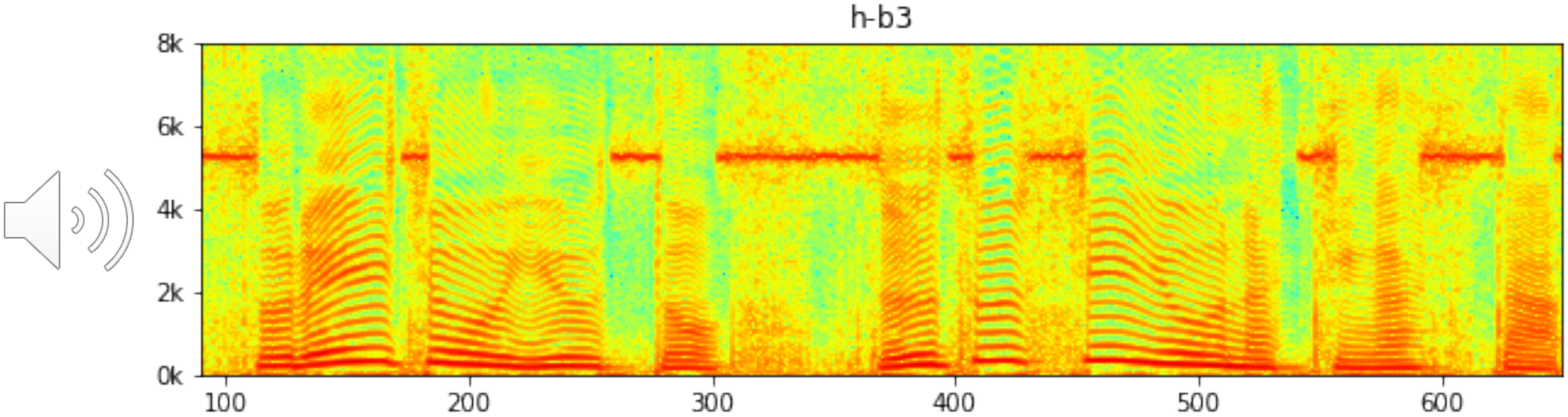
Waveform generation: step by step

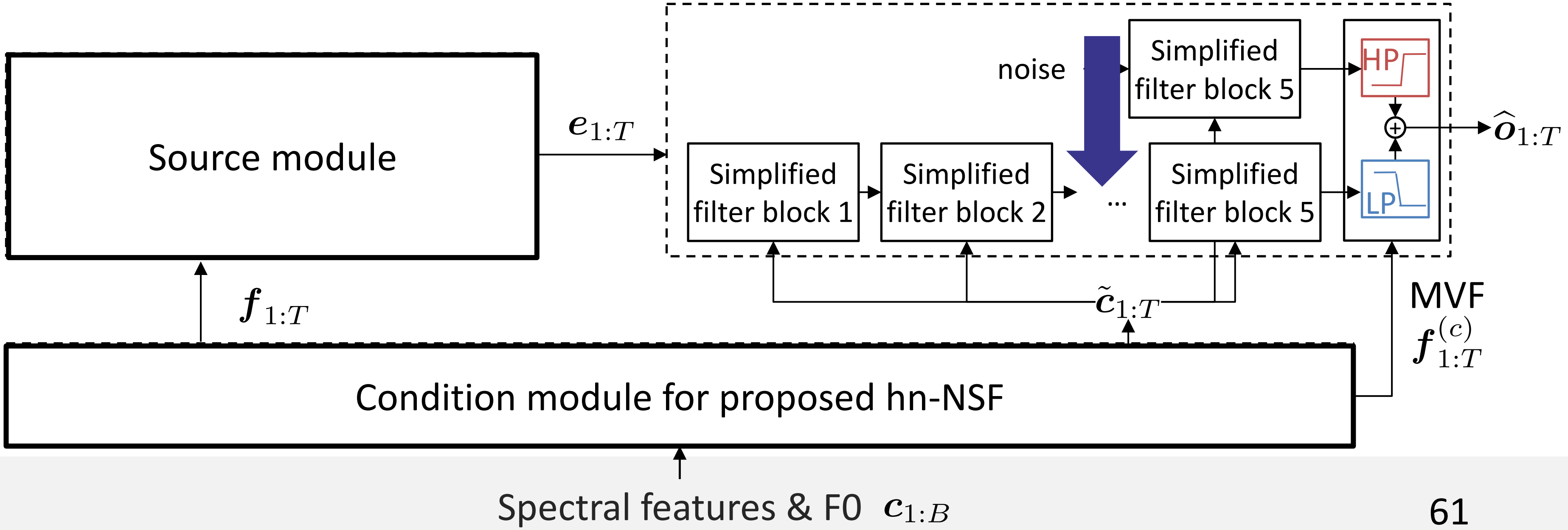




EXPERIMENTS

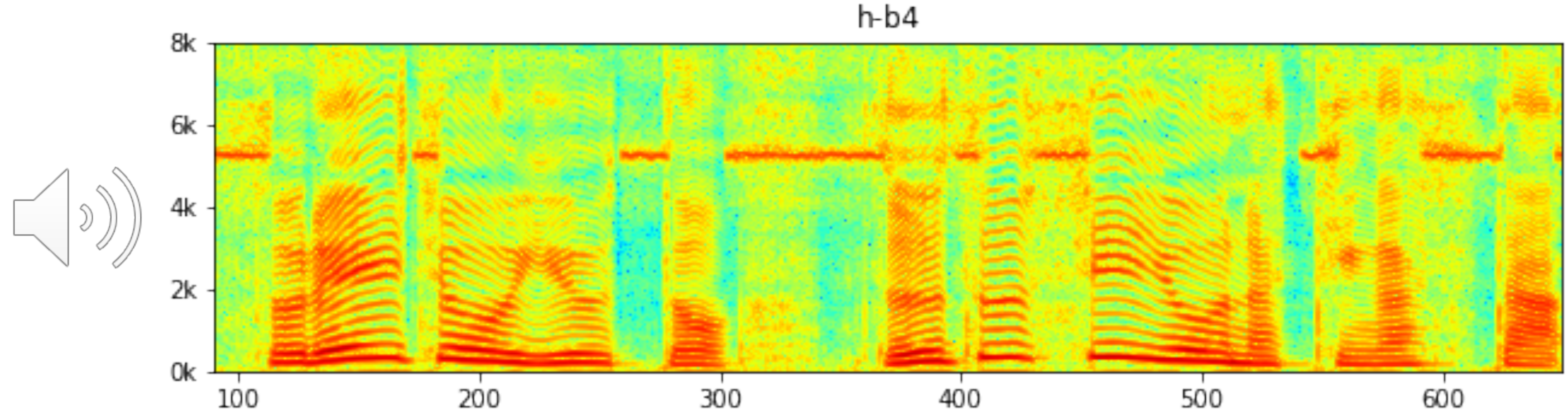
