



APSIPA ASC 2024

SDNet: Noise-Robust Bandwidth Extension under Flexible Sampling Rates

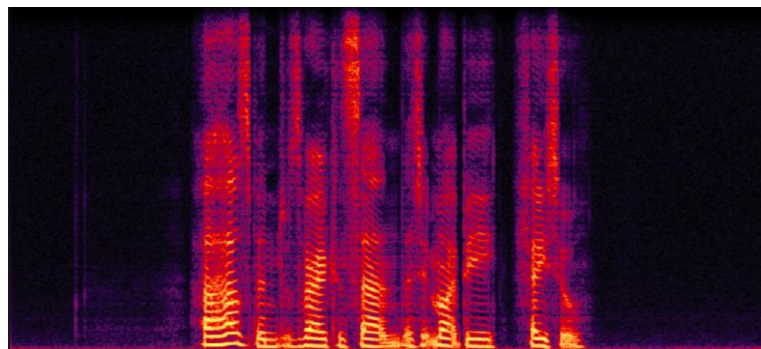
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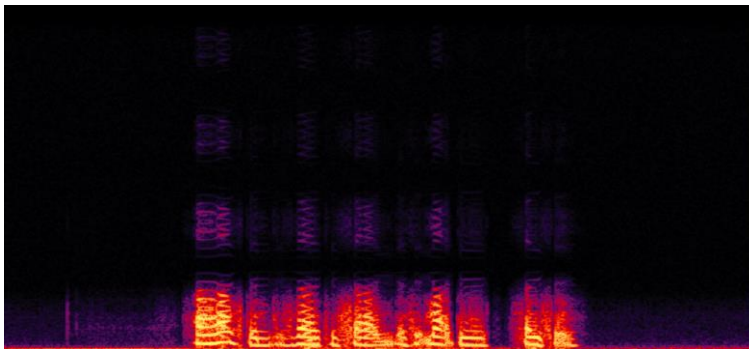
vivo AI Lab

Introduction

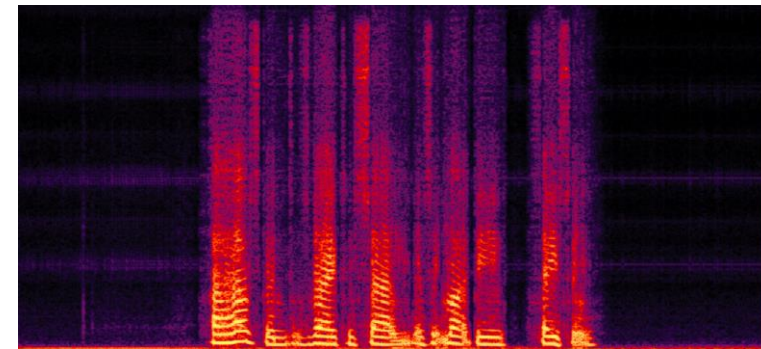
- What is Bandwidth Extension (also named as Audio Super-Resolution)?
Recovering high-resolution (HR) signals from low-resolution (LR) counterparts.
- Applications: wireless communication, speech recognition, text-to-speech.



