Building a mixed-lingual neural TTS system with only monolingual data

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Abstract
When deploying a Chinese neural text-to-speech (TTS) synthesis system, one of the challenges is to synthesize Chinese utterances with English phrases or words embedded. This paper looks into the problem in the encoder-decoder framework when only monolingual data from a target speaker is available. Specifically, we view the problem from two aspects: speaker consistency within an utterance and naturalness. We start the investigation with an Average Voice Model which is built from multi-speaker monolingual data, i.e. Mandarin and English data. On the basis of that, we look into speaker embedding for speaker consistency within an utterance and phoneme embedding for naturalness and intelligibility, and study the choice of data for model training. We report the findings and discuss the challenges to build a mixed-lingual TTS system with only monolingual data.

Index Terms: speech synthesis, encoder-decoder, mixed-lingual

1. Introduction
When deploying a non-English Text-to-Speech (TTS) system, it is very common that we have to address the mixed-lingual problem. A mixed-lingual TTS system is expected to synthesize utterances with embedded phrases or words from a different language. A straightforward way to build a mixed-lingual TTS system is to use a bilingual speech database recorded by a bilingual speaker. However, it’s very hard to find a speaker with excellent multiple language skills and consistent articulation across different languages, and it is not flexible to use pre-recorded data which only has monolingual data. In this work, we look into the mixed-lingual TTS in Mandarin Chinese context with English phrases or words embedded.

1.1. Related work
A mixed-lingual TTS system is expected to generate high-quality speech and be perceived as from one speaker when switching languages in mixed-lingual utterances. Several studies have been conducted to assess the mixed-lingual problem. In [10], Traber et al. builds a mixed-lingual TTS system using a bilingual speech database recorded by a bilingual speaker. In [8], HMM states are shared across languages and speech data from multiple languages are used. In [3, 4, 5], Mandarin and English context-dependent HMM states are shared, and the mapping is learned from a bilingual dataset recorded by a bilingual speaker. In [6], He et al. proposes an approach to convert a monolingual TTS into multilingual by employing a bi-linear frequency warping function, and taking into account of cross-language F0 variations and equalizing speaking rate difference between source speaker and reference speaker. Besides, speaker adaptation and voice conversion are also effective ways to mixed-lingual synthesis using a set of monolingual or multilingual speech databases. In [7], Ramani et al. creates a polyglot corpus using voice conversion on a set of multilingual speech databases including Tamil, Telugu, Malayalam, and Hindi. The HMM-based polyglot TTS built with the polyglot database can synthesize mixed-lingual speech for four languages in target speaker voice. In [8, 9], Sitaram et al. presents a code-mixed TTS framework, in which the languages are not written in their native script but borrow the script of the other language. Then, the mapping between the phonemes of both languages is used to synthesize the text using a TTS system trained on a single language. In [10], Chandu et al. further extends their code-mixed TTS to a bilingual system using two monolingual speech datasets and a combined phone set for speech synthesis of mixed-language navigation instructions. For deep neural network (DNN) based synthesis, a cross-lingual TTS is built using Kullback-Leibler divergence (KLD) [11].

Recently, encoder-decoder framework has been successfully applied to TTS synthesis. In [12], Li et al. presents two end-to-end models: Audio-to-Byte (A2B) and Byte-to-Audio (B2A), for multilingual speech recognition and synthesis, which modeling text using a sequence of Unicode bytes, specifically, the UTF-8 variable length byte sequence for each character. The B2A model is able to synthesize code-switching text and the speech is fluent, but the speaker voice is changed for different language.

1.2. The contribution
We conduct investigations based on the encoder-decoder framework, which is proven to generate speech with better prosody. In this study, we attempt to answer the following questions:

- Can the encoder-decoder model learn meaningful phonetic representations in the encoder part? Does the encoder interpret Mandarin and English phonemes differently?
- What is the impact of speaker embedding on speaker consistency within mixed-lingual utterances?
- Can phonetic information, i.e. phoneme embedding, be used in attention alignment and context vector and as a result improve naturalness and speaker consistency when switching languages in an utterance?
- Is monolingual data enough to build a mixed-lingual TTS system?