Waveform generation: step by step

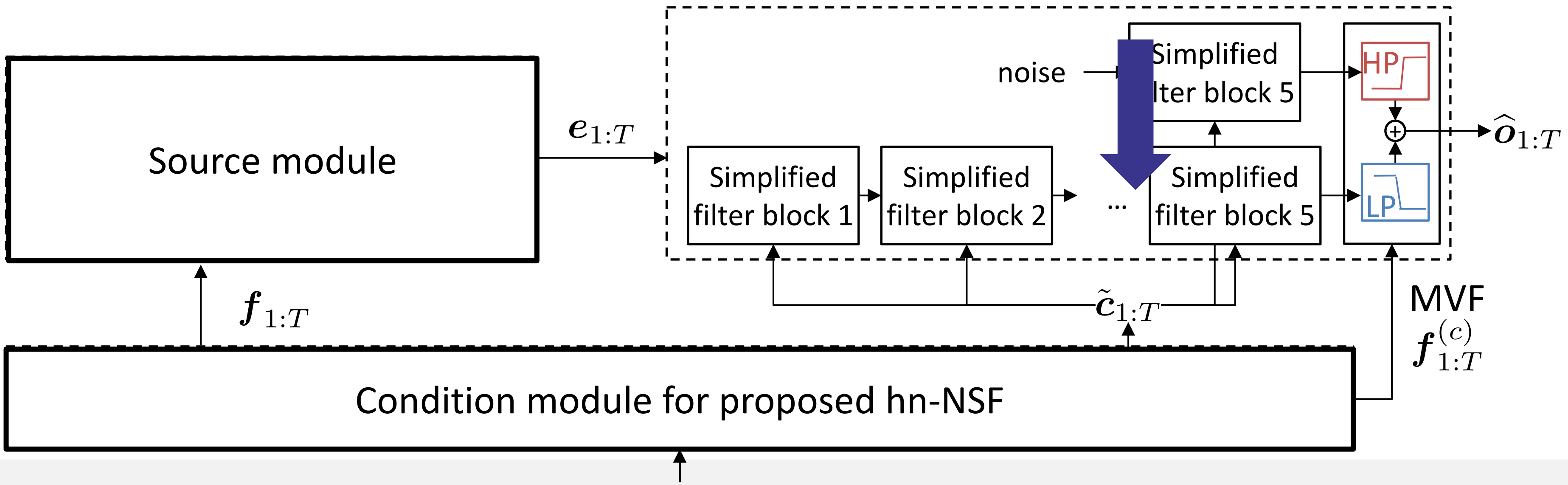




EXPERIMENTS

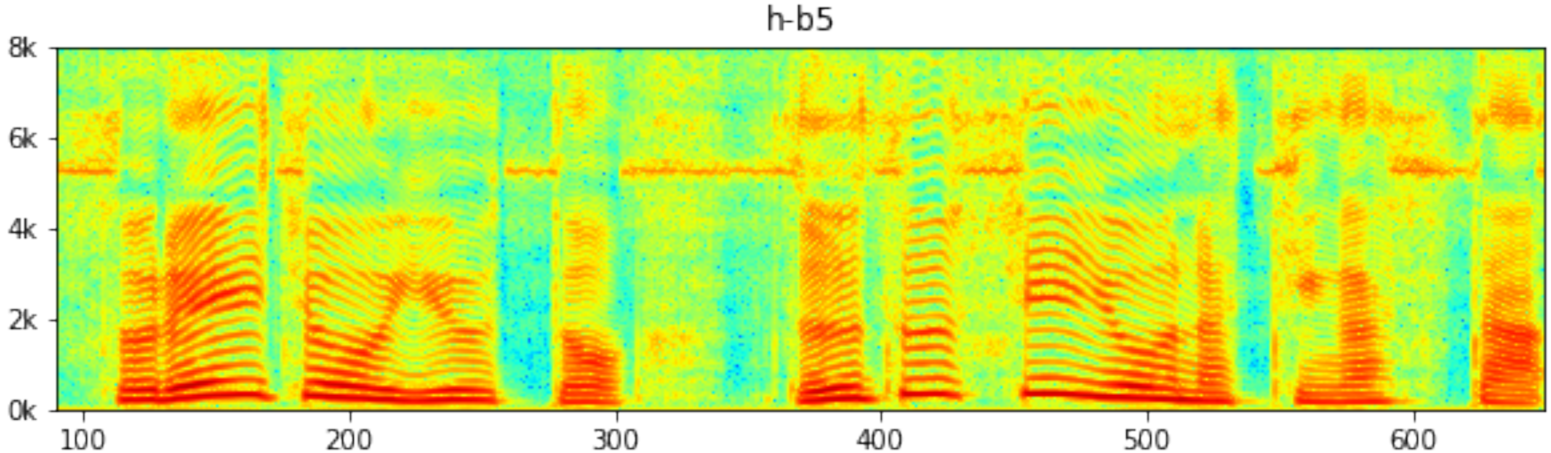
Waveform generation: step by step

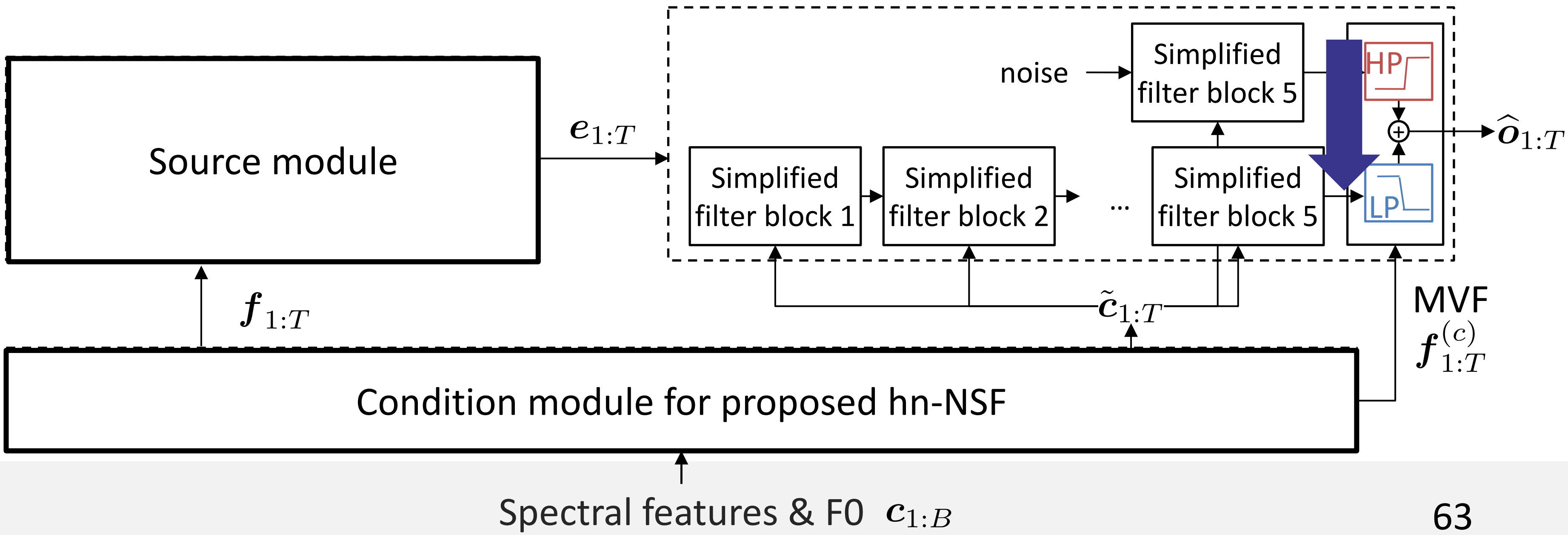




