

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

Vevo: Controllable Zero-Shot Voice Imitation with Self-Supervised Disentanglement



Xueyao Zhang, Xiaohui Zhang, Kainan Peng, Zhenyu Tang, Vimal Manohar, Yingru Liu, Jeff Hwang, Dangna Li, Yuhao Wang, Julian Chan, Yuan Huang, Zhizheng Wu, Mingbo Ma

The Chinese University of Hong Kong, Shenzhen

Meta AI

Motivation: To design a unified, controllable, and zero-shot voice imitation system

Task	Source	Reference	Target	Related Areas
Zero-Shot Timbre Imitation			 Content Style Timbre	Voice Conversion
Zero-Shot Style Imitation	 Content Style Timbre	 Content Style Timbre	 Content Style Timbre	Accent Conversion, Emotion Conversion
Zero-Shot Voice Imitation	 TEXT Content		 Content Style Timbre	Voice Conversion Text to Speech

Question 1

How can we accomplish various zero-shot imitation tasks using a **unified framework**?

Question 2

How can we **minimize dependency on annotated data** to maximize the benefits of large-scale self-supervised learning?

Question 3

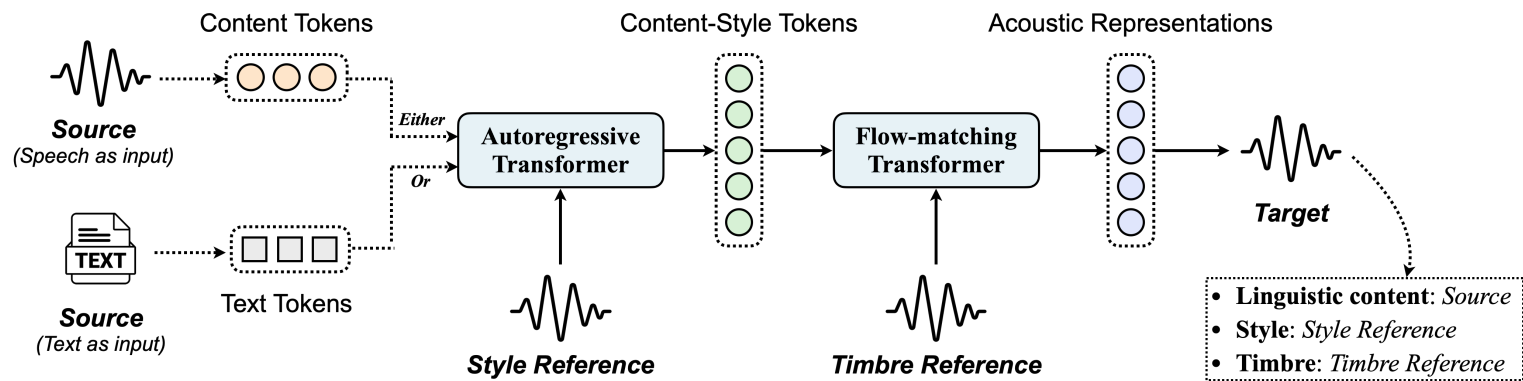
How can we **effectively decouple timbre, style, and content** to achieve controllable generation?

Content What to speak?

Style How to speak?

Timbre Who speaks?

Vevo: A Versatile Zero-Shot Voice Imitation Framework with Controllable Timbre and Style

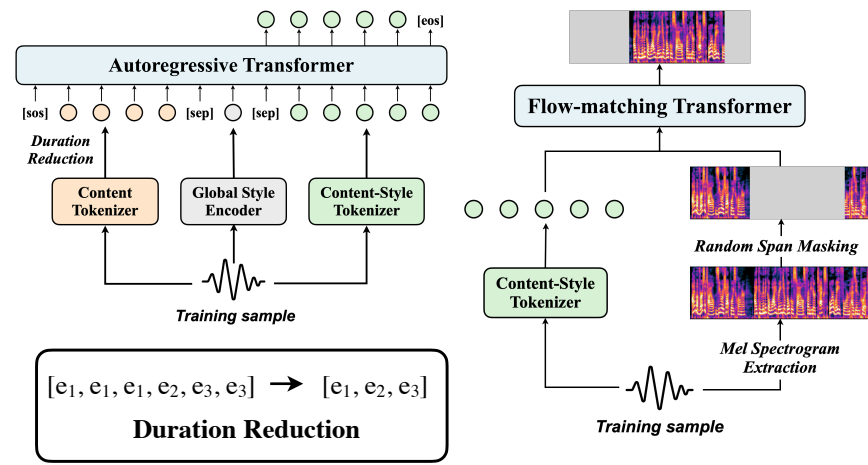


Given a source speech (U_i) or text (T_i), and a reference speech (U_r):

