Dense CNN with Self-Attention for Time-Domain Speech Enhancement

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Outline

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- Methodology
- Architecture
- Experiments
- Conclusion

Introduction

When the voice is polluted by background noise, not only the magnitude will be affected,but also the phase will also change, but the risk of adjusting the phase is extremely high,and it is very likely that the voice quality will become very bad.

Introduction

On the other hand, when processing signals in the time domain, the magnitude and phase can be changed together,and it is safer than processing the phase in the frequency domain.

Therefore, this paper proposes a time-domain speech enhancement model that combines Dense CNN and Self Attention,and uses a new loss function that simultaneously constrains speech and background sounds.

Methodology

U-Net

+

Dense Net

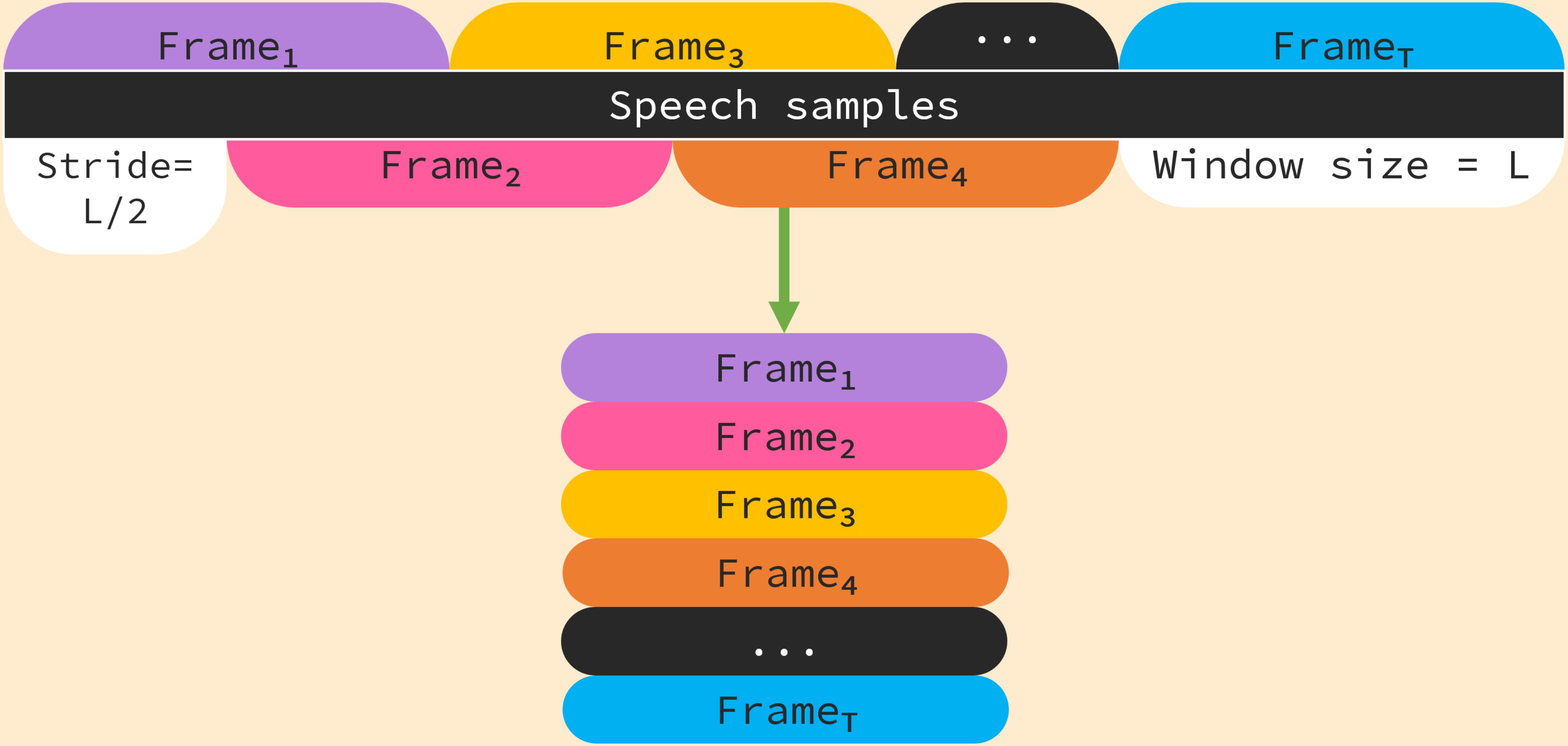
+

Sub-pixel Convolution

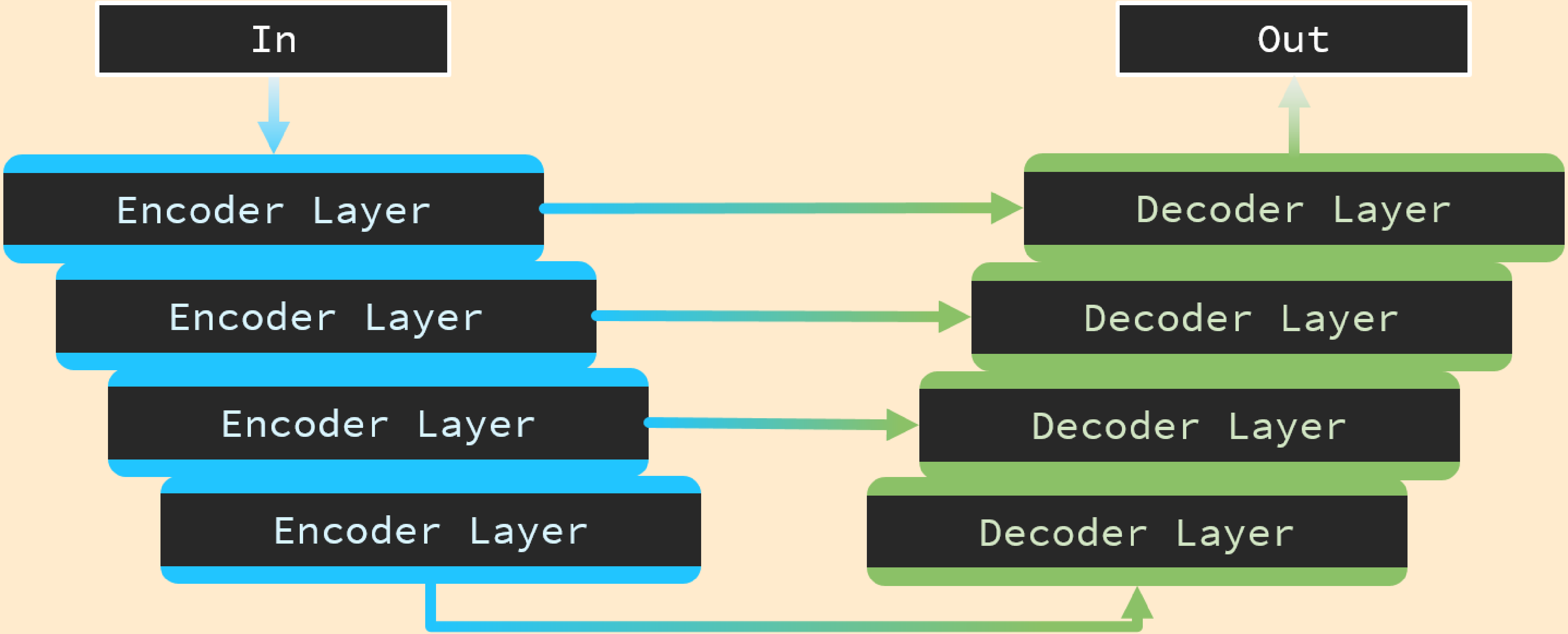
+

Self Attention

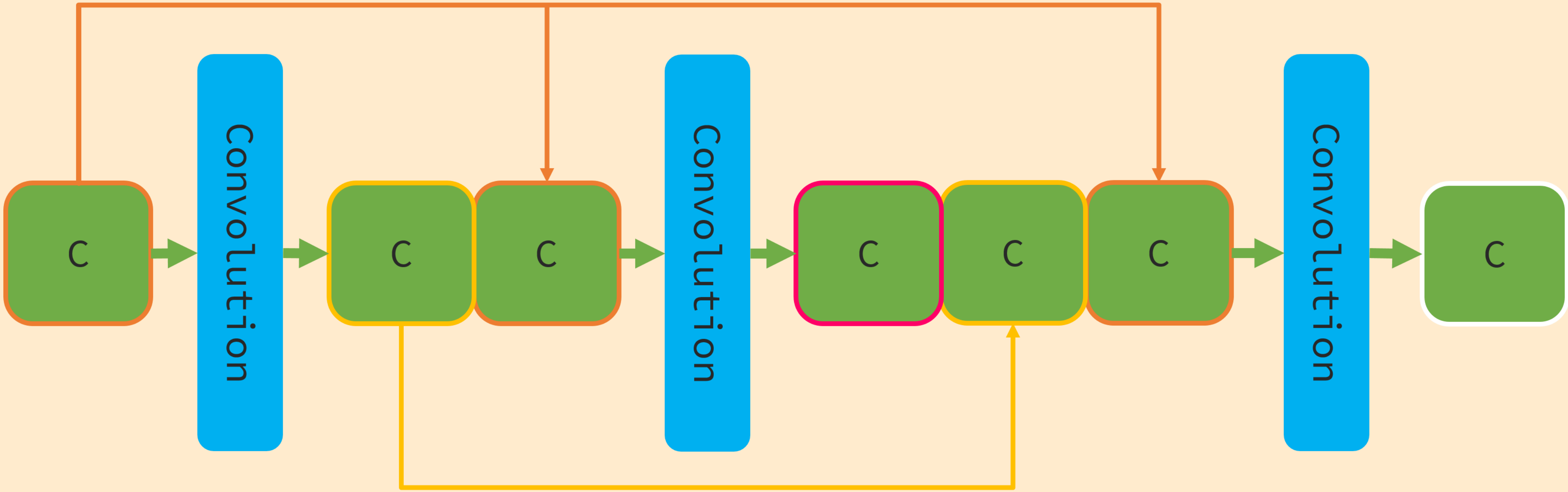
Input


$Frame_1$
$Frame_3$
...
$Frame_T$
Speech samples
Stride= L/2
$Frame_2$
$Frame_4$
Window size = L
$Frame_1$
$Frame_2$
$Frame_3$
$Frame_4$
...
$Frame_T$

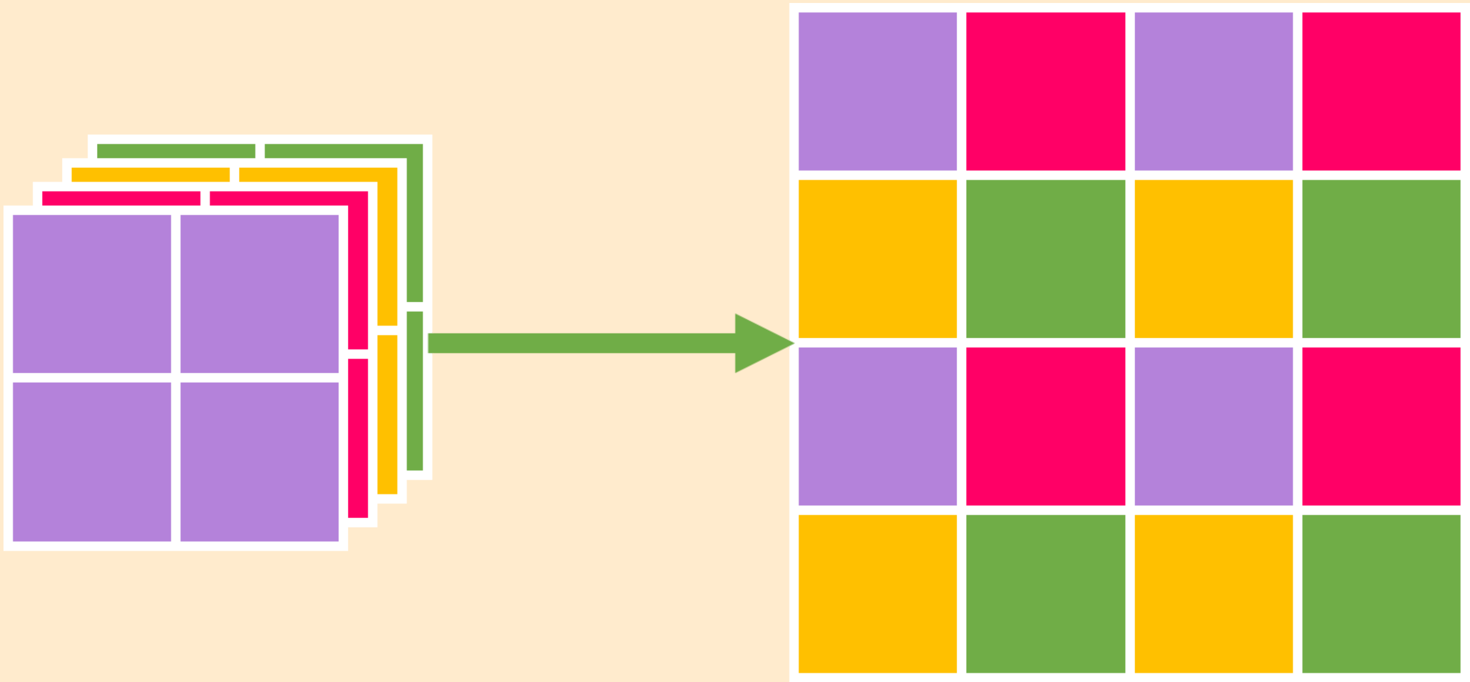
U-Net


In
Out
Encoder Layer
Encoder Layer
Encoder Layer
Encoder Layer
Decoder Layer
Decoder Layer
Decoder Layer
Decoder Layer