EXPERIMENTS

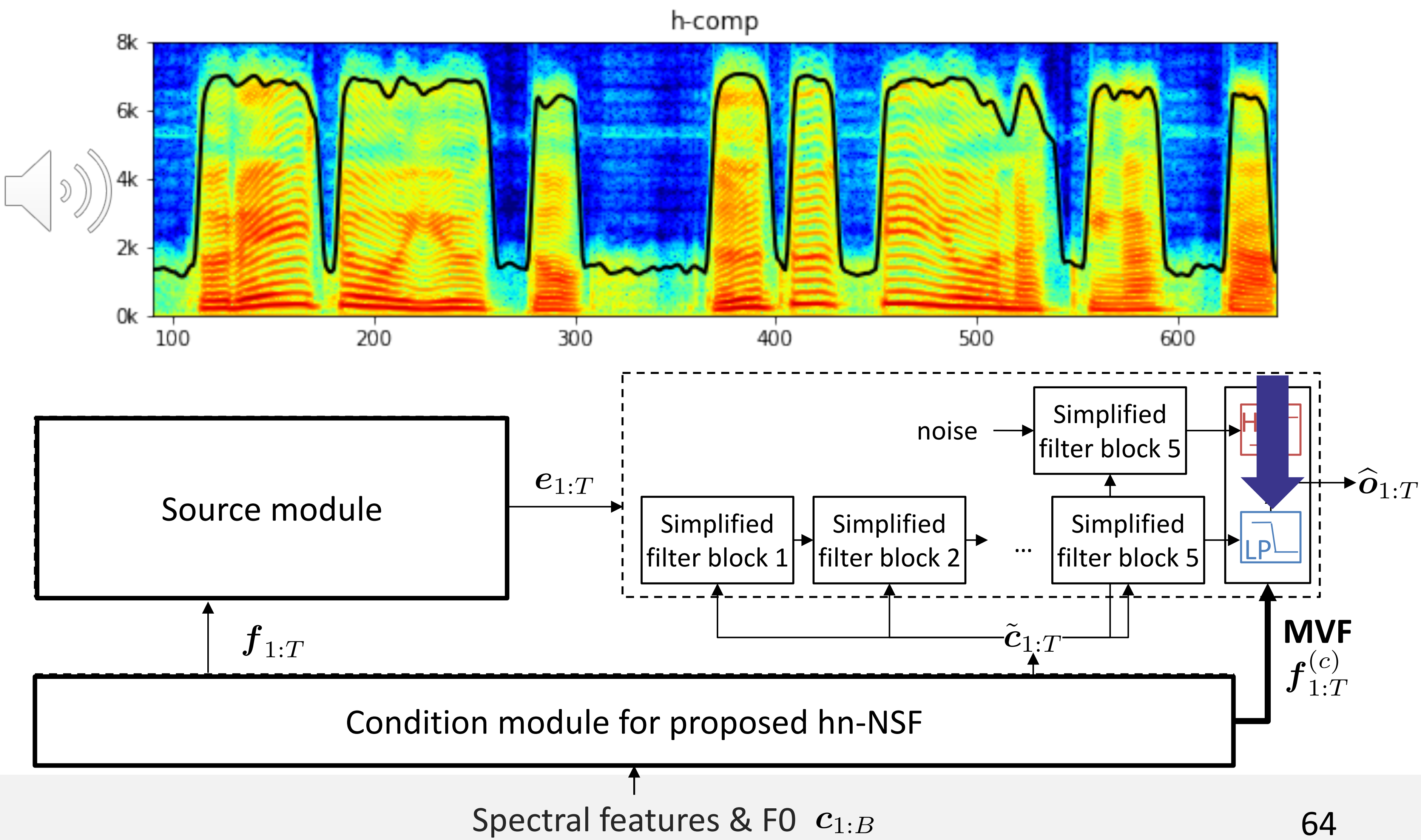
Waveform generation: step by step





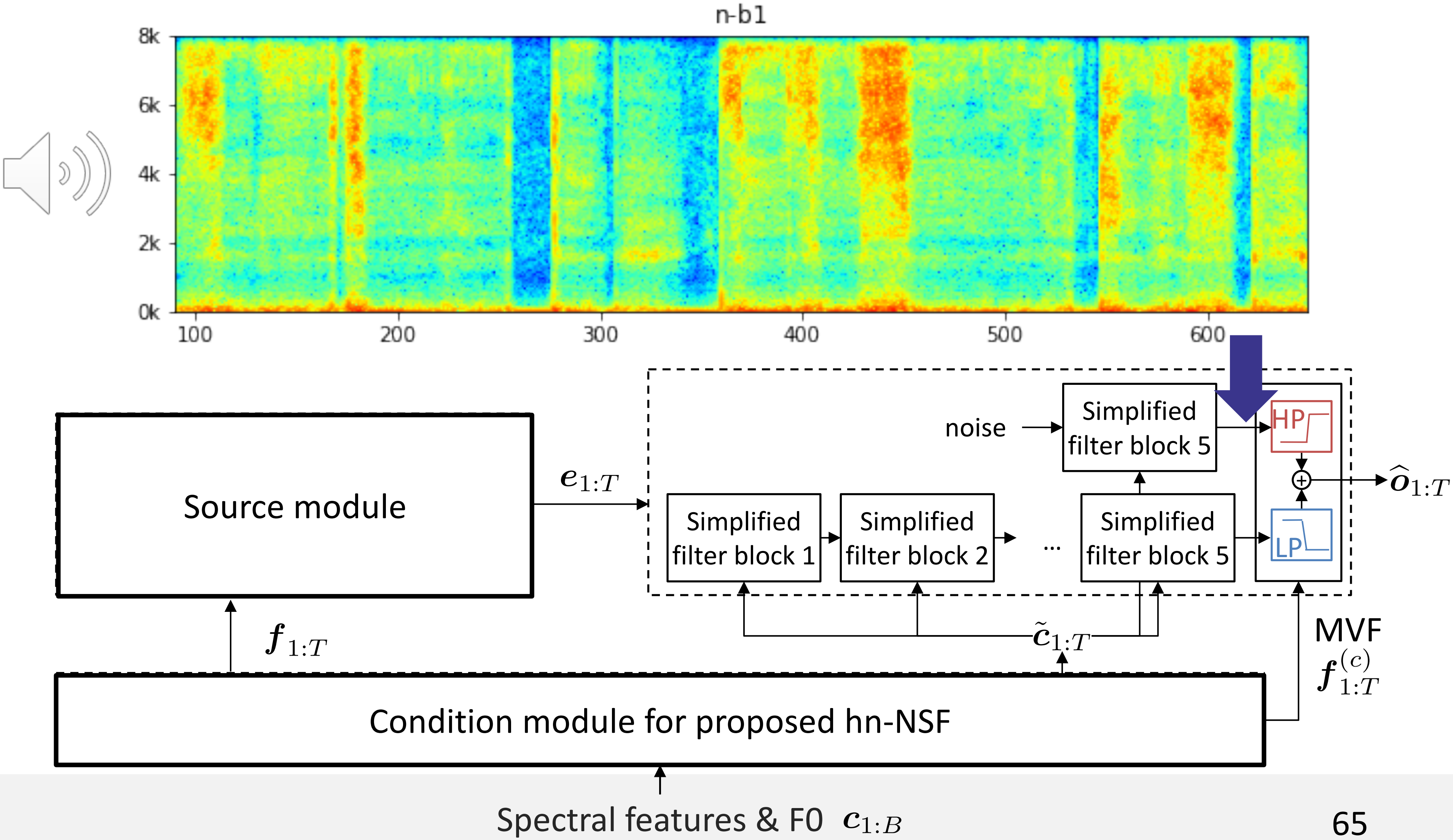
EXPERIMENTS

Waveform generation: step by step