To answer these questions, we conduct analysis on phoneme embeddings to understand what the encoder-decoder model is learning, and present the phoneme-informed attention for the encoder-decoder model. Besides, we compare...
speaker embedding at different positions to analyze its effects on speaker consistency among mixed-lingual utterances. We also study the way of model training in terms of the choice of training data.

2. Mixed-lingual neural TTS system

Even though there are two languages in one utterance, a mixed-lingual TTS system is expected to produce synthesized utterances that sound like one speaker. Hence, speaker consistency within an utterance, intelligibility and naturalness are all important factors for the mixed-lingual TTS.

It will be very challenging if not impossible to learn bilingual phonetic coverage when only monolingual data is available. Hence, we start our investigations from building an Average Voice Model (AVM) with multi-speaker monolingual dataset, specifically, the data from 35 monolingual Mandarin Chinese speakers and 35 monolingual English speakers. We note that the Chinese corpus does not have English words and the English corpus does not have Chinese pronunciations. To control speaker consistency, speaker embedding is investigated, and phoneme embedding is also studied to better understand how the encoder-decoder model learns phonetic information.

2.1. Multi-speaker voice modeling

There are two ways to build an AVM from multi-speaker data. One way is to mix all the data together and treat the data as from a single speaker. The resultant AVM can be used for adaptation or as a base model for retraining when the data of a target speaker is available. The other way is to assign each speaker a label (e.g. speaker code), and use the label to distinguish data from different speakers in the model training process.

In this work, we use speaker embeddings to distinguish speakers, but when we analyze phoneme embeddings or phonetic representations from encoder, the former AVM training method is used. Experimental comparison is also performed for the two methods.

2.2. Speaker embedding

We use speaker embedding to help the AVM training with multi-speaker monolingual data. The speaker embeddings are assumed to construct a speaker space. There are various approaches proposed for modeling the speaker space [13][14][15]. Speaker embedding has been extensively used in multi-speaker speech synthesis to generate the speech of the specific speaker [13][14][16][17][18]. It has been proved that speaker embedding is an effective way to model a speaker space [19]. In general, speaker embedding can be concatenated with encoder output [15][20] or fed into decoder as an extra input [17]. In this paper, we use a speaker look-up table to store speaker embeddings, which is trained jointly with the encoder-decoder network. The speaker embeddings are utilized to condition speech synthesis to control the speaker voice in both training and inference.

To investigate how to place speaker embedding in the encoder-decoder architecture for better speaker consistency, we concatenate speaker embedding at two different positions: 1) concatenating speaker embedding at the encoder output (SE-ENC) and 2) concatenating speaker embedding at the decoder input (SE-DEC). To get the target speaker characteristic, we use two approaches: 1) excluding the target speaker data in the AVM but using it to retrain decoder; 2) including the target speaker data in the AVM to learn speaker embeddings simultaneously.

2.3. Phoneme embedding

Phonetic coverage and the relationship between English and Mandarin phonemes are important to the naturalness and intelligibility for a mixed-lingual TTS system. To this end, we analyze the phoneme embeddings and encoder outputs to understand how the encoder-decoder model learns phonetic representations and how to interpret encoder outputs. Phoneme embeddings are vectorized presentations of discrete phonemes, while encoder outputs are derived from phoneme embeddings, which also have a direct impact on the decoder via attention modeling and the resultant context vector.