Dense Net



Sub-pixel Convolution



Self Attention

Causal : $\mathrm{Softmax}(\mathrm{Mask}(QK^T))V$

Non Causal : $\mathrm{Softmax}(QK^T)V$

Loss

- Time-Domain Loss

$$\mathcal{L}_T(s,\hat{s}) = MSE(s,\hat{s})$$

- STFT Magnitude Loss

$$\mathcal{L}_{SM}(s,\hat{s}) = MAE(mag(s), mag(\hat{s}))$$

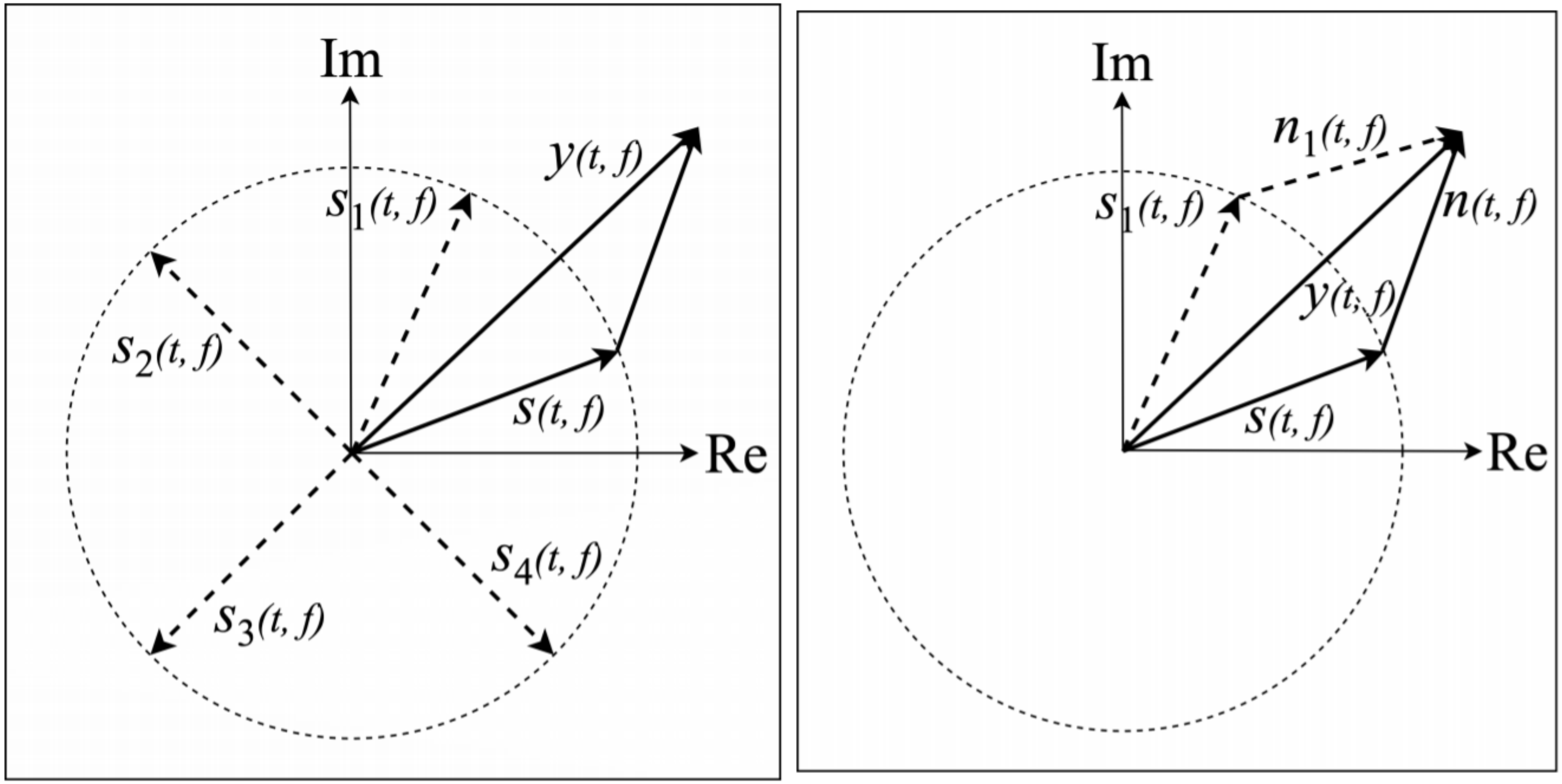
- Time-frequency Loss

$$\mathcal{L}_{TF}(s,\hat{s}) = \alpha\mathcal{L}_T + (1\text{-}\alpha)\,\mathcal{L}_{SM}$$

