

ENHANCING MULTILINGUAL TTS WITH VOICE CONVERSION BASED DATA AUGMENTATION AND POSTERIOR EMBEDDING

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< Demo >

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Motivation

- Creating a multilingual, multi-speaker (MM) text-to-speech (TTS) system is challenging due to the difficulties in collecting polyglot data from multiple speakers.
- To address this issue, we utilize a voice conversion (VC)-based data augmentation method to train the MM-TTS model.
- However, simply including the augmented dataset with the recorded dataset can cause a quality degradation issue. In our case, we observed muffled sound issue in synthesized audio.
- Therefore, we use posterior embeddings (1) to capture the acoustic dissimilarity between the recorded and augmented datasets and (2) to utilize a posterior embedding derived from only the recorded data when synthesizing audio.

Voice Conversion for Data Augmentation

- **Model**
 - Many-to-many Scyclone model with pitch augmentation [1]
 - Each of monolingual training corpus is reproduced by adjusting pitch values in several semitone-levels to cover a variety of prosodies from multiple speaker and languages.
- **Dataset**
 - Monolingual internal dataset.
 - Korean, English, Japanese, with a single male and female speaker for each.
 - **Number of utterances per speaker:** 500 utterances
- **Process**
 - The original set of 500 sentences is augmented with voices from five other speakers, resulting in a total of 2,500 augmented data. This augmentation process is repeated for each speaker in the dataset.
 - **Outcome:** Through this augmentation, each speaker's original dataset is expanded by a factor of six (3,000), enhancing the diversity and volume of data available for model training.

Posterior encoder

- We train the **posterior encoder** [3] to focus on capturing the distributions of recorded and augmented data by providing it with explicit speaker and language information.
- During inference, the encoder selectively retrieves posterior embeddings from the entire recorded dataset within the training set, averaging these to obtain the final posterior embedding.
- As illustrated in the Figure1, data clusters in the latent space are distinguishable based on their origin from either recorded or augmented data.

