



NANYANG
TECHNOLOGICAL
UNIVERSITY

NTU-NPU System for Voice Privacy 2024 Challenge

Nikita Kuzmin, Hieu-Thi Luong, Jixun Yao, Lei Xie, Kong Aik Lee, Eng-Siong Chng

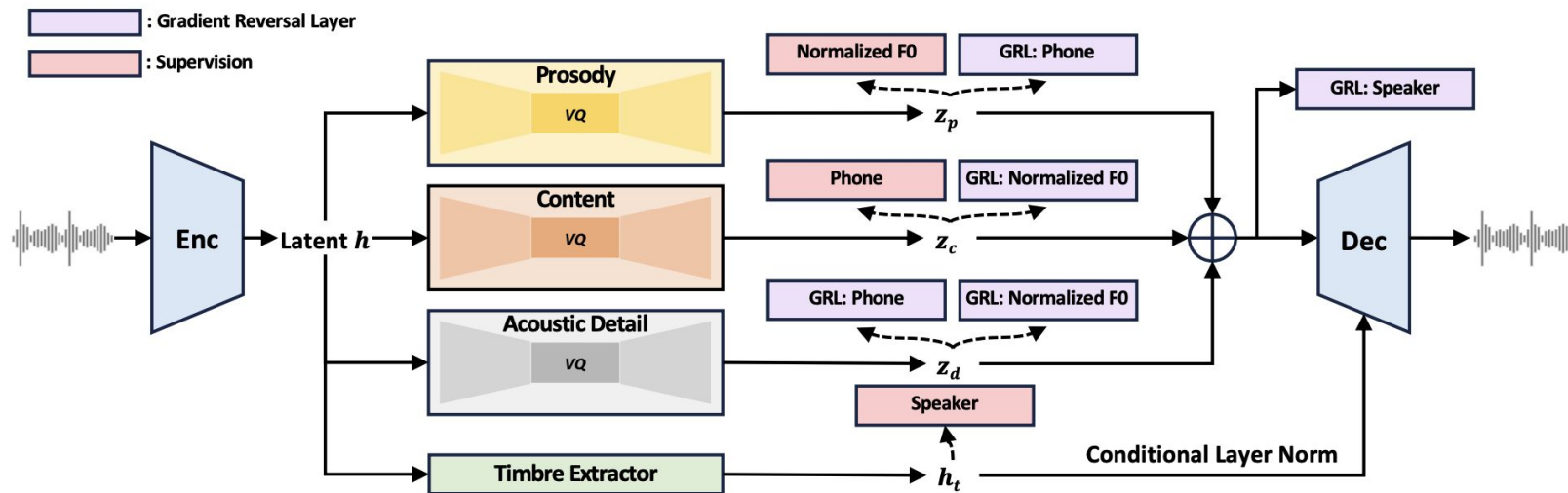


Motivation

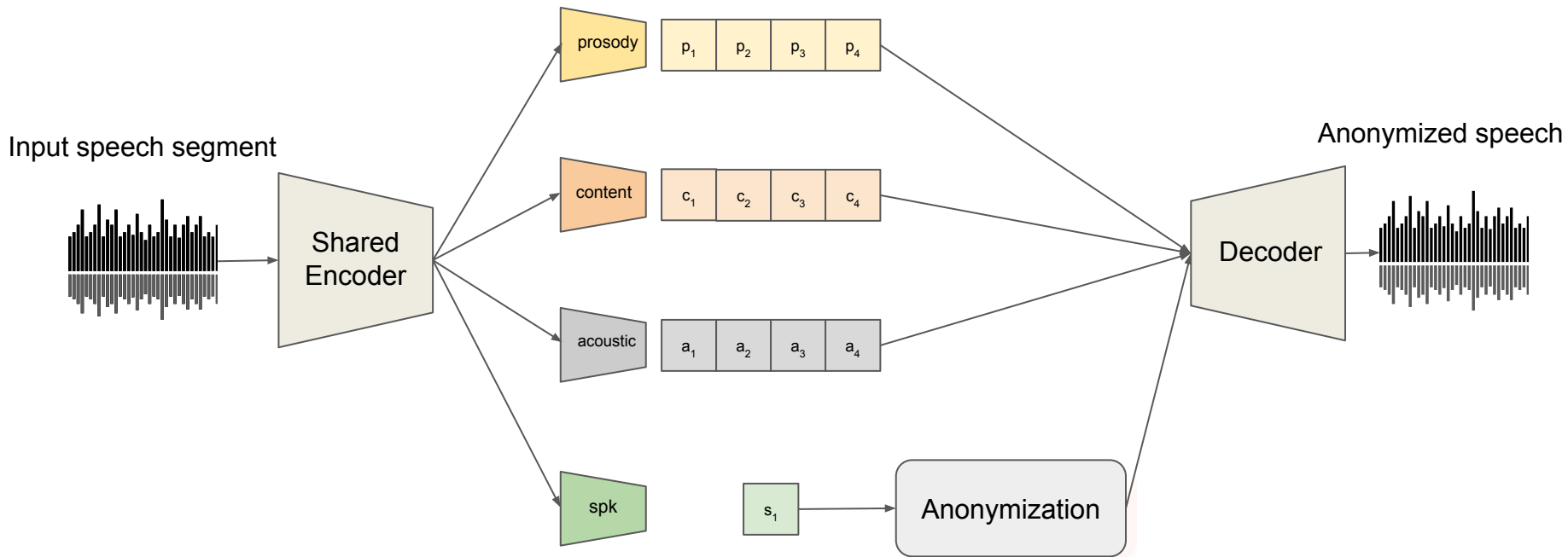
1. Analysis of baseline systems and push baseline performance for privacy and utility metrics.
2. Baseline models are lacking of Emotion recognition performance.
3. Interest in disentanglement-based models such as NaturalSpeech3 FACodec.

NaturalSpeech3 FACodec [1]

NaturalSpeech3 FAcodec [1]



NaturalSpeech3 FACodec [1]



NaturalSpeech3 FACodec [1]

#	Module	Description	Output features	Data
1	Encoder [2]	4 Downsampling Convolution-based Layers with Snake activation function Input: speech waveform	Output vector ²⁵⁶	Librilight train[3]
2	Prosody extractor	Factorized Vector Quantization with 1 quantizer, codebook size: 1024	Prosody vector ²⁵⁶	Librilight train
3	Content extractor	Factorized Vector Quantization with 2 quantizers, codebook size: 1024	Content vector ²⁵⁶	Librilight train
4	Speaker embedding extractor	Several Conformer blocks	Speaker embedding ²⁵⁶	Librilight train
5	Speaker anonymization module	Averaged 100 embeddings randomly selected from a pool of 200 farthest embeddings from source by cosine scoring AWGN with scale= 0.075 Cross-gender	Anonymized speaker embedding ²⁵⁶	LibriTTS: [4] train-clean-100
6	Decoder [2]	Upsampling Convolution-based Layers with Snake activation function	speech waveform	Librilight train