- Phase Constrained Magnitude Loss

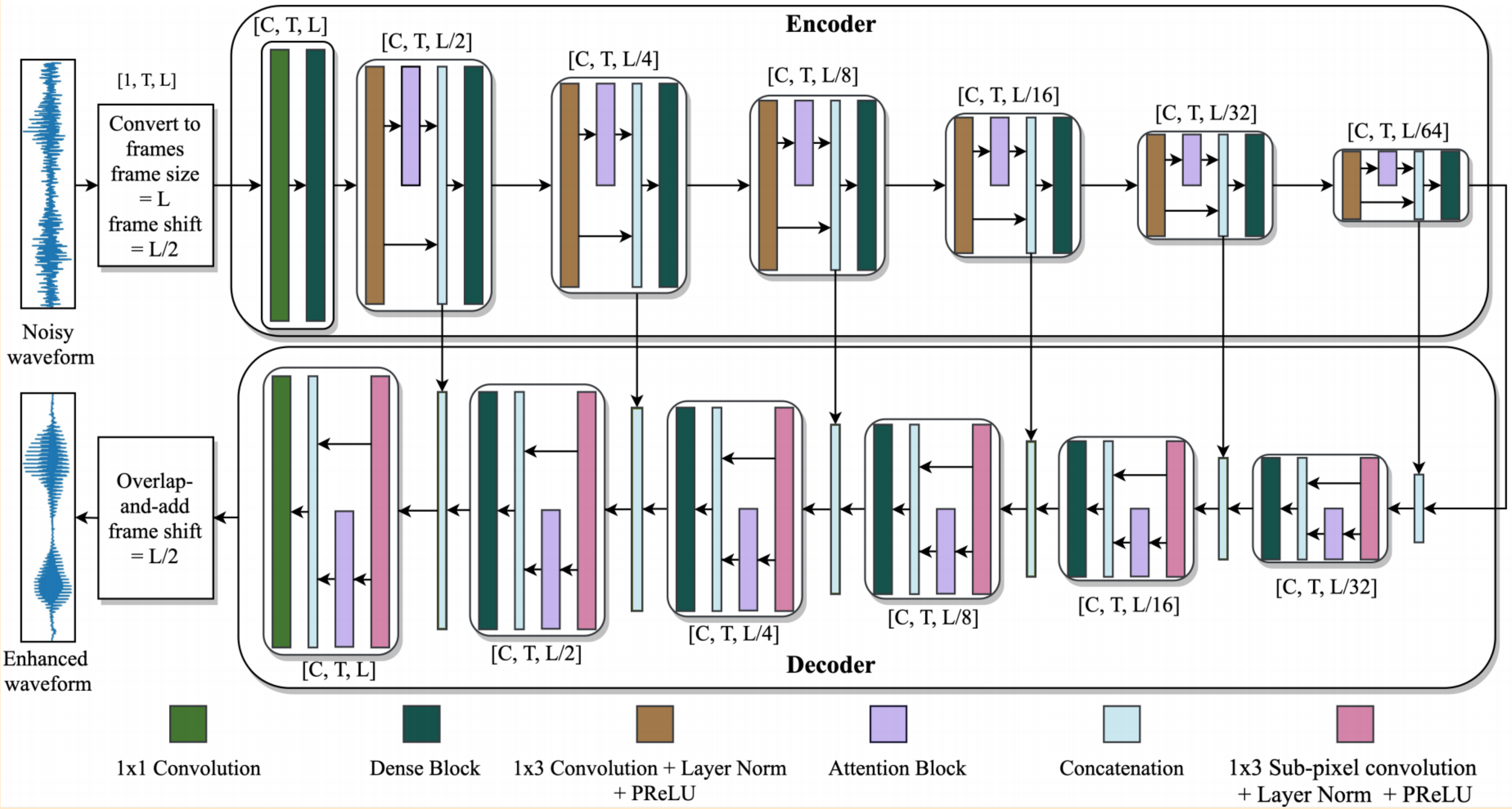
$$\mathcal{L}_{PCM}(s,\hat{s}) = 0.5\mathcal{L}_{SM}(s,\hat{s}) + 0.5\mathcal{L}_{SM}(n, x-\hat{s})$$