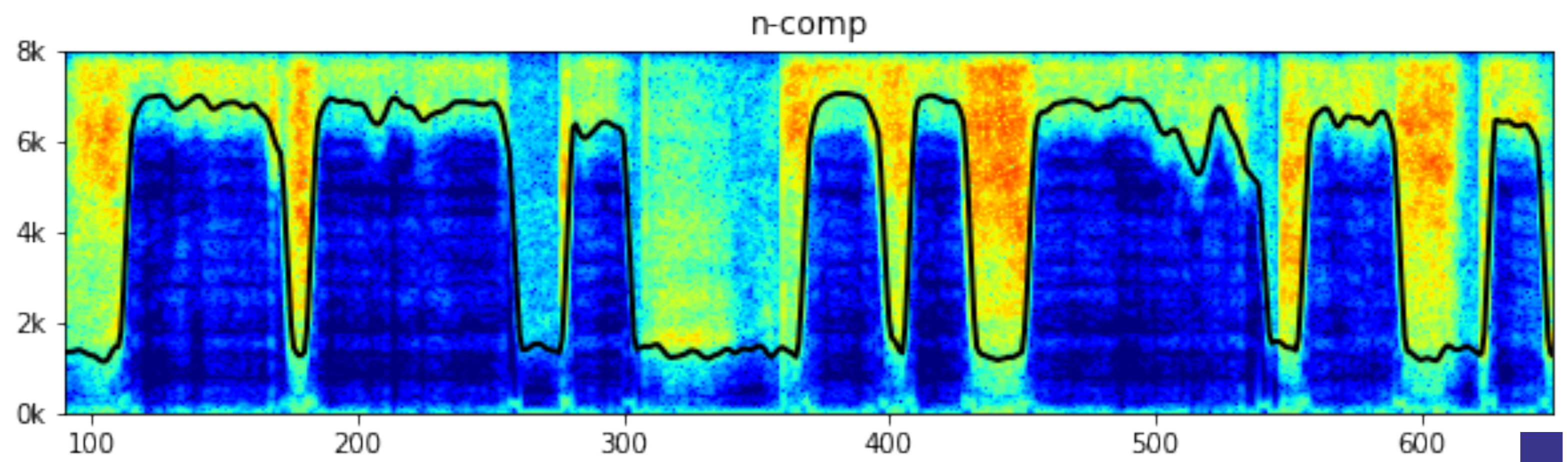
EXPERIMENTS

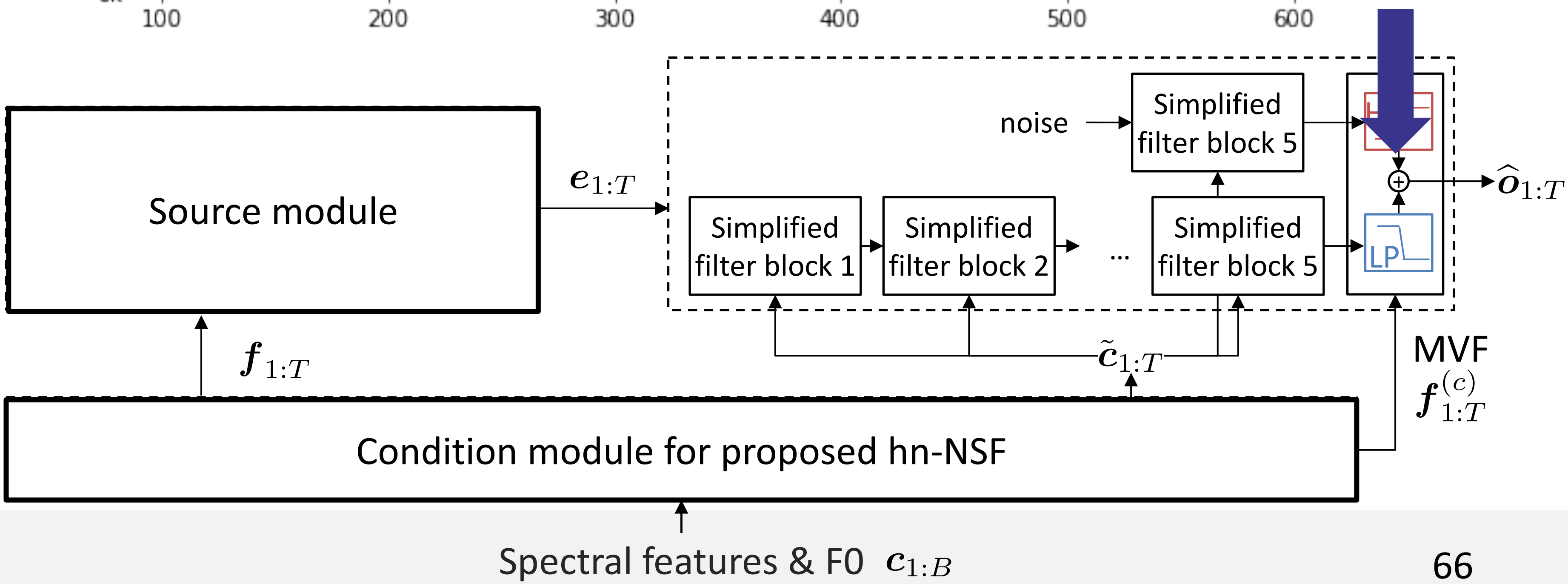
Waveform generation: step by step



EXPERIMENTS

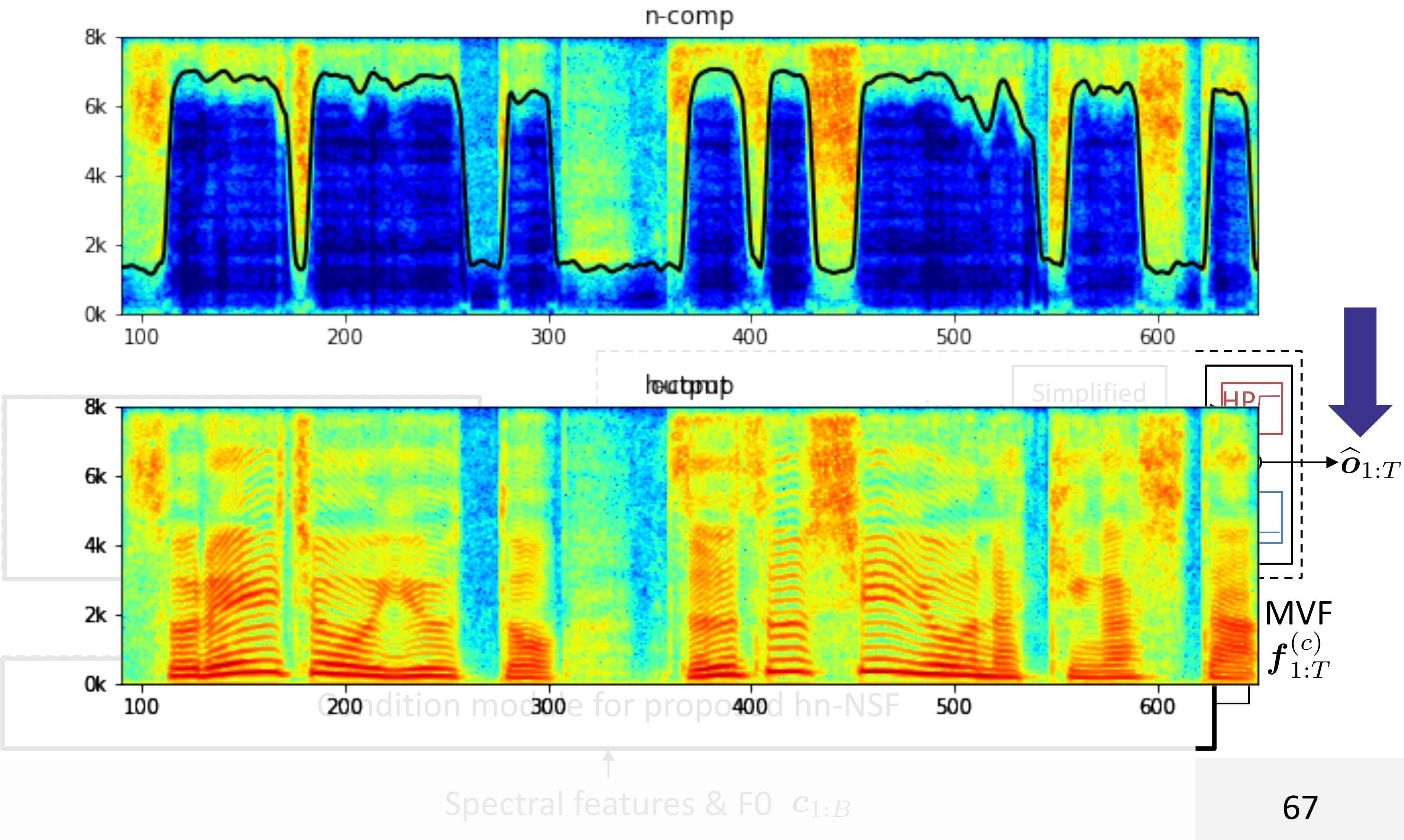