Original



Low-Resolution

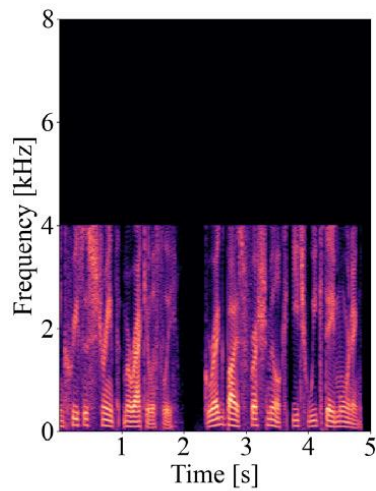


Super-Resolution

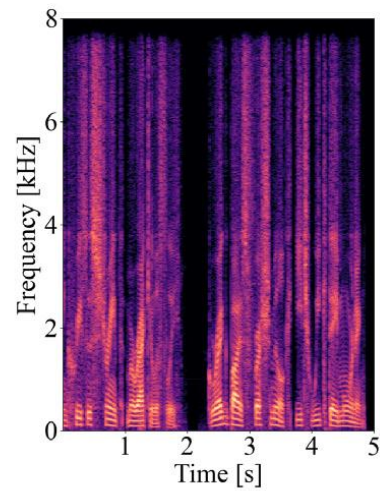
- Problem: Current models struggle with noisy environments and flexible sampling rates.
- Goal: Jointly handle noise reduction and bandwidth extension and support multiple sampling rates with a single model.

Challenges in BWE

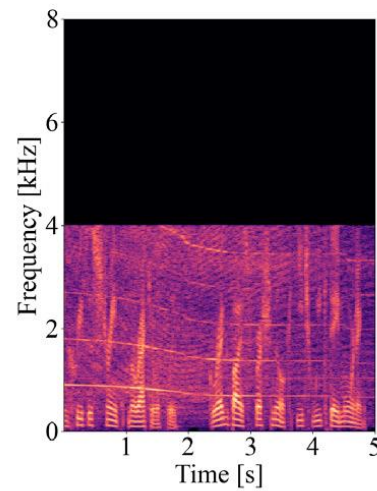
- Ineffectiveness in noisy environments
Noise interference biases high-frequency predictions.



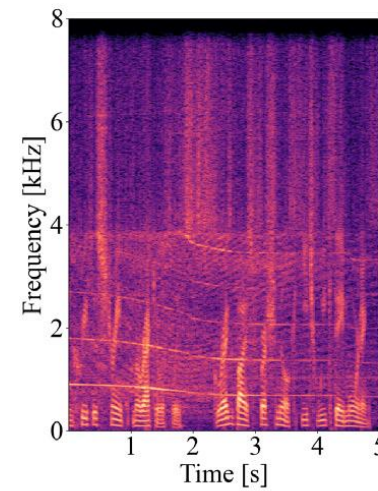
(a)



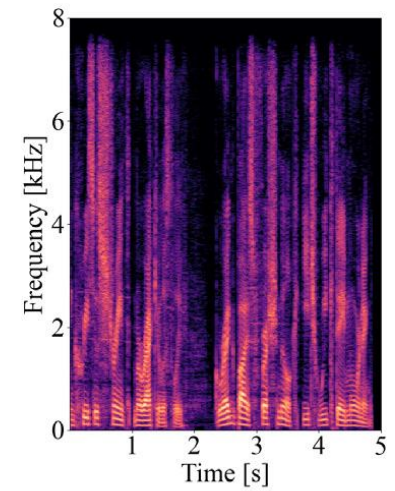
(b)



(c)



(d)



(e)

Challenges in BWE

- Limited flexibility: Fixed sampling rates in most models.

Ratio	Obj.	SingleSpeaker			MultiSpeaker			Piano		
		Spline	DNN	Ours	Spline	DNN	Ours	Spline	DNN	Ours
$r = 2$	SNR	20.3	20.1	21.1	19.7	19.9	20.7	29.4	29.3	30.1
	LSD	4.5	3.7	3.2	4.4	3.6	3.1	3.5	3.4	3.4
$r = 4$	SNR	14.8	15.9	17.1	13.0	14.9	16.1	22.2	23.0	23.5
	LSD	8.2	4.9	3.6	8.0	5.8	3.5	5.8	5.2	3.6
$r = 6$	SNR	10.4	n/a	14.4	9.1	n/a	10.0	15.4	n/a	16.1
	LSD	10.3	n/a	3.4	10.1	n/a	3.7	7.3	n/a	4.4