PCM Loss

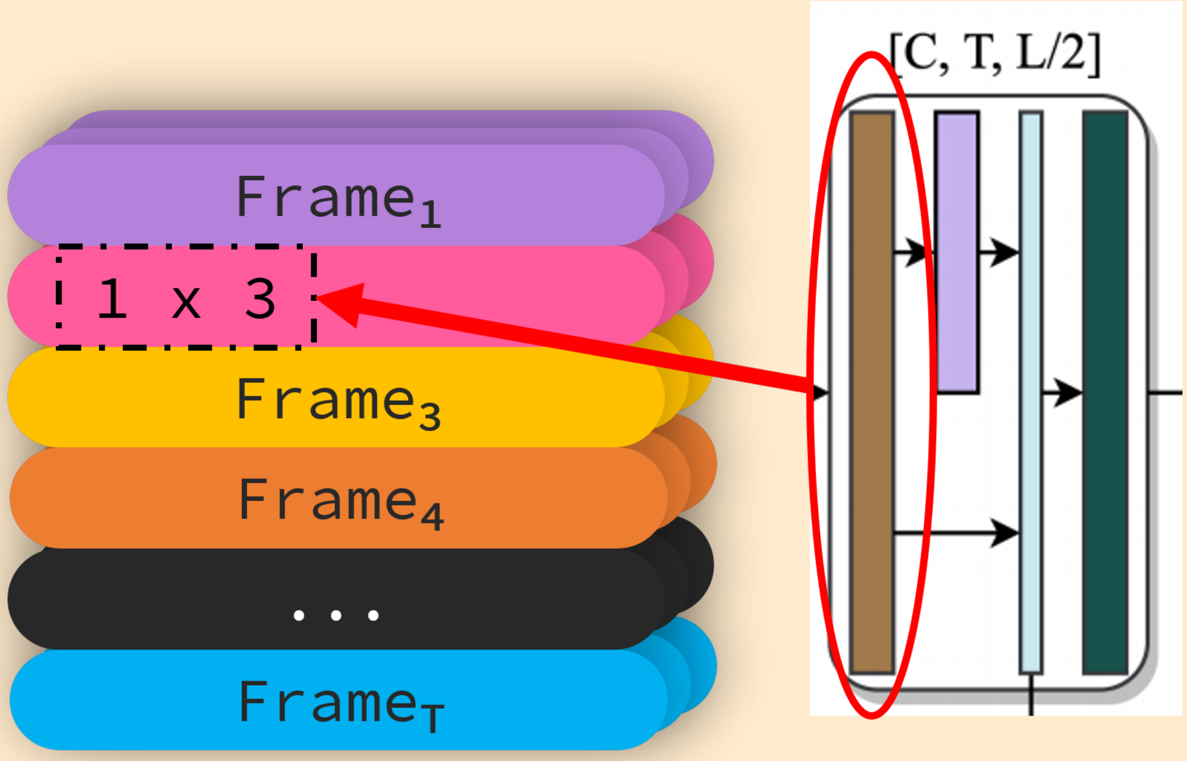


(a) L_{SM} (b) L_{PCM}

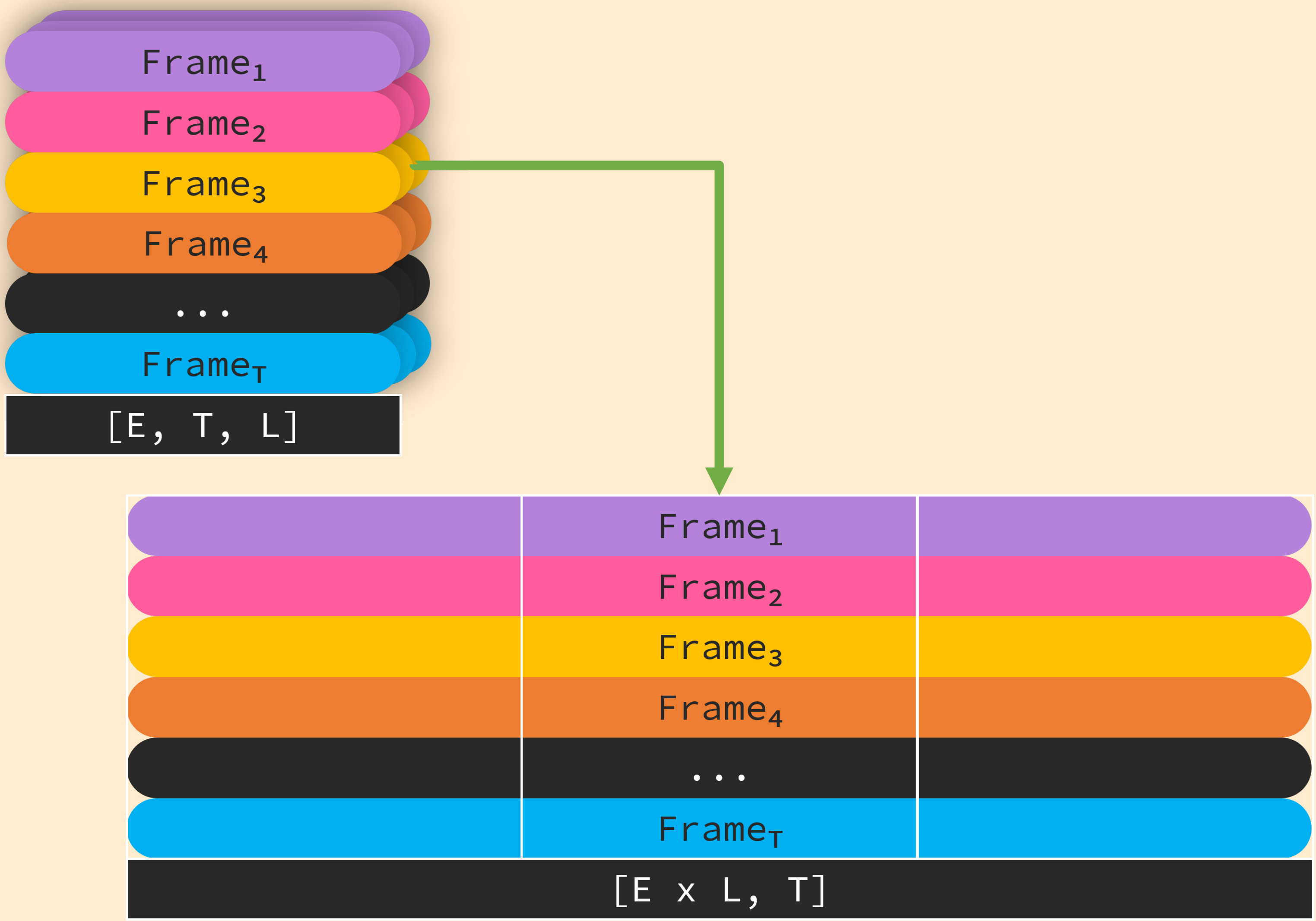
Architecture



1 x 3 Conv

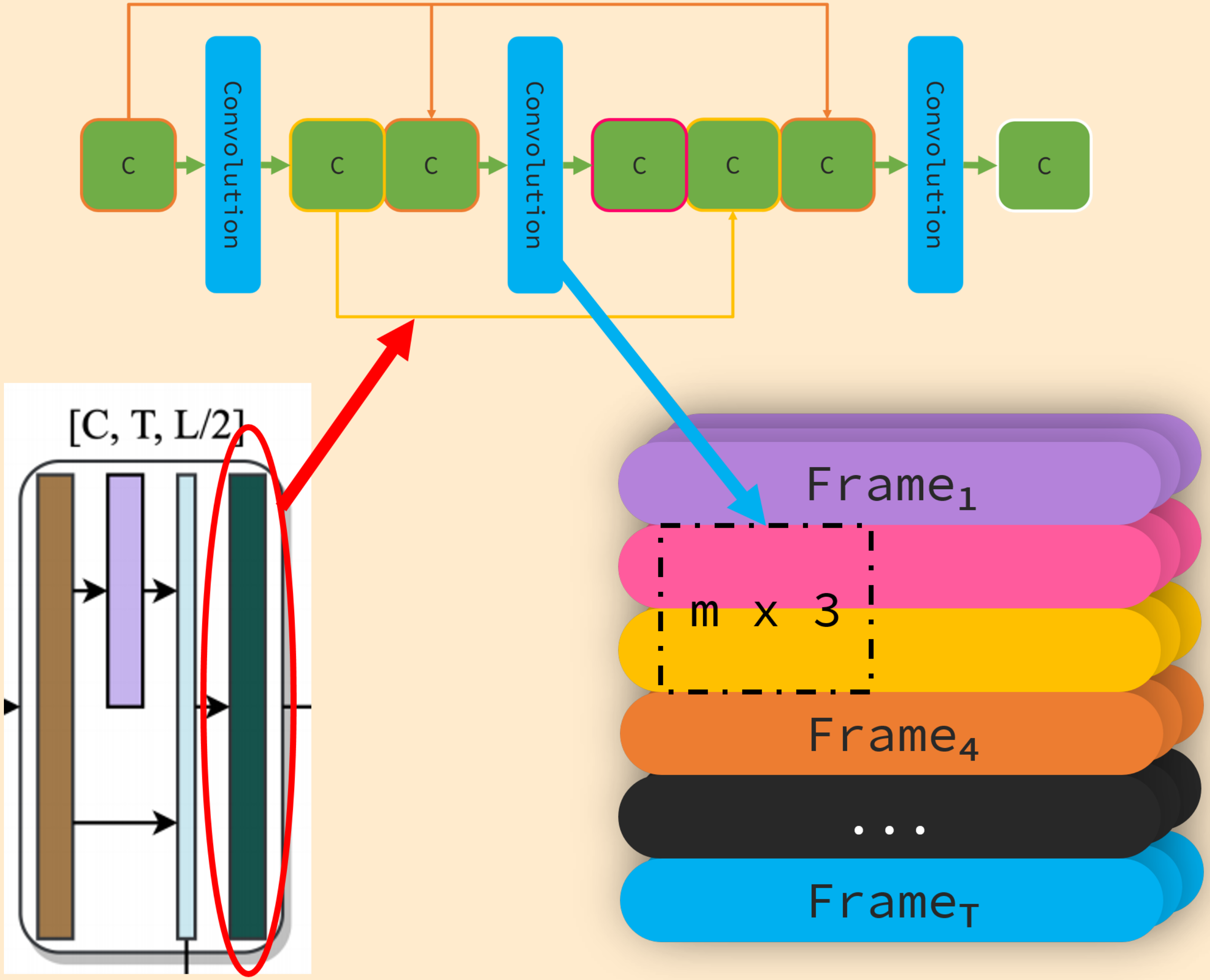


Self Attention Shape