Waveform generation: step by step





Experiments

Waveform generation: step by step



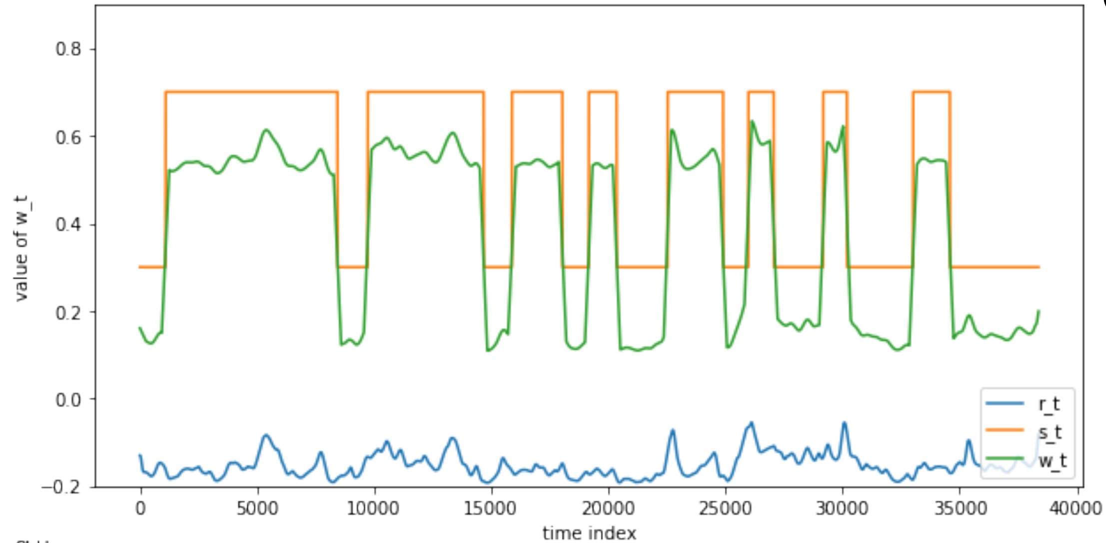
SINC-BASED H-NSF