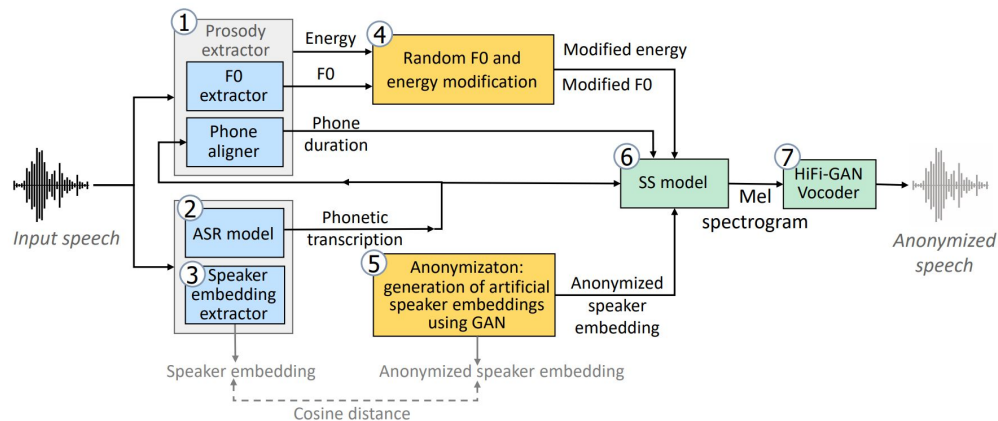
Experiments. NS3 + AWGN to Speaker Embedding + Cross Gender

Speaker Anon	AWGN	Cross Gender	EER		UAR		WER	
			dev	test	dev	test	dev	test
—	—	—	7.40	6.25	63.36	62.46	2.69	2.51
+	—	—	9.29	8.78	51.64	52.89	2.97	2.77
+	+	—	12.25	9.14	48.00	48.09	4.66	4.63
+	+	+	12.09	10.46	49.20	49.12	4.97	4.60

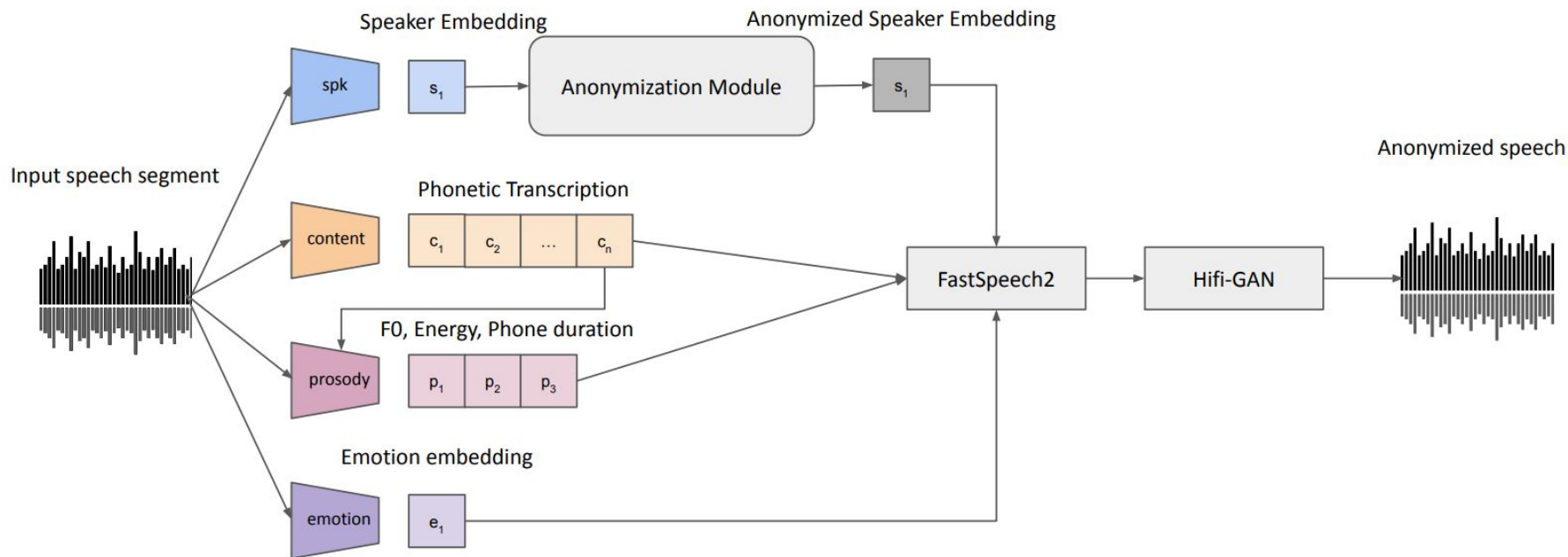
Baseline B3 [5]