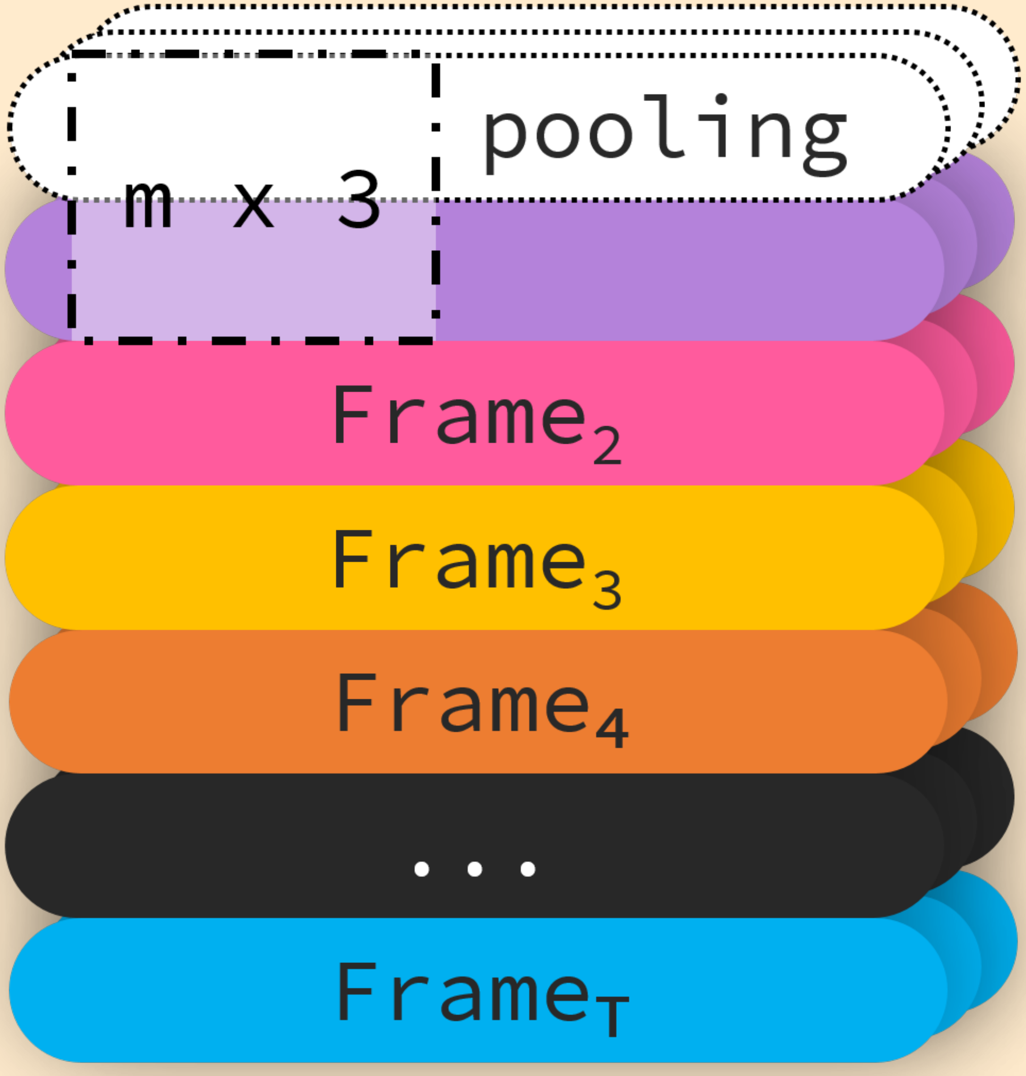


Self Attention Shape

Dense Net Conv



Causal



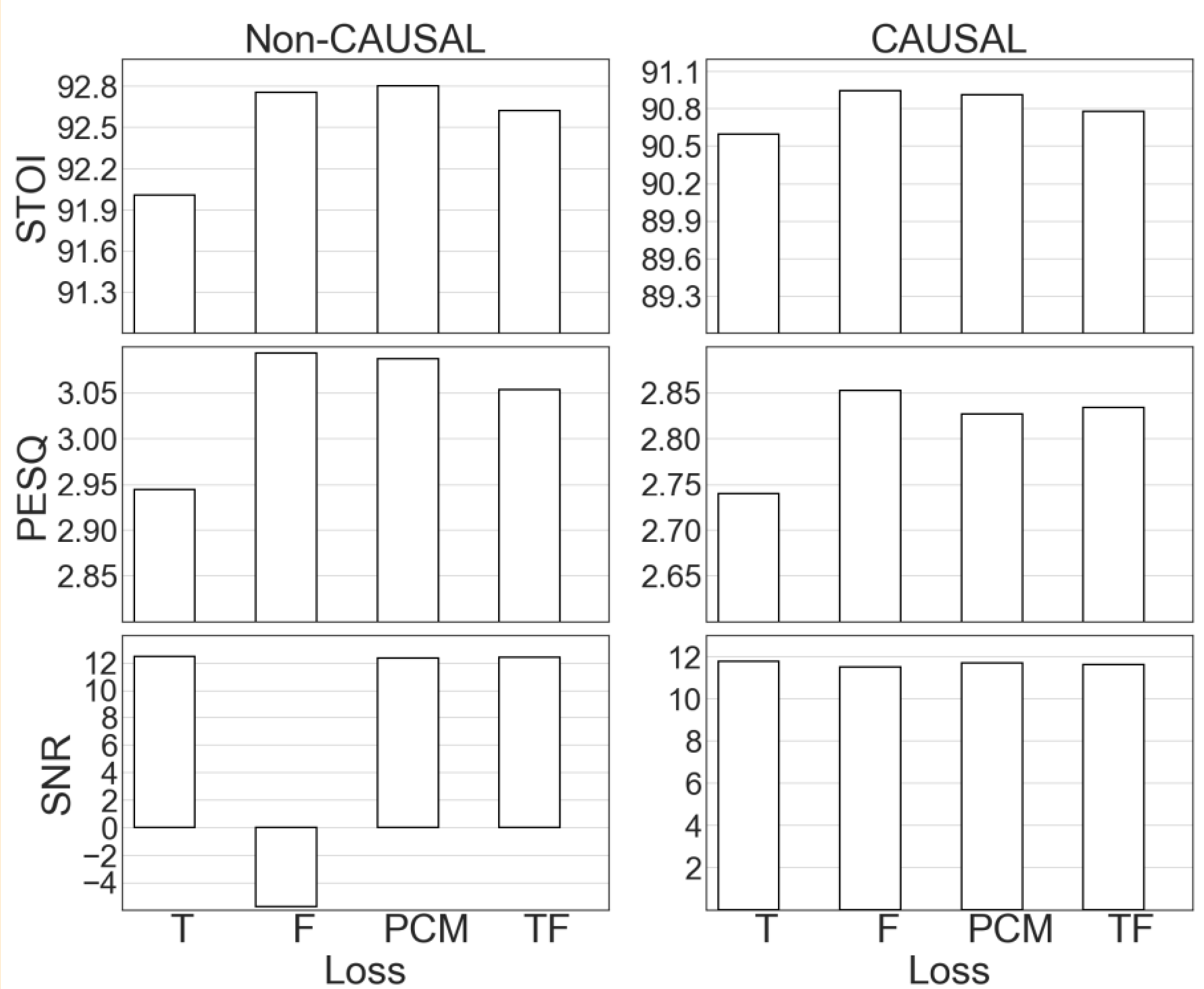
Experiments

- Sample rate：16kHz
- Hamming window
  - size：512
  - stride：256
- Optimizer：Adam