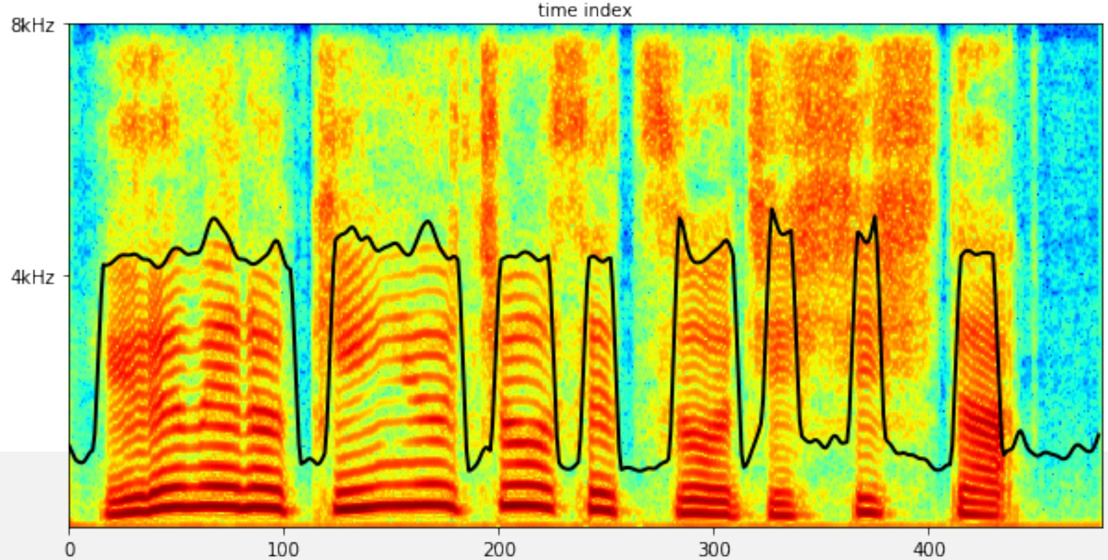
System 1

- W_t is well trained

$$w_t = v_t + 0.2 \cdot r_t \qquad w_t \in \begin{cases} (0.5, 0.9), \text{voiced} \\ (0.1, 0.5), \text{unvoiced} \end{cases}$$