Baseline B3

#	Module	Description	Output features	Data
1	Prosody extractor	Phone aligner: 6-layer CNN + LSTM with CTC loss F0 estimation using Praat F0, energy, durations normalized by each vector's mean	$F0^1$, energy ¹ phone durations ¹	LibriTTS: train-clean-100
2	ASR	End-to-end with hybrid CTC-attention Input: log mel Fbank ⁸⁰ Encoder: Branchformer Decoder: Transformer Output: phone sequences CTC and attention criteria	phonetic transcript with pauses and punctuation	LibriTTS: train-clean-100 train-other-500
3	Speaker embedding extractor	GST trained jointly with SS model Input: mel spectrogram ⁸⁰ 6 hidden layers + 4-head attention Output: GST speaker embedding ¹²⁸	GST speaker embedding ¹²⁸	LibriTTS: train-clean-100
4	Prosody modification module	Value-wise multiplication of F0 and energy with random values in [0.6, 1.4)	$F0^1$, energy ¹	-
5	Speaker anonymization module	Wasserstein GAN Input: Random noise ¹⁶ from normal distribution Generator: ResNet with three residual blocks, 150k params Critic: ResNet with three residual blocks, 150k params Output: MSE and Quadratic Transport Cost criteria	pseudo- speaker GST embeddings ¹²⁸	LibriTTS: train-clean-100 RAVDESS ESD
6	SS model	<i>IMS Toucan</i> implementation of <i>FastSpeech2</i> Input: $F0^1$ + energy ¹ + phone duration ¹ + phonetic transcript + GST embeddings ¹²⁸ Training criterion defined in <i>FastSpeech2</i>	mel spectrogram ⁸⁰	LibriTTS: train-clean-100
7	Vocoder	HiFi-GAN vocoder Input: mel spectrogram ⁸⁰ Training criterion defined in HiFi-GAN	speech waveform	LibriTTS: train-clean-100



Modified B3



Modified B3

#	Module	Description	Output features	Data
1	Prosody extractor	Phone aligner: 6-layer CNN + LSTM with CTC loss F0 estimation using Praat F0, energy, durations normalized by each vector's mean	$F0^1$, energy ¹ phone durations ¹	LibriTTS: train-clean-100
2	ASR	End-to-end with hybrid CTC-attention Input: log mel Fbank ⁸⁰ Encoder: Branchformer Decoder: Transformer CTC and attention criteria	phonetic transcript with pauses and punctuation	LibriTTS: train-clean-100 train-other-500
3	Speaker embedding extractor	GST, trained jointly with SS model Input: mel spectrogram ⁸⁰ 6 hidden layers + 4-head attention	GST speaker embedding ¹²⁸	LibriTTS: train-clean-100
4	Emotion embedding extractor	1b, 2a: Dimensional Speech Emotion Recognition Model based on Wav2vec 2.0 Input: Wav2vec 2.0 Large features	emotion embedding ¹⁰²⁴	MSP-Podcast (v1.7)
		2b: –	–	–
5	Prosody modification module	1b, 2b: – 2a: Value-wise multiplication of F0 and energy with random values in [0.7, 1.3]	– $F0^1$, energy ¹	– LibriTTS: train-clean-100
6	Speaker anonymization module	1b: Averaged 100 embeddings randomly selected from a pool of 200 farthest embeddings from source by cosine scoring + cross-gender 2a, 2b: Random Speaker selection per each source utterance + cross-gender	Anonymized speaker embedding ¹²⁸	LibriTTS: train-clean-100
7	SS model	IMS Toucan implementation of FastSpeech2 Input: $F0^1$ + energy ¹ + phone durations ¹ + phonetic transcript + GST embeddings ¹²⁸ (1b, 2a: + emotion embeddings ¹⁰²⁴) Training criterion defined in FastSpeech2	mel spectrogram ⁸⁰	LibriTTS: train-clean-100
8	Vocoder	HiFi-GAN vocoder Input: mel spectrogram ⁸⁰ Training criterion defined in HiFi-GAN	speech waveform	LibriTTS: train-clean-100