Data Set

- 語音：WSJ0 SI-84 dataset
- 訓練用噪音：10000 non-speech sounds from Sound Ideas
- 測試用噪音：babble and cafeteria noises from an Auditec CD

Experiments



Experiments

Metric				STOI							
Test noise				Babble				Cafeteria			
Test SNR (dB)				-5	0	5	Avg.	-5	0	5	Avg.
Mixture				58.4	70.5	81.3	70.1	57.1	69.7	81.0	69.2
Causal	1	✗	✗	76.7	88.0	93.2	86.0	76.4	87.8	92.9	85.7
	2	✗	✗	81.6	91.3	95.0	89.3	80.5	90.2	94.3	88.3
	2	✓	✗	83.5	91.9	95.2	90.2	81.4	90.5	94.5	88.8
	2	✓	✓	84.9	92.2	95.3	90.8	82.1	90.7	94.6	89.1
	2	✗	✓	**85.3**	**92.3**	**95.4**	**91.0**	**82.3**	**90.8**	**94.7**	**89.3**
	1	✗	✓	83.9	91.8	95.2	90.3	81.0	90.3	94.5	88.6
Non-causal	3	✗	✗	84.7	92.5	95.7	90.9	83.1	91.4	95.0	89.8
	3	✓	✗	86.6	92.9	95.7	91.7	84.1	91.7	95.0	90.3
	3	✓	✓	**87.9**	**93.5**	96.0	92.4	85.0	92.0	95.2	90.8
	3	✗	✓	**87.9**	**93.5**	**96.1**	**92.5**	**85.0**	**92.1**	**95.3**	**90.8**
	1	✗	✓	83.7	91.5	95.2	90.1	80.1	89.8	94.3	88.1
	m	Dil.	Att.								

Experiments

Metric				PESQ							
Test noise				Babble				Cafeteria			
Test SNR (dB)				-5	0	5	Avg.	-5	0	5	Avg.
Mixture				1.56	1.82	2.12	1.83	1.46	1.77	2.12	1.78
Causal	1	✗	✗	1.90	2.39	2.76	2.35	2.02	2.49	2.84	2.45
Causal	2	✗	✗	2.13	2.70	3.08	2.64	2.17	2.68	3.05	2.63
Causal	2	✓	✗	2.23	2.75	3.12	2.70	2.21	2.70	3.07	2.66
Causal	2	✓	✓	2.30	2.77	3.14	2.74	2.23	2.71	3.08	2.67
Causal	2	✗	✓	**2.34**	**2.81**	**3.17**	**2.77**	**2.24**	**2.72**	**3.09**	**2.68**
Causal	1	✗	✓	2.23	2.72	3.09	2.68	2.15	2.62	3.01	2.59
Non-causal	3	✗	✗	2.37	2.88	3.22	2.82	2.34	2.82	3.16	2.77
Non-causal	3	✓	✗	2.53	2.96	3.24	2.91	2.44	2.88	3.19	2.84
Non-causal	3	✓	✓	**2.61**	3.02	3.32	2.98	**2.47**	**2.91**	**3.24**	**2.87**
Non-causal	3	✗	✓	**2.61**	**3.04**	**3.33**	**2.99**	2.45	**2.91**	3.23	2.86
Non-causal	1	✗	✓	2.24	2.71	3.09	2.68	2.13	2.59	2.98	2.57
	m	Dil.	Att.								

Experiments

Metric				SNR							
Test noise				Babble				Cafeteria			
Test SNR (dB)				-5	0	5	Avg.	-5	0	5	Avg.
Mixture				-5.0	0.0	5.0	0	-5.0	0.0	5.0	0.0
Causal	1	✗	✗	5.5	9.9	13.4	9.6	6.5	10.4	13.4	10.1
Causal	2	✗	✗	7.4	11.5	14.7	11.2	7.7	11.4	14.4	11.2
Causal	2	✓	✗	7.7	11.8	15.0	11.5	7.9	11.5	14.5	11.3
Causal	2	✓	✓	8.2	12.0	**15.1**	11.8	**8.2**	**11.7**	**14.7**	**11.5**
Causal	2	✗	✓	**8.5**	**12.1**	**15.1**	**11.9**	**8.2**	**11.7**	**14.7**	**11.5**
Causal	1	✗	✓	7.9	11.8	15.0	11.6	7.9	11.5	14.5	11.3
Non-causal	3	✗	✗	8.2	12.2	15.2	11.9	8.3	11.8	14.7	11.6
Non-causal	3	✓	✗	9.1	12.5	15.3	12.3	8.7	12.0	14.8	11.8
Non-causal	3	✓	✓	**9.6**	**12.9**	15.7	12.7	**8.9**	12.2	15.0	12.0
Non-causal	3	✗	✓	**9.6**	**12.9**	**15.8**	**12.8**	**8.9**	**12.3**	**15.1**	**12.1**
Non-causal	1	✗	✓	8.3	12.0	15.2	11.8	7.8	11.4	14.6	11.3
	m	Dil.	Att.								