Figure 1 and Figure 2 present the t-SNE visualization of phoneme embeddings and encoder outputs, respectively. From the phoneme embedding representations, it is clear that each phoneme is grouped in the same cluster. The English and Mandarin phonemes are separated in some sense but do not have a clear boundary like that in the visualization of encoder outputs. In the visualization of encoder outputs, however, the clustering changes a bit. Mandarin and English phonemes are grouped into two separate clusters. It implies the properties of phoneme embeddings have been changed a bit after several layers of transformations. We suspect that the encoder output is affected more by the audio information which is passed down through back-propagation. We also argue that if the attention alignment is not accurate, and it may also introduce errors into encoder through back-propagation. Hence, it might be useful to have phonetic information when computing the attention alignment or context vector.
2.4. Phoneme-informed attention

Motivated by the analysis of phoneme embeddings and encoder outputs, we investigate the impact of phoneme-informed attention from two directions. One is to calculate an additional phoneme embedding context vector (PECV) by applying attention weights to phoneme embeddings and concatenate it with the attention context vector which is fed to the decoder. As phoneme embeddings and encoder outputs have a one-to-one direct mapping, attention weights based on encoder outputs can be applied directly to phoneme embeddings for PECV. However, phoneme embeddings cannot have an impact to the attention alignment. The other is to use a residual encoder (RES) architecture by adding the phoneme embeddings to encoder outputs directly. More details about the phoneme-informed attention are described in Sections 2.4.1 and 2.4.2.

2.4.1. Phoneme embedding context vector

The phoneme embedding context vector is computed just like the attention context vector. In the attention mechanism [24], a context vector $c_i$ of $i$-th decoder output step depends on the encoder outputs ($h_1, \cdots, h_T$). The context vector is computed as a weighted sum of the encoder outputs $h_j$:

$$c_i = \sum_{j=1}^{T} \alpha_{ij} h_j$$

(1)

The weights $\alpha_{ij}$ of each $h_j$ is calculated as:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j=1}^{T} \exp(e_{ij})}$$

(2)

where

$$e_{ij} = a(s_{i-1}, h_j)$$

(3)

is the score computed on the decoder hidden state $s_{i-1}$ and the $j$-th representation $h_j$ of the encoder outputs.

In our work, the additional context vector $c'_i$ at $i$-th decoder output step is computed based on phoneme embeddings ($s_1, \cdots, s_T$) and shares the same weights $\alpha_{ij}$ with the attention context vector $c_i$:

$$c'_i = \sum_{j=1}^{T} \alpha_{ij} s_j$$

(4)

Then, we concatenate the attention context vector and the phoneme embedding context vector as the new attention context vector $C_i$:

$$C_i = [c_i; c'_i]$$

(5)

Of course, dimension reduction is performed to the context vector before passing to the decoder.

2.4.2. Residual encoder

The structure of residual encoder is shown in Figure 3 in which phoneme embeddings are added to encoder outputs to improve encoder representation. It should be noted that phoneme embeddings have the same dimensions as encoder outputs.

The phoneme embedding context vector impact on the context vector only. While the residual encoder affects the whole attention calculation process, including scores, attention weights and context vector. We expected it can improve the overall performances of attention and resultant synthesized speech.

An illustration of the architectures investigated in this study can be found in Figure 4. The experiments in the next section will follow the illustration.

3. Experimental Results and Analysis

3.1. Experimental setup

In this paper, the goal is to study how to build a female Mandarin-English mixed voice using only Mandarin data. We limit the number of training utterances from the target speaker to 500. As the target speaker is a female, only female datasets are utilized to reduce the effect of gender factor. Hence, as we described earlier, to build an AVM, we use an internal Mandarin monolingual dataset from 35 female speakers and an English monolingual dataset from 35 female speakers with American accents, which is a subset of the public available dataset VCTK [22]. Each Mandarin monolingual speaker has around 500 sentences, in total of 1,7197 sentences, which is approximately 17 hours audio. Each English monolingual speaker has varied number of utterances from 200 to 500, in total of 1,4464 utterances, about 8 hours audio.