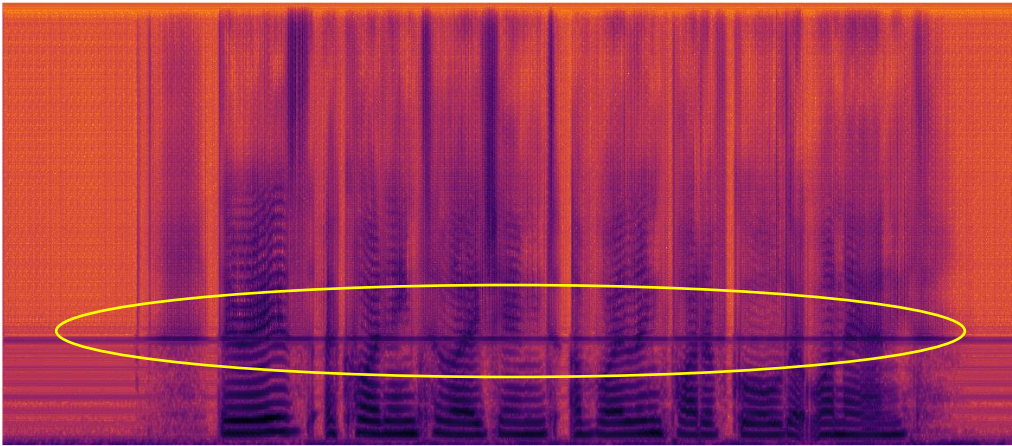
Table 2: Accuracy evaluation of audio-super resolution methods (in dB) on each of the three super-resolution tasks at upscaling ratios $r = 2, 4, 6$.

Table 1: L, V and M denote LSD, ViSQOL and MUSHRA respectively. MUSHRA score is specified with a \pm Confidence Interval of 0.95.

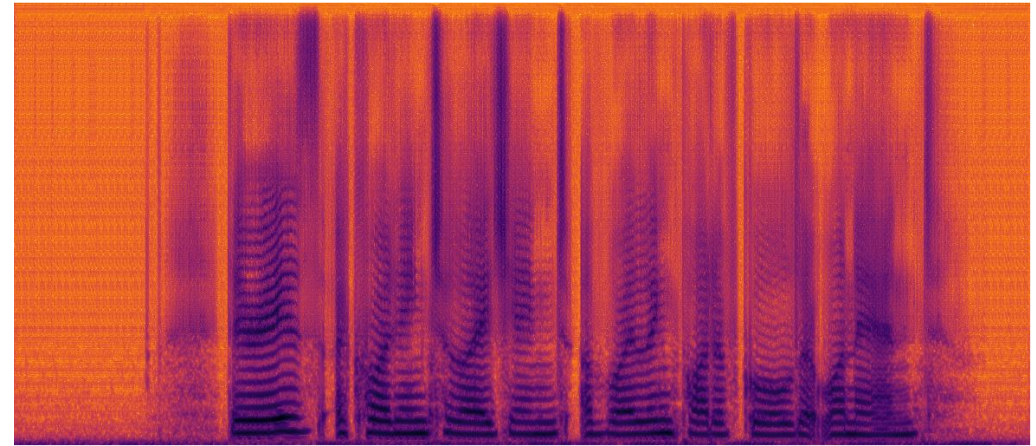
	8-16			8-24			4-16			11-44		
	L↓	V↑	M↑	L↓	V↑	M↑	L↓	V↑	M↑	L↓	V↑	M↑
Reference	-	-	96.25±1.5	-	-	97.16±1.4	-	-	96.18±1.5	-	-	95.30±2.5
Anchor	-	-	54.65±4.3	-	-	56.21±4.4	-	-	41.14±3.8	-	-	46.55±7.4
Sinc	2.32	3.41	60.13±4.7	2.96	3.41	59.49±4.8	3.59	2.27	43.03±3.9	3.91	1.97	47.61±8.0
TFiLM [4]	1.27	3.18	58.53±4.0	-	-	-	1.77	2.25	41.91±4.0	-	-	-
SEANet [5]	0.79	4.08	91.23±2.9	0.91	4.06	94.16±2.2	0.99	3.16	89.40±3.2	1.13	2.88	80.52±7.0
BEHMGAN [17]	-	-	-	-	-	-	-	-	-	1.80	2.01	46.27±8.3
Ours ($2^{56}/512$)	0.84	4.02	90.58±2.3	0.99	4.03	96.40±1.9	1.04	3.04	86.14±3.4	1.16	2.88	81.21±6.4
Ours ($1^{28}/512$)	0.80	4.11	92.63±2.4	0.91	4.12	95.41±2.0	0.99	3.15	92.05±2.7	1.16	2.89	81.67±6.8
Ours ($6^4/512$)	0.77	4.16	94.64±1.6	0.90	4.17	94.45±2.1	0.94	3.28	90.61±3.1	1.12	2.88	84.18±5.6