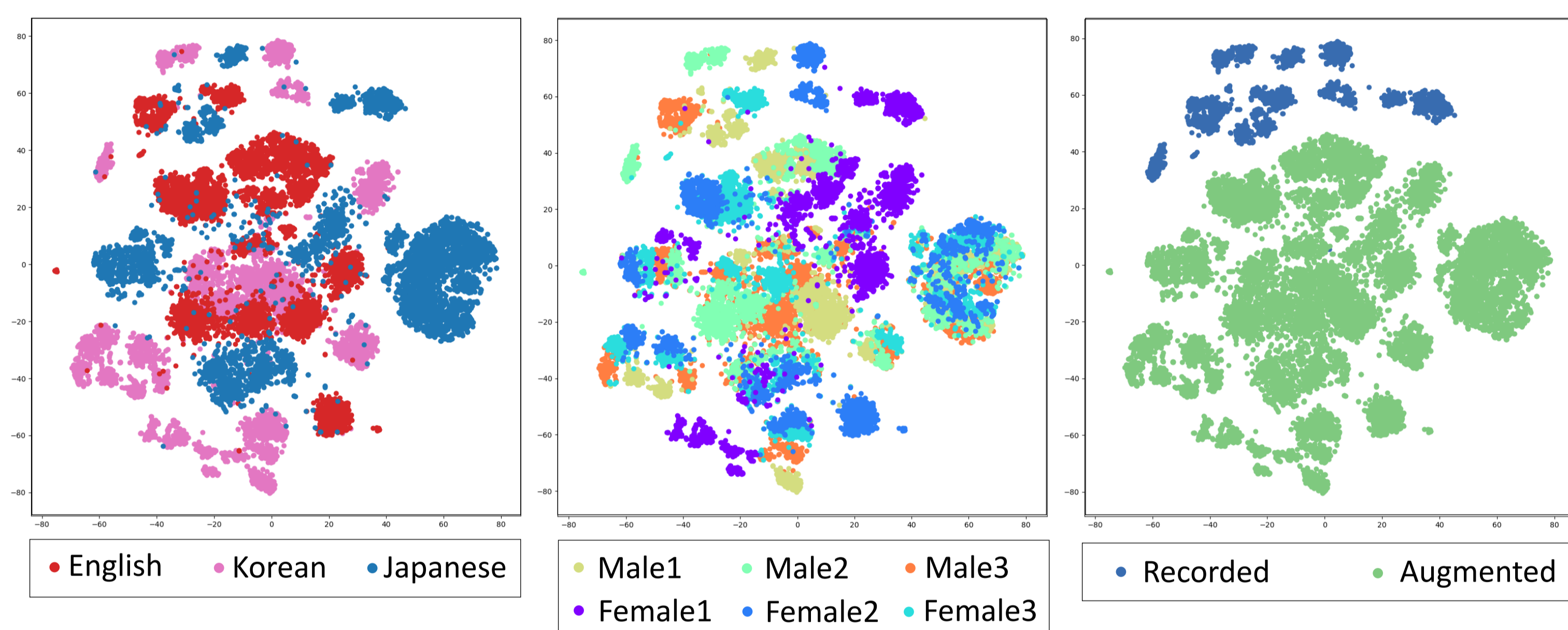


Figure1: t-SNE plots

Text-to-speech model

- The system includes a **context encoder**, a **duration predictor**, an **autoregressive decoder**, and a **PWG vocoder** [4], complemented by a **speaker and language look-up table** as well as a **posterior encoder**.

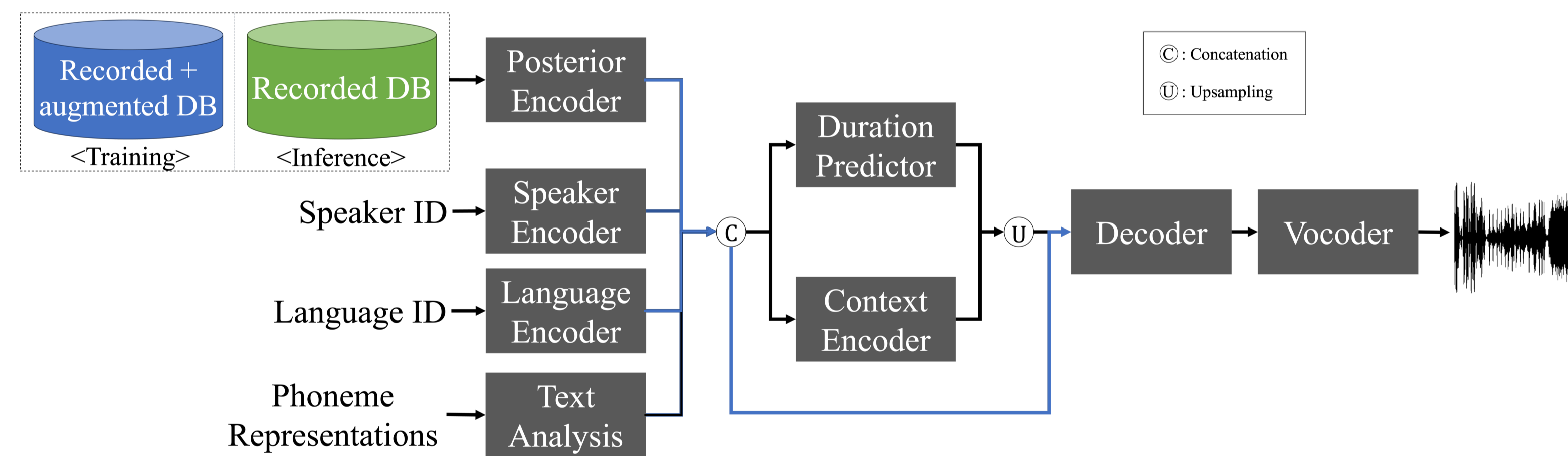


Figure2: Model diagram

Multilingual, multi-speaker TTS system

- **Unified phoneme representation**
 - We integrate 42 English, 47 Korean, and 50 Japanese phonemes into a unified set consisting of **102 phonemes**.
 - We follow the **International Phonetic Alphabet (IPA)** [2] for merging phonemes from different languages and phonemes with similar pronunciations (e.g. 'm', 'n' in nasal sound) are combined. (details are provided in the Table1)