Experiments. B3 + Emotion embedding

Speaker Anonymization	Speaker Embedder	Prosody Anonymization	Emotion Embedding	EER		UAR		WER	
				dev	test	dev	test	dev	test
–	–	–	–	5.72	4.59	69.08	71.06	1.80	1.85
+	GST	+	–	25.76	28.42	37.97	37.39	4.33	4.33
+	GST	+	+	22.59	24.09	42.52	41.74	4.39	4.40

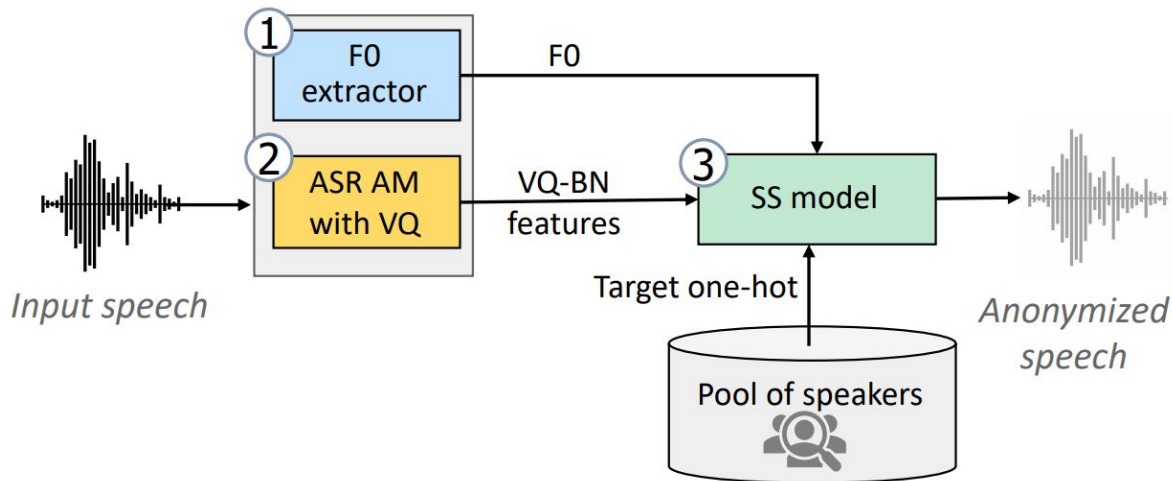
Experiments. B3 + Prosody Modification

Multiplier Range	EER		UAR		WER	
	dev	test	dev	test	dev	test
[0.6, 1.4]	25.76	28.42	37.97	37.39	4.33	4.33
[0.7, 1.3]	23.93	25.62	37.49	37.59	4.07	4.05
[0.8, 1.2]	22.70	25.92	38.01	37.96	3.89	3.91
[0.9, 1.1]	19.88	22.62	39.03	37.17	3.80	3.77
—	19.47	21.82	38.91	38.11	3.70	3.75

Baseline B5 [5]