Model	Source	Style Reference	Timbre Reference
Vevo-Timbre	U_i	/	U_r
Vevo-Style	U_i	U_r	U_i
Vevo-Voice	U_i	U_r	U_r
Vevo-TTS	T_i	U_r	U_r

KEY POINT: Codebook size as the disentanglement bottleneck

Representations	#Vocab	WER (↓)	S-SIM (to ref) (↑)	S-SIM (to src) (↓)	FPC (to src) (↑)	Analysis
Ground Truth	-	5.526	0.762	0.087	1.000	-
24th layer features	-	5.706	0.266	0.400	0.768	Pros: Intelligibility, Style consistency Cons: Timbre imitation
18th layer features	-	5.324	0.250	0.505 ↑	0.824	
12th layer features	-	5.348	0.200	0.626 ↑	0.805	
PPG features	-	6.143	0.449	0.157	0.741	Pros: Intelligibility, Timbre imitation Cons: Style consistency
ASR tokens	29	7.836	0.463	0.125	0.698	
K-means tokens	1024	11.493	0.398	0.150	0.734	Worse than VQ-VAE tokens (1024)
Content-style Tokens	16384	6.807	0.398	0.306	0.826	As the vocabulary size decreases, Pros: Timbre imitation ↑ Cons: Intelligibility ↓ Style consistency ↓
	4096	6.908 ↑	0.403	0.236 ↓	0.797 ↓	
VQ-VAE tokens	1024	6.967 ↑	0.418	0.249	0.764 ↓	
	32	9.731 ↑	0.426	0.161 ↓	0.706 ↓	
Content Tokens	16	13.169 ↑	0.441	0.146 ↓	0.672 ↓	
	8	21.813 ↑	0.392	0.109 ↓	0.675	



60K hours of audiobook speech data

Content / Content-Style Tokenizer: VQ-VAE tokenizer (32 / 4096) on HuBERT, Fully Self-Supervised Learning (SSL)

Large-scale In-Context Learning (ICL)

Experiments and Results

Model	AR?	Training Data (ContRep / Model)	Natural ness	Prosody Similarity	Speaker Similarity	Accent Similarity	Emotion Similarity
HierSpeech++	×	500K / 2.8K	3.04	3.08	3.15	3.13	2.55
LM-VC	✓	1K / 60K	2.40	2.16	2.56	3.02	2.46
UniAudio	✓	1K / 100K	2.95	2.51	2.39	2.42	2.41
FACodec	×	60K / 60K	2.36	3.10	3.19	3.01	2.30
Vevo-Timbre	×	60K / 60K	3.43	3.45	3.46	3.55	2.66
Vevo-Voice	✓	60K / 60K	3.24	2.60	3.70	3.90	3.20

TAKE HOME MESSAGE

Large-scale Data

HuBERT (SSL)

VQ-VAE (SSL)

Autoregressive Transformer

(SSL, ICL)

Flow-matching Transformer

No Style-Specific Annotations

Self-Supervised Learning at Scale

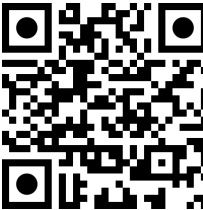
Versatile and Controllable Imitation

Model	Zero-Shot	Supervision			CMOS		
		Parallel Corpus	Style Labels	Text	Natural alnes	Accente dness	Emotive ness
VoiceShop	×	✓	✓	✓	0.00	0.00	-
Vevo-Style	✓	×	×	×	0.12	0.13	-
Emovox	×	×	✓	✓	0.00	0.00	-
Vevo-Style	✓	×	×	×	1.78	-	0.49

Model	AR?	Training Data	Natural ness	Speaker Similarity	Accent Similarity	Emotion Similarity
CosyVoice	✓	171K	-0.18	4.11	3.99	3.66
MaskGCT	×	100K	-0.04	4.16	4.38	3.76
VALL-E	✓	45K	-1.24	2.82	2.77	2.63
Voicebox	×	60K	-0.35	3.87	3.49	3.61
VoiceCraft	✓	9K	-0.50	3.47	3.29	3.52
Vevo-TTS	✓	60K	-0.14	4.05	4.12	4.03

More Information

Paper and Demo



Code and Checkpoint