Challenges in BWE

- Significant artifacts



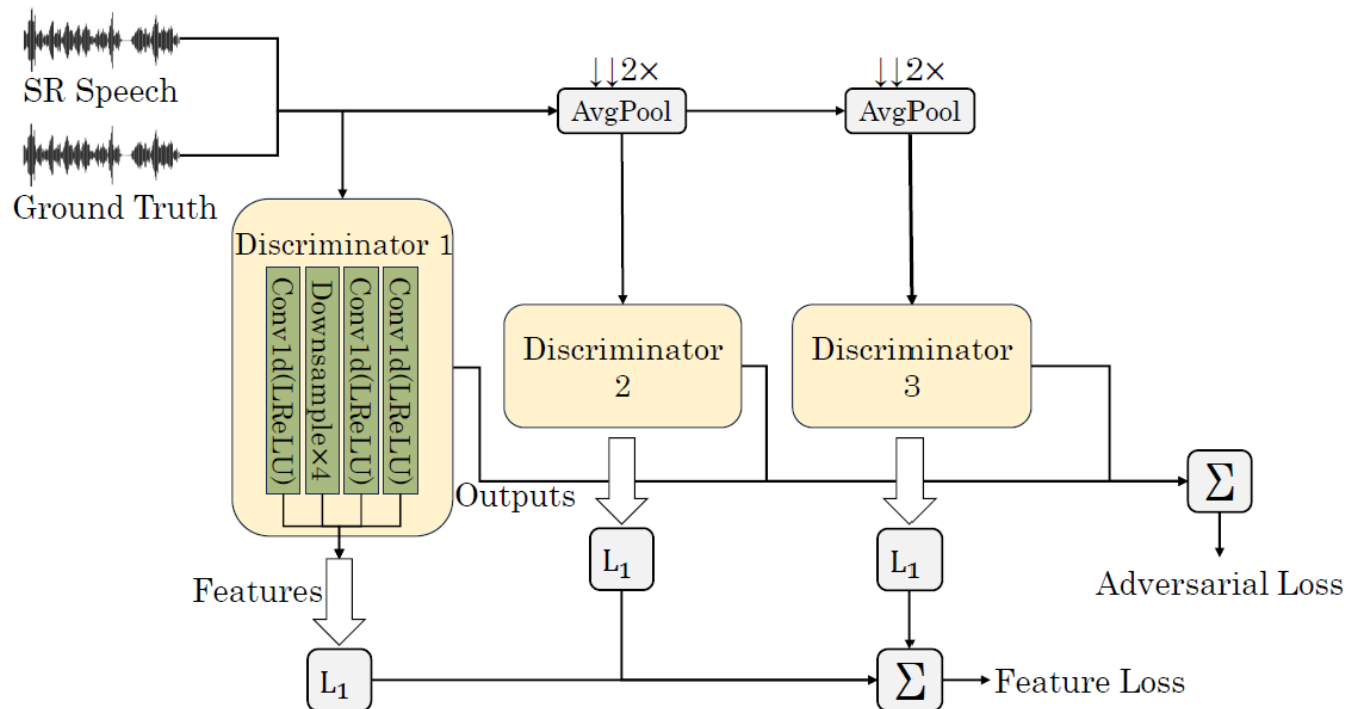
Super-Resolution Speech



Ground Truth

- Lack of joint optimization for noise suppression and super-resolution. There are relatively few studies on noise-robust BWE compared to noise-free BWE.