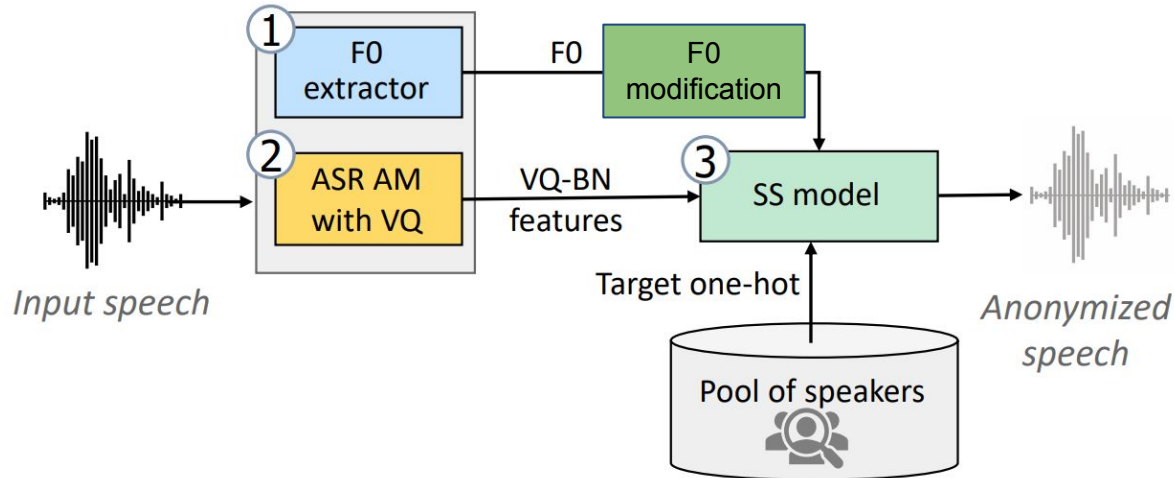
Baseline B5

#	Module	Description	Output features	Data
1	F0 extractor	F0 extracted with s pytorch implementation of YAAPT	F0	N/A
2	ASR AM with VQ	Acoustic Model trained to identify left bi-phones and a VQ bottleneck layer	Linguistic representation	VoxPopuli Librispeech: train-clean-100
3	Speaker embedding	One-hot vector represented speaker in training set	Speaker embedding	LibriTTS: train-clean-100
4	Speech Synthesis	HiFi-GAN vocoder Input: F0 + linguistic representation + speaker embedding	Speech waveform	LibriTTS: train-clean-100



Modifications of B5

#	Module	Description	Output features	Data
1	F0 extractor	F0 extracted with s pytorch implementation of YAAPT 3: Using Mean Reversion F0 ($\alpha = 0.75$) in inference 4: Using Mean Reversion F0 ($\alpha = 0.75$) and 10-db AWGN	F0	N/A
2	ASR AM with VQ	Acoustic Model trained to identify left bi-phones and a VQ bottleneck layer	Linguistic representation	VoxPopuli Librispeech: train-clean-100
3	Speaker embedding	One-hot vector represented speaker in training set	Speaker embedding	LibriTTS: train-clean-100
4	Speech Synthesis	HiFi-GAN vocoder Input: F0 + linguistic representation + speaker embedding	Speech waveform	LibriTTS: train-clean-100