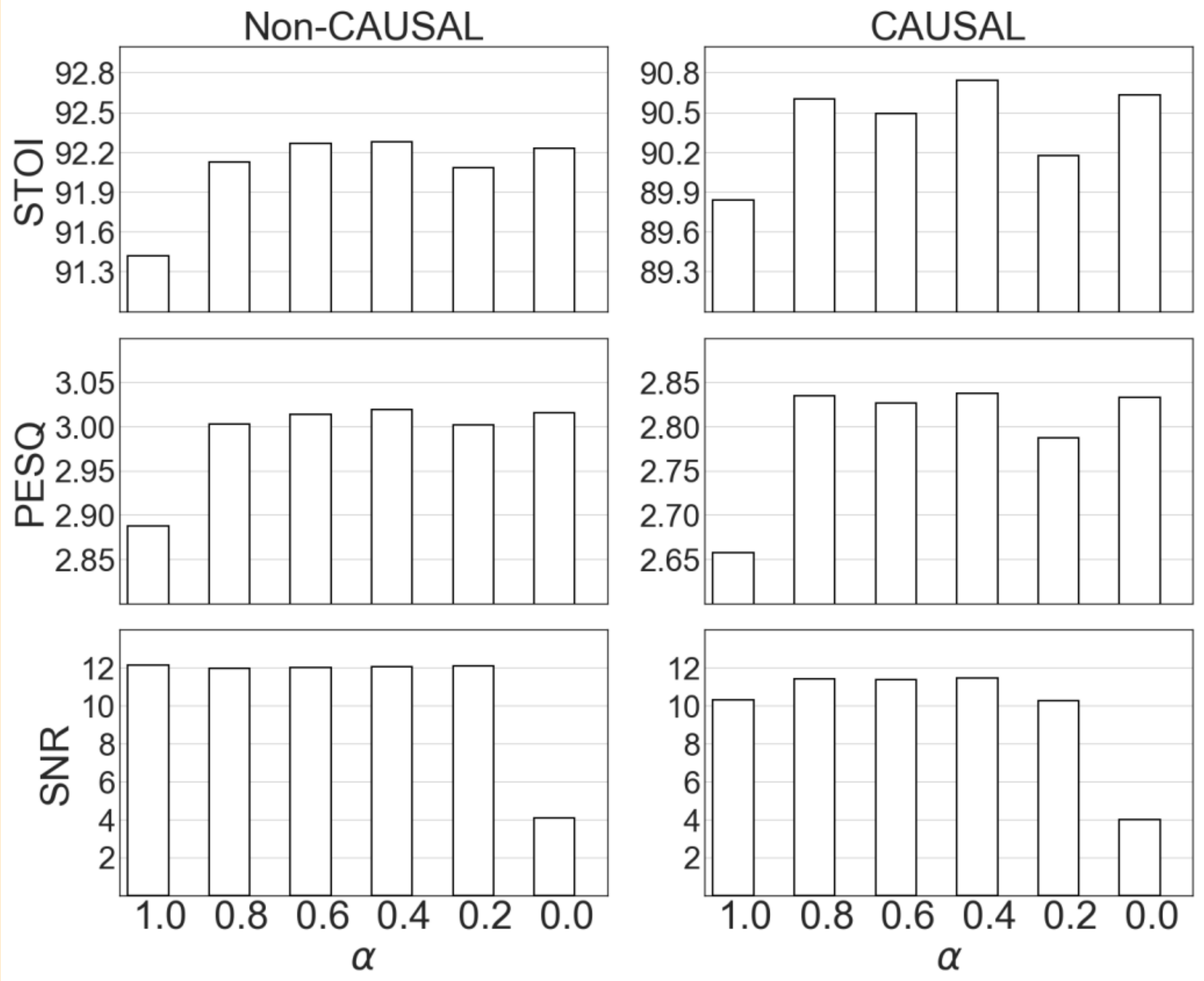
Experiments

Approach	Causal?	Real-time?	Metric	STOI							
			Test Noise	Babble				Cafeteria			
			Test SNR	-5 db	0 dB	5 dB	AVG	-5 dB	0 dB	5 dB	AVG
			Mixture	58.4	70.5	81.3	70.1	57.1	69.7	81.0	69.2
a)	✗	✗	BLSTM [12]	77.4	85.8	91.0	84.7	76.1	84.7	90.5	83.7
b)	✗	✗	GRN [13]	80.2	88.9	93.4	87.5	79.4	88.0	92.9	86.8
c)	✓	✓	GCRN [19]	82.4	90.9	94.8	89.4	79.1	89.3	94.0	87.5
	✗	✗	NC-GCRN [19]	87.0	93.0	95.6	91.9	84.1	91.7	95.1	90.3
d)	✓	✗	SEGAN-T [20]	81.5	90.3	94.1	88.6	79.8	89.5	93.5	87.6
	✓	✗	AECNN-SM [24]	82.6	91.5	95.1	89.7	81.1	90.7	94.5	88.8
	✓	✓	TCNN [25]	82.8	91.3	94.8	89.6	80.6	89.8	94.0	88.1
	✓	✓	DCN-T	**85.3**	92.3	95.4	91.0	82.3	90.8	94.7	89.3
	✓	✓	DCN-SM	85.2	**92.7**	**95.8**	**91.2**	**82.5**	**91.3**	**95.1**	**89.6**
	✓	✓	DCN-PCM	85.1	**92.7**	**95.8**	**91.2**	**82.5**	**91.3**	**95.1**	**89.6**
	✗	✗	NC-DCN-T	87.9	93.5	96.1	92.5	85.0	92.1	95.3	90.8
	✗	✗	NC-DCN-SM	**89.1**	94.2	96.5	**93.3**	**85.8**	92.9	95.8	**91.5**
	✗	✗	NC-DCN-PCM	89.0	**94.3**	**96.6**	**93.3**	85.6	**93.0**	**95.9**	**91.5**

Experiments

Approach	Causal?	Real-time?	Metric	PESQ							
			Test Noise	Babble				Cafeteria			
			Test SNR	-5 db	0 dB	5 dB	AVG	-5 dB	0 dB	5 dB	AVG
			Mixture	1.56	1.82	2.12	1.83	1.46	1.77	2.12	1.78
a)	×	×	BLSTM [12]	1.97	2.37	2.69	2.34	2.01	2.38	2.51	2.30
b)	×	×	GRN [13]	2.16	2.63	2.97	2.59	2.23	2.62	2.96	2.60
c)	✓	✓	GCRN [19]	2.17	2.70	3.07	2.65	2.10	2.60	2.99	2.56
	×	×	NC-GCRN [19]	2.53	2.96	3.25	2.91	2.40	2.85	3.17	2.81
d)	✓	×	SEGAN-T [20]	2.11	2.62	2.97	2.57	2.15	2.61	2.94	2.57
	✓	×	AECNN-SM [24]	2.21	2.80	3.17	2.73	2.23	2.76	3.12	2.70
	✓	✓	TCNN [25]	2.18	2.70	3.06	2.65	2.14	2.62	2.98	2.58
	✓	✓	DCN-T	2.34	2.81	3.17	2.77	2.24	2.72	3.09	2.68
	✓	✓	DCN-SM	**2.35**	**2.93**	**3.31**	**2.86**	**2.33**	**2.85**	**3.22**	**2.80**
	✓	✓	DCN-PCM	2.31	2.91	3.30	2.84	2.29	2.82	**3.22**	2.78
	×	×	NC-DCN-T	2.61	3.04	3.33	2.99	2.45	2.91	3.23	2.86
	×	×	NC-DCN-SM	**2.75**	**3.19**	3.46	**3.13**	**2.61**	**3.07**	3.37	**3.02**
	×	×	NC-DCN-PCM	2.71	3.18	**3.48**	3.12	2.56	3.07	**3.39**	3.01

Experiments



Demo

https://web.cse.ohio-state.edu/~wang.77/pnl/demo/PandeyDCN.html

Conclusion

- This paper proposes a time-domain-based DCN model with a time-frequency loss function to obtain good results in the task of speech enhancement.

- Although SM loss has good results in the evaluation indicators of STOI and PESQ, when judged by human ears, the effect of PCM loss is closer to clean speech.

Conclusion

- The author mentioned that DNN-based speech enhancement methods are not easy to generalize to speech that has not been learned.
- Time domain loss can help improve SNR, and frequency domain loss can improve scores on STOI and PESQ.