Proposed Solution: SDNet



Where k is the number of discriminators, l is the number of layer in one discriminator.

Total Loss:

$$\mathcal{L} = \mathcal{L}_{MSTFT} + \mathcal{L}_G^{adv} + \lambda_f \mathcal{L}_f \quad \lambda_f = 100$$

$$\mathcal{L}_{MSTFT} = E_{(x,y) \sim p_{data}} \left[\sum_{m=1}^3 \left(\frac{\|s(y, \theta_m) - s(x, \theta_m)\|_F}{\|s(y, \theta_m)\|_F} + \frac{1}{N} \left\| \log \frac{s(y, \theta_m)}{s(x, \theta_m)} \right\| \right) \right]$$

$\|\cdot\|_F$ and $\|\cdot\|_1$ are Frobenius and ℓ_1 -norms, N is the number of elements in the magnitude.

FFT bins $\in \{512, 1024, 2048\}$ and hop length $\in \{50, 120, 240\}$. The window lengths are $\{240, 600, 1200\}$.

$$\mathcal{L}_G^{adv} = E_{x \sim p_{data}} \left[\frac{1}{K} \sum_k \max(0, 1 - D_k(G(x))) \right],$$

$$\mathcal{L}_f = E_{(x,y) \sim p_{data}} \left[\frac{1}{KL} \sum_{k,l} \|D_k^l(y) - D_k^l(G(x))\|_1 \right],$$

Proposed Solution: SDNet

Training Data Augmentation:

Data: $y \in \mathbb{Y}$

Result: The high-quality speech y and its downsampled version x

$x = s;$

type = random type (Chebyshev, Elliptic, Butterworth, Boxcar);

$f_{cut} \sim U(C_{low}, C_{high});$

$order \sim U(O_{low}, O_{high});$

$x = x * Filter(type, f_{cut}, order);$

if resample, **then**

$x = Resample(Resample(x, 16000, f_{cut} \times 2), f_{cut} \times 2, 16000);$

end if

We use a filter with random parameters when doing downsampling, the types include *Chebyshev*, *Elliptic*, *Butterworth* and *Boxcar*, the order is a random integer from 2 to 10, the cutoff frequency is an integer from 2000 to 8000 Hz. SNR: [-5, 20] dB.

Datasets(noise & speech):

DNS Challenge dataset, Valentini-Botinhao dataset.



Handle uncertain low sampling rate inputs and artifacts.

TABLE I
TEST RESULTS OF NOISE-ROBUST BWE MODELS ON VALENTINI-BOTINHAO NOISY TEST SET DOWNSAMPLED TO 8 KHZ.

Method	PESQ-WB↑	STOI (%)↑	CSIG↑	CBAK↑	COVL↑	LSD↓
UEE [15]	2.23	93	2.27	2.39	2.17	2.72
MTL-MBE [8]	2.55	94	2.64	3.21	2.46	2.29
EP-WUN [9]	2.25	92	3.50	2.94	2.86	1.23
AFiLM + I-DTLN [4]	2.54	90	2.63	2.87	2.18	1.54
Ours	2.67	95	3.29	3.32	2.92	1.16