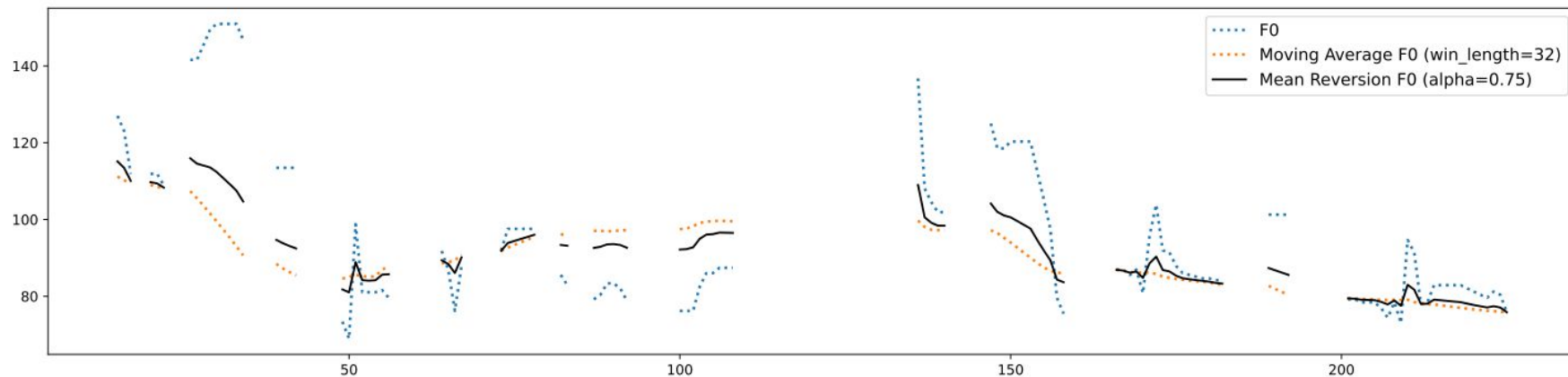
Mean Reversion of F_0

F_0 – original prosody

$\bar{F}_0$ – n-frame moving
average (n=32)

$$\hat{F}_0 = (1 - \alpha)F_0 + \alpha\bar{F}_0$$

Experiments. B5 + Mean Reversion F0

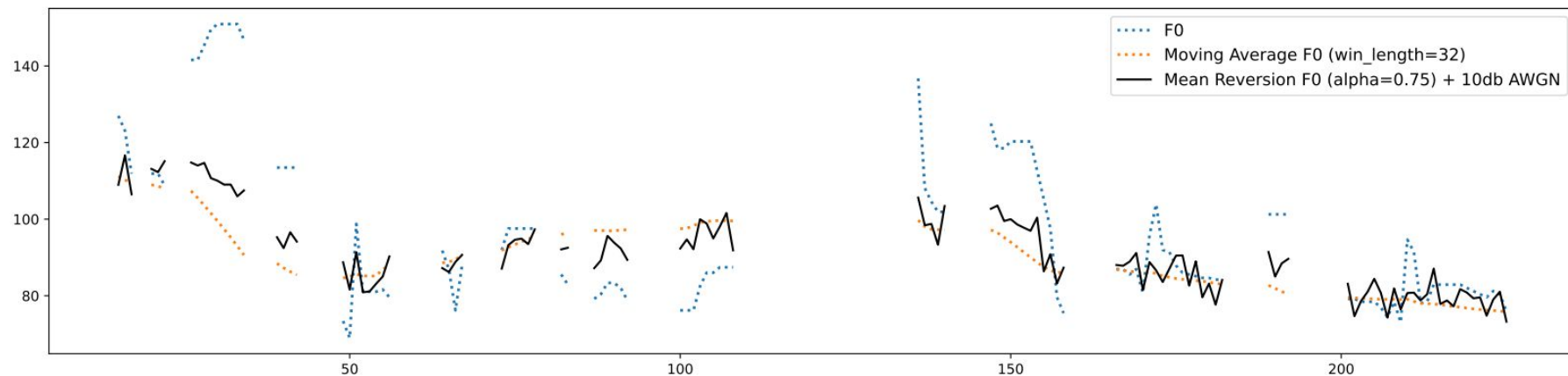


(a) Mean Reversion F0

Experiments. B5 + Mean Reversion F0

α	EER		UAR		WER	
	dev	test	dev	test	dev	test
0.00	31.64	31.36	39.18	38.24	4.79	4.44
0.25	32.13	32.03	39.61	38.38	4.74	4.54
0.50	33.48	34.08	38.60	37.34	4.62	4.54
0.75	38.56	37.48	38.06	37.60	4.70	4.47
1.00	37.91	37.93	38.50	38.78	4.79	4.43

Experiments. B5 + Mean Reversion F0 + AWGN



Experiments. B5 + Mean Reversion F0 + AWGN

dB	EER		UAR		WER	
	dev	test	dev	test	dev	test
0	38.56	37.48	38.06	37.60	4.70	4.47
5	39.58	40.00	38.91	37.12	4.67	4.49
10	42.46	43.15	39.41	38.47	4.63	4.40
15	42.97	40.36	38.50	37.49	4.66	4.50
30	41.43	39.62	38.41	37.88	4.77	4.64