Table1: Unified phonemes table

CONSONANTS (PULMONIC)		Unified symbol	Original IPA symbol		
			ko	jp	en
Plosive	Bilabial	p	ㅍ (피랑)	パ (パン)	p (pack)
		b	ㅂ (바람)	バ (ばしょ)	b (back)
	Alveolar	t	ㅌ (타다)	タ (たべる)	t (time)
		d	ㄷ (다수)	ド (どうも)	d (dog)
	Velar	k	ㅋ (크기)	ク (くる)	k (kiss)
		g	ㄱ (가방)	ガ (がっこう)	g (gaggle)
Nasal	Bilabial	m	ㅁ (마음)	マ (まあ)	m (much)
	Alveolar	n	ㄴ (나무)	ナ (なっとう)	n (note)
Fricative	Labiodental	f	ㅍ (피랑)	フ (ふく)	f (fish)
		s	ㅅ (사랑)	ス (さっそう)	s (soup)
	Alveolar	z	ㅈ (자유)	ジ (ざくろ)	z (zip)
		ʃ	ㅅ (사랑)	シ (しき)	ʃ (ship)
	Alveolo-palatal & Postalveolar	h	ㅎ (하늘)	ハ (はな)	h
		ch	ㅈ (차)	チ (ちゃ)	ch (chair)
Affricate	Postalveolar	ch	ㅈ (차)	チ (ちゃ)	ch (chair)
Trill & Approximant	Labiodental	r	ㄹ (라멘)	ラ (ラーメン)	r (run)

Experiments

- **Compared models**
 - **CM-TTS:** cross-lingual, multi-speaker TTS model
 - **MM-TTS:** VC-augmented multilingual, multi-speaker TTS model
 - **MM-TTS_{vae}:** MM-TTS with posterior embeddings
- **Objective evaluation**
 - **Intelligibility:** WER(%), CER(%)
 - **Acoustic similarity:** F0_{rmsc}(Hz), log spectral distance (LSD)(dB)
- **Subjective evaluation**
 - **Naturalness:** MOS

Model	English				Korean				Japanese			
	WER(%)	CER(%)	F0 _{rmsc} (Hz)	LSD(dB)	WER(%)	CER(%)	F0 _{rmsc} (Hz)	LSD(dB)	WER(%)	CER(%)	F0 _{rmsc} (Hz)	LSD(dB)
CM-TTS	3.11	1.29	37.58	4.58	19.88	6.88	29.64	4.64	16.04	10.50	25.75	4.53
MM-TTS	16.74	10.28	37.73	4.22	27.76	11.74	26.41	4.42	21.24	14.01	24.72	4.27
MM-TTS _{vae}	4.87	2.34	36.57	4.15	15.13	4.36	26.28	4.59	14.45	9.51	24.24	4.36

Table2: Objective evaluation

Model	First language : English			First language : Korean			First language : Japanese		
	English	Korean	Japanese	English	Korean	Japanese	English	Korean	Japanese
	CM-TTS	2.71 ± 0.12	1.96 ± 0.11	2.16 ± 0.11	1.70 ± 0.08	2.75 ± 0.10	1.75 ± 0.09	1.77 ± 0.10	1.84 ± 0.10
MM-TTS	2.93 ± 0.12	1.47 ± 0.08	1.91 ± 0.11	1.52 ± 0.08	2.15 ± 0.10	1.89 ± 0.09	1.96 ± 0.12	2.31 ± 0.13	2.98 ± 0.12
MM-TTS _{vae}	3.13 ± 0.12	2.15 ± 0.12	2.20 ± 0.12	2.13 ± 0.09	3.03 ± 0.10	2.34 ± 0.11	2.30 ± 0.12	2.66 ± 0.12	3.15 ± 0.12
Recorded	4.65 ± 0.08	-	-	-	4.94 ± 0.03	-	-	-	4.73 ± 0.06

Table3: Subjective evaluation

[1] R. Terashima et al., "Cross-speaker emotion transfer for low-resource text-to-speech using non-parallel voice conversion with pitch-shift data augmentation", Interspeech, 2022
[2] I. P. Association, "Handbook of the International Phonetic Association: A guide to the use of the International Phonetic Alphabet", Cambridge University Press, 1999
[3] E. Song et al., "TTS-by-TTS 2: Data-selective augmentation for neural speech synthesis using ranking support vector machine with variational autoencoder", Interspeech, 2022
[4] H. Yoon et al., "Language model-based emotion prediction methods for emotional speech synthesis systems", Interspeech 2022