Experiment Results

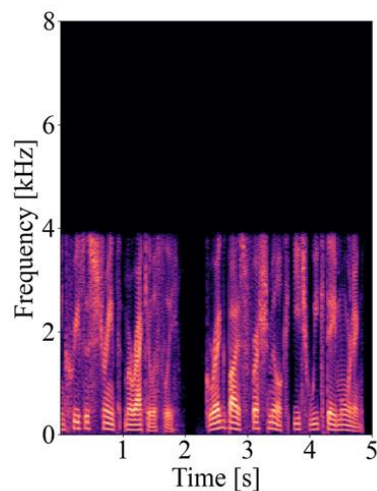
TABLE II

TEST RESULTS FOR DIFFERENT TASK ON DNS-CHALLENGE NO-REVERB TEST. “B” IS NOISE-FREE BWE, “D” IS DENOISE, AND “RB” IS NOISE-ROBUST BWE. “SOURCE” AND “NOISE” REPRESENT THE SAMPLING RATE OF INPUTS AND THE CASE WHETHER THE INPUTS CONTAIN NOISES.

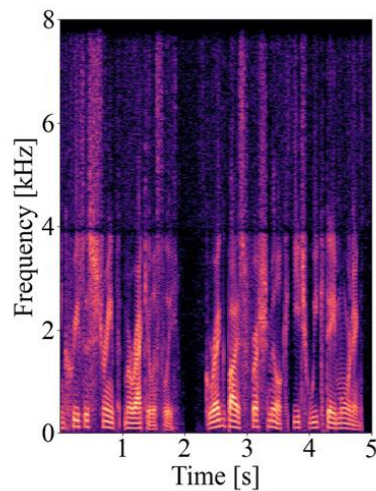
Method	Task	Source	Noise	PESQ-NB↑	PESQ-WB	STOI(%)	CSIG	CBAK	COVL	LSD	MOS↑
WSRGlow	B	8 kHz	✗	4.365	2.811	99.4	3.946	4.068	3.433	0.929	4.21
NU-Wave 2				4.353	2.646	99.4	3.663	2.869	3.209	1.328	4.08
AERO				4.369	3.295	98.5	4.287	4.273	3.844	0.802	4.27
Ours				4.377	3.661	98.6	4.103	4.553	3.935	0.783	4.55
DCCRN	D	16 kHz	✓	3.17	2.64	92.9	—	—	—	—	—
FullSubNet				3.28	2.72	95.3	—	—	—	—	—
DPT-FSNet				3.28	2.72	95.3	—	—	—	—	—
Ours				3.29	2.80	96.0	—	—	—	—	—
VoiceFixer	RB	8 kHz	✓	2.535	1.679	84.0	2.532	1.914	2.043	1.323	3.83
Ours				3.554	2.777	97.1	3.313	3.532	3.063	1.218	4.38
VoiceFixer	RB	4-16 kHz	✓	2.540	1.822	84.2	2.737	1.984	2.222	1.280	3.89
Ours				3.550	3.013	97.3	3.657	3.726	3.355	1.112	4.43

Experiment Results

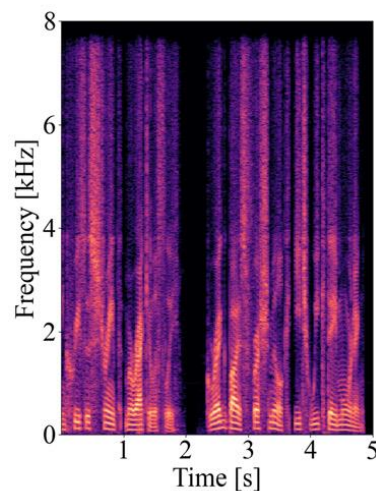
BWE:



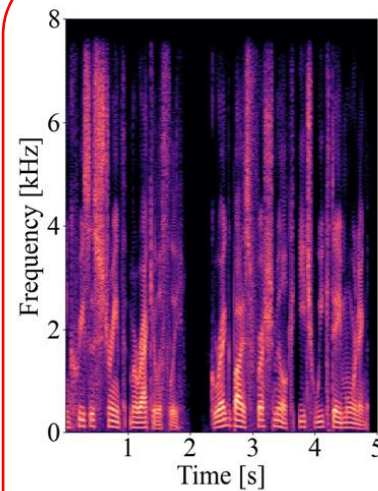
(a)