Conclusion

Conclusion

Condition	Model	EER (avg-dev)	EER (avg-test)	UAR (dev)	UAR (test)	WER (dev)	WER (test)
—	Orig.	5.72	4.59	69.08	71.06	1.80	1.85
>20% EER	B3	28.43	22.04	37.57	38.09	4.29	4.35
>30% EER	B4	32.71	30.26	41.97	42.78	6.15	5.90
>30% EER	B5	34.37	34.34	38.08	38.17	4.73	4.37
>30% EER	B6	23.05	21.14	36.39	36.13	9.69	9.09
>10% EER	1a (NS3)	12.09	10.46	49.20	49.12	4.97	4.60
>10% EER	1b (B3)	16.88	17.45	42.76	43.21	3.81	3.83
>20% EER	2a (B3)	21.47	24.13	44.67	42.78	4.21	4.29
>20% EER	2b (B3)	20.07	22.85	39.18	37.67	3.61	3.68

Conclusion

Condition	Model	EER (avg-dev)	EER (avg-test)	UAR (dev)	UAR (test)	WER (dev)	WER (test)
—	Orig.	5.72	4.59	69.08	71.06	1.80	1.85
>20% EER	B3	28.43	22.04	37.57	38.09	4.29	4.35
>30% EER	B4	32.71	30.26	41.97	42.78	6.15	5.90
>30% EER	B5	34.37	34.34	38.08	38.17	4.73	4.37
>30% EER	B6	23.05	21.14	36.39	36.13	9.69	9.09
>30% EER	3 (B5)	38.56	37.48	38.06	37.60	4.70	4.47
>40% EER	4 (B5)	42.46	43.15	39.41	38.47	4.63	4.40

Key Takeaways

1. NaturalSpeech3 FACodec:
 - Promising results for ER and ASR
 - But there may be leakage of speaker identity in other branches (content/acoustic)
2. Emotion Embeddings:
 - Helps to improve ER performance
 - But leads to speaker identity leakage
3. Cross-Gender anonymization:
 - Improves privacy protection and ER metrics
 - But reduces ASR performance
4. Mean-reversion of F_0 and AWGN:
 - Improves privacy protection while keeping ASR and ER
 -

Thank you

References

- [1] Z. Ju, Y. Wang, K. Shen, X. Tan, D. Xin, D. Yang, Y. Liu, Y. Leng, K. Song, S. Tang, Z. Wu, T. Qin, X.-Y. Li, W. Ye, S. Zhang, J. Bian, L. He, J. Li, and S. Zhao, “Naturalspeech 3: Zero-shot speech synthesis with factorized codec and diffusion models,” ArXiv, vol. abs/2403.03100, 2024.
- [2] R. Kumar, P. Seetharaman, A. Luebs, I. Kumar, and K. Kumar, “High-fidelity audio compression with improved rvqgan,” Advances in Neural Information Processing Systems, vol. 36, 2024.
- [3] J. Kahn, M. Rivi`ere, W. Zheng, E. Kharitonov, Q. Xu, P.-E. Mazar`e, J. Karadayi, V. Liptchinsky, R. Collobert, C. Fuegen, T. Likhomanenko, G. Synnaeve, A. Joulin, A. Mohamed, and E. Dupoux, “Libri-Light: A Benchmark for ASR with Limited or No Supervision,” arXiv e-prints, p. arXiv:1912.07875, Dec. 2019
- [4] H. Zen, V. Dang, R. Clark, Y. Zhang, R. J. Weiss, Y. Jia, Z. Chen, and Y. Wu, “LibriTTS: A corpus derived from LibriSpeech for text-to-speech,” in Interspeech, 2019, pp. 1526–1530.
- [5] <https://www.voiceprivacychallenge.org/>