Epoch 001





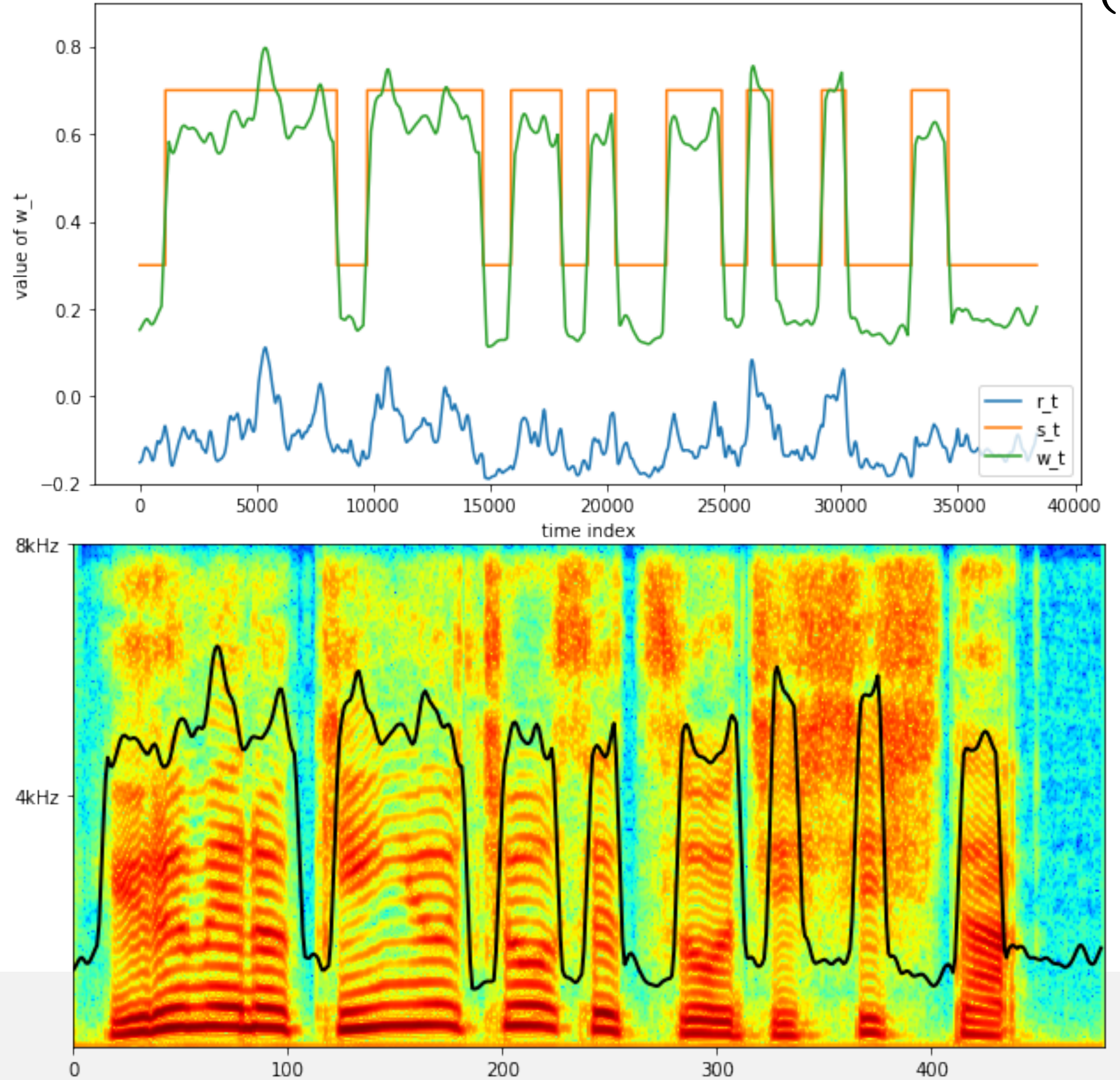
SINC-BASED H-NSF

System 1

- W_t is well trained

$$w_t = v_t + 0.2 \cdot r_t \qquad w_t \in \begin{cases} (0.5, 0.9), \text{voiced} \\ (0.1, 0.5), \text{unvoiced} \end{cases}$$