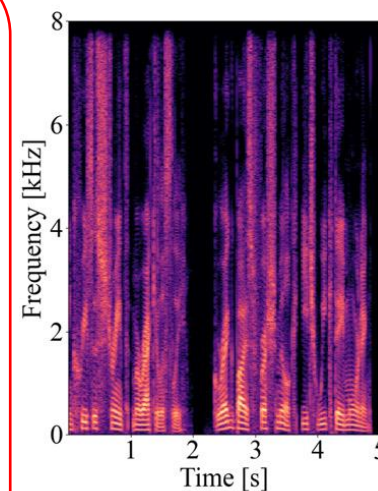
(b)



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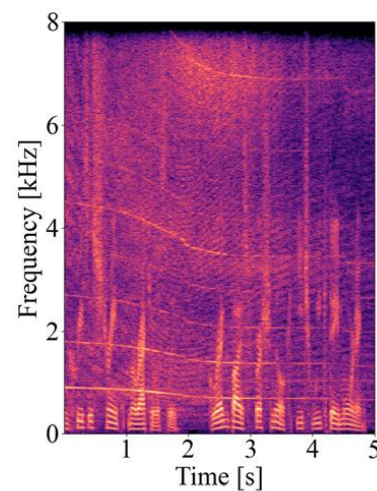


(d)

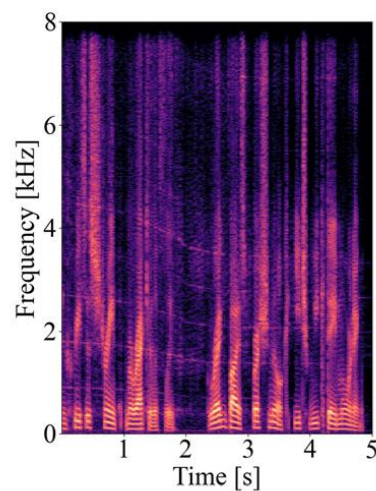


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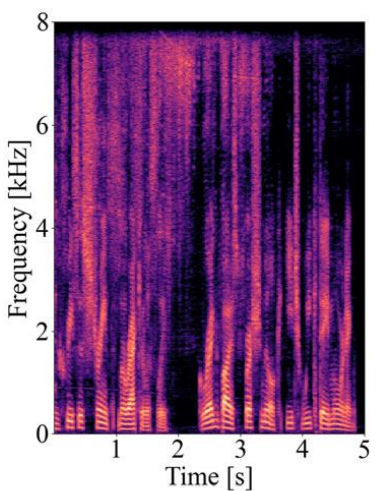
Denoise:



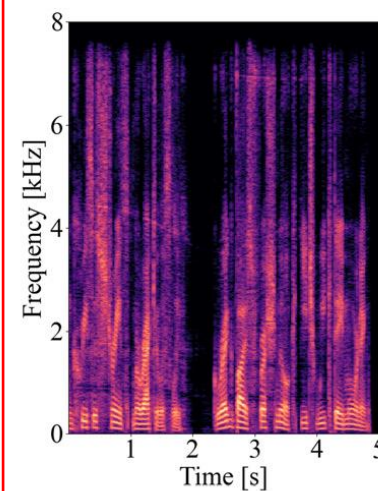
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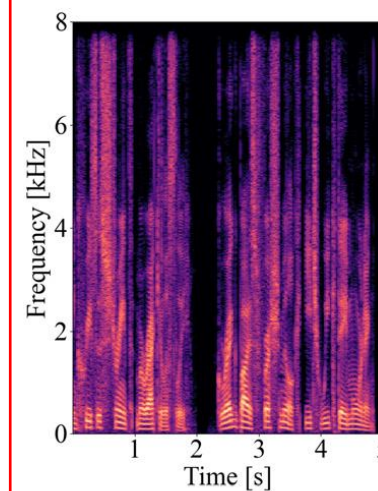
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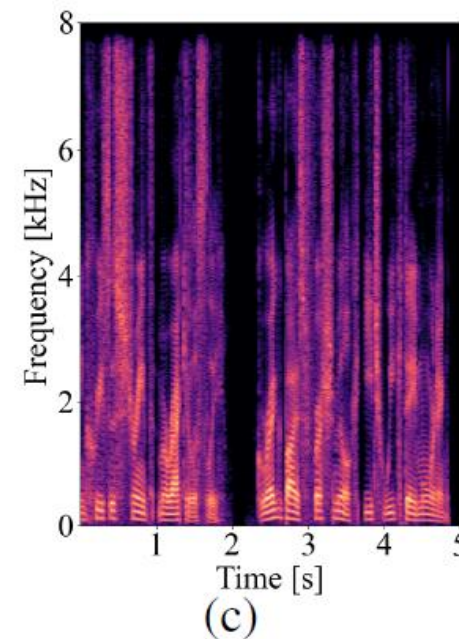
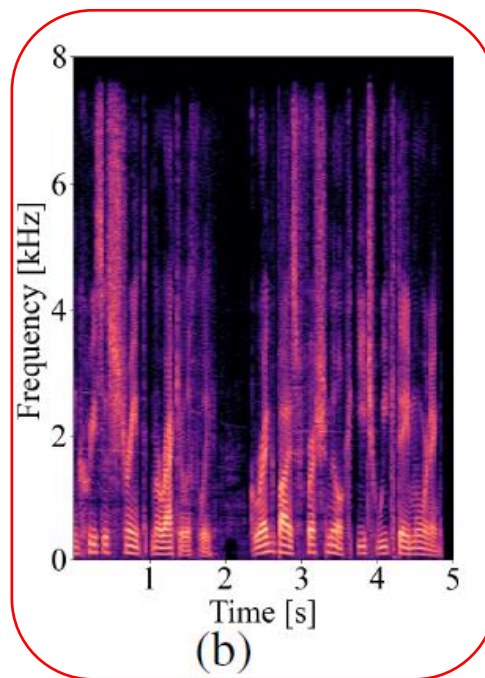
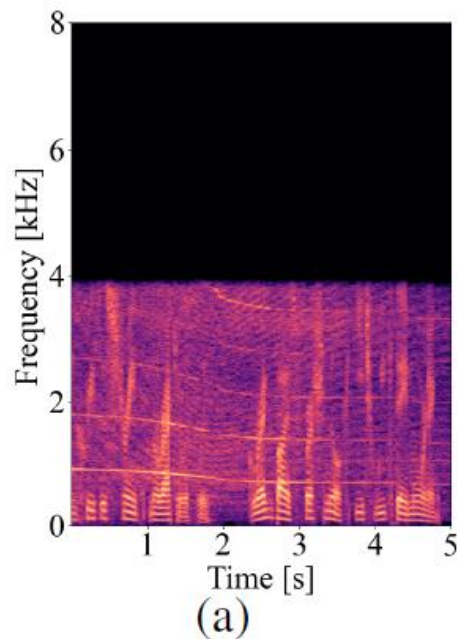
(d)



(e)

Experiment Results

Noise-Robust
BWE:



More samples in our demo page:



<https://sdnetdemo.github.io/>

Conclusions

SDNet Contributions:

- First noise-robust BWE supporting flexible sampling rates.
- Joint optimization for noise reduction and super-resolution.
- Superior performance across diverse scenarios.

Limitations:

- Challenges with higher resolution (e.g., 48 kHz).

Future Work:

- Extend to music datasets and higher resolutions.

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