Epoch 010



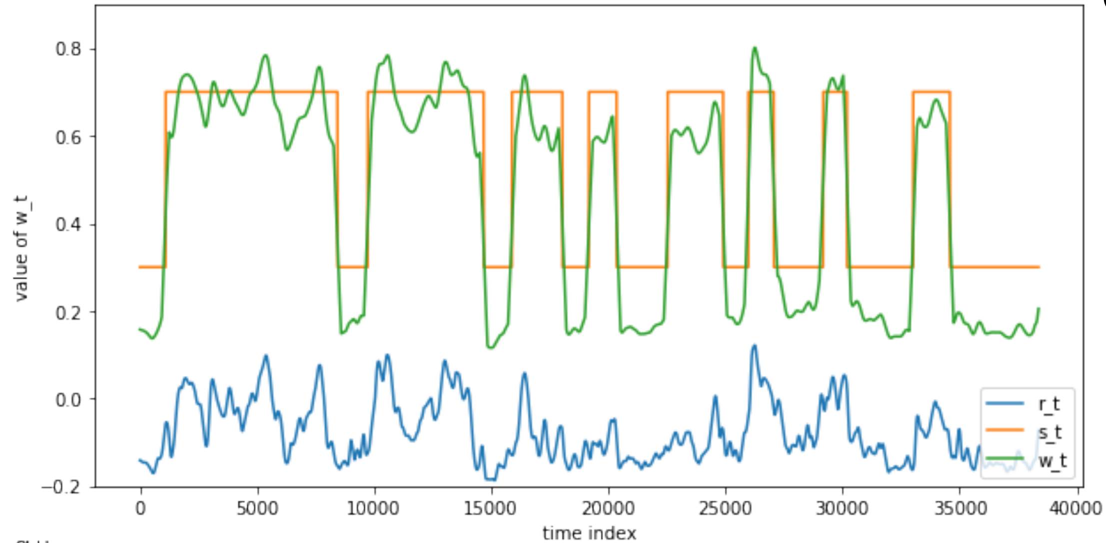
Sinc-based H-NSF

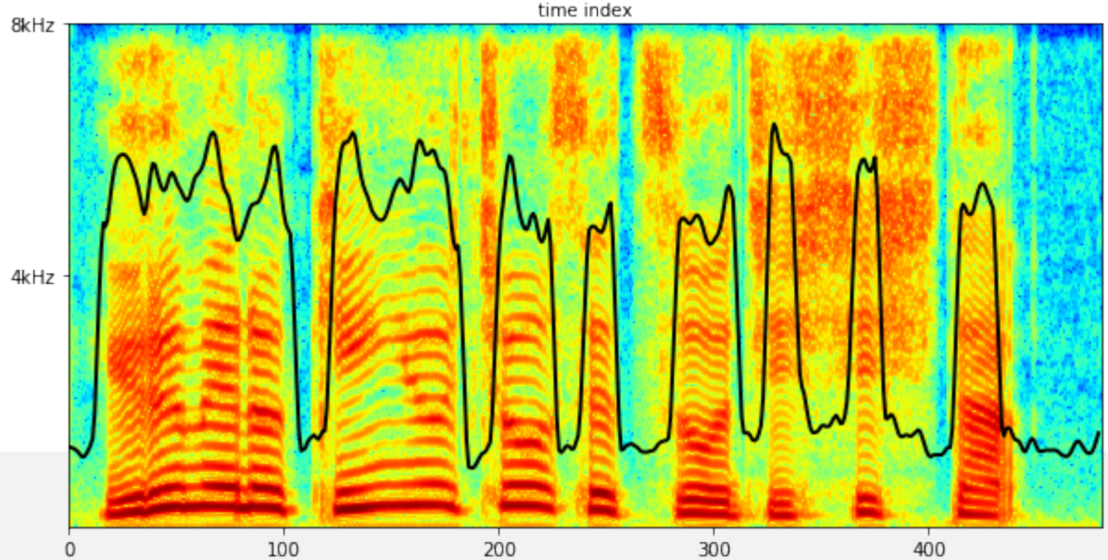
System 1

- W_t is well trained

$$w_t = v_t + 0.2 \cdot r_t \qquad w_t \in \begin{cases} (0.5, 0.9), \text{voiced} \\ (0.1, 0.5), \text{unvoiced} \end{cases}$$

Epoch 020





SINC-BASED H-NSF

System 1

- W_t is well trained

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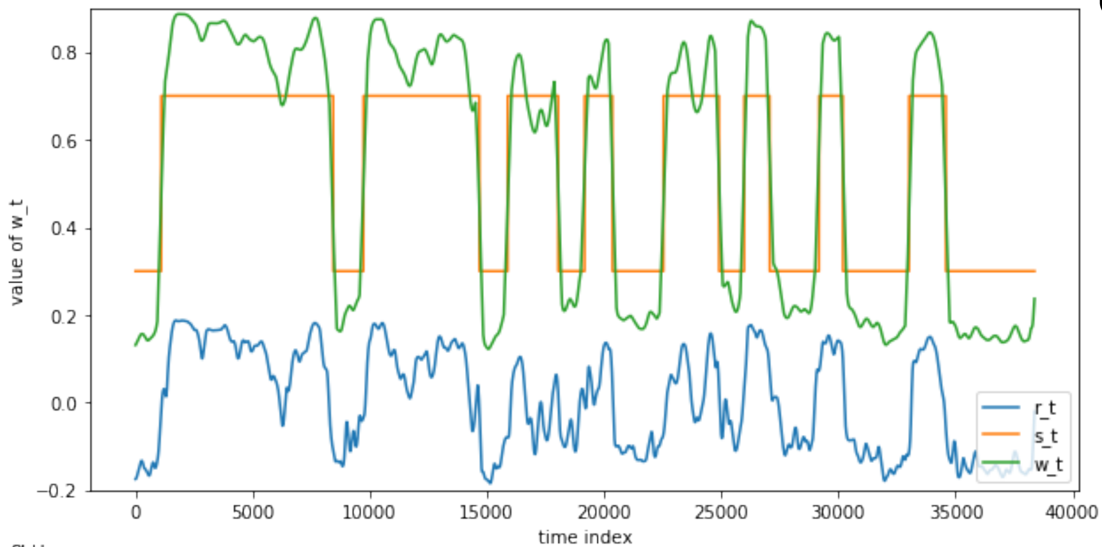
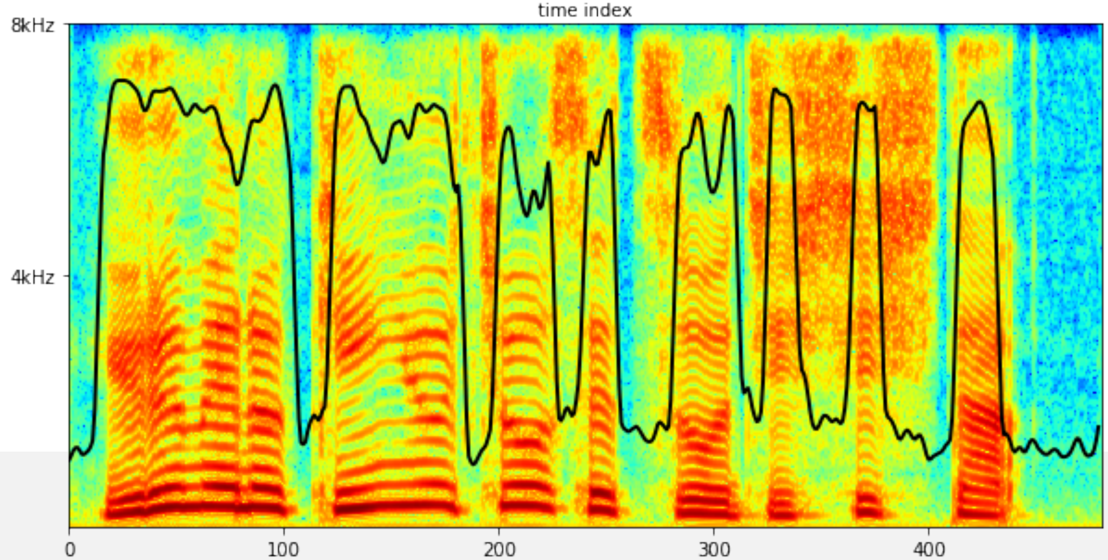
Epoch 030





SINC-BASED H-NSF

System 1

- W_t is well trained

$$w_t = v_t + 0.2 \cdot r_t \qquad w_t \in \begin{cases} (0.5, 0.9), \text{voiced} \\ (0.1, 0.5), \text{unvoiced} \end{cases}$$

Epoch last