All audios are down-sampled to 24kHz. The beginning silence are all trimmed, and ending silence are trimmed to a fixed length. 80-dimensional mel-spectrograms and 1024-dimensional linear spectrograms are extracted from audios as the model target output. Phoneme sequences are fed to the model as input to predict spectrogram. In this paper, experiments are performed based on the encoder-decoder neural TTS system [23]. Since our work focuses on generating mixed-lingual speech with satisfied intelligibility and a consistent voice, we use the Griffin-Lim [24] algorithm to synthesize waveform from the predicted linear spectrogram like Tacotron-1 [25], instead of using a WaveNet vocoder like Tacotron-2 [25].

3.2. Experiments analysis

We perform AB preference tests in terms of naturalness and speaker consistency to assess the performances of different methods. In detail, the speaker consistency AB preference tests are conducted on mixed-lingual sentences, which focus on the voice consistency within mixed sentences. Meanwhile, the naturalness AB preference tests are performed on Mandarin, English and mixed-lingual sentences. For each language, 30 sentences are randomly selected from test set. A group of 18 lis-
3.2.1. Analysis of speaker embedding

We first analyze the effect of speaker embedding by comparing different positions of speaker embedding in the encoder-decoder architecture. Here, the 500 Mandarin data of target speaker is mixed with data from the speakers for AVM. We compare the effects of speaker embedding at encoder output (SE-ENC) and decoder input (SE-DEC). Note that when speaker embedding is located at decoder input, it also affects the prenet, not only top layers in the decoder. The results show that SE-DEC brings better performances of speaker similarity and naturalness, as described in Figure 5. Placing speaker embedding at decoder input is surprisingly effective for mixed-lingual utterances. We argue that because the speaker embedding can affect the prenet when it is used at decoder input, it can handle language switching better and make the switch across languages more smooth.

3.2.2. Including versus excluding the target speaker data in the AVM training

We then analyze how to use the data of the target speaker to generate mixed-lingual speech properly. The AVM excluding the target speaker data is pre-trained and used to adapt to the target speaker. We retrain decoder based on the AVM (Retrain-AVM) using 500 Mandarin data of the target speaker. Besides, as suggested by the results above, SE-DEC can achieve better performance than SE-ENC. Thus, the AVM including the target speaker data with speaker embedding at decoder (SE-DEC) is built to get the target speaker voice. We compare the performance between Retrain-AVM and SE-DEC. The results in Figure 6 show that the SE-DEC can achieve better performances than Retrain-AVM in terms of naturalness of three languages and speaker consistency. It suggests that including the target

1Samples can be found at [https://angelkeepmoving.github.io/mixed-lingual-tts/index.html](https://angelkeepmoving.github.io/mixed-lingual-tts/index.html)

3.2.3. The choice of training data

We then use the SE-DEC structure and study the impact of the choice of training data. Note that the data of target speaker is involved in the AVM training. We use three independent training sets from the same target speaker, 500 Mandarin utterances (CORPUS-MAN), 500 English utterances (CORPUS-ENG) and 500 mixed Mandarin–English utterances (CORPUS-MIX). This is to answer whether monolingual training data can achieve the same performance as that with mixed-lingual training data. The listening test results are presented in Figures 7 and 8. On the mixed-lingual test set, it is always preferred to have mixed-lingual training data. In the case of no mixed-lingual training data, listeners prefer the synthesized audio generated from model trained by Mandarin data. We argue that it may because the primary language of the built TTS system is Mandarin, and better Mandarin synthesis helps in the listening tests. To synthesize monolingual Mandarin, Mandarin training data is always preferred, followed by mixed-lingual. However, to synthesize monolingual English, even though English training data is always preferred, surprisingly Mandarin data is preferred than mixed-lingual data when no English training data is available. We plan to investigate further on this aspect.

3.2.4. The use of phoneme-informed attention

We also examine the impact of phoneme-informed attention. On the basis of SE-DEC model, two methods are performed: an additional phoneme embedding context vector (SE-DEC-PECV) and a residual encoder (SE-DEC-RES). Preference comparisons for the additional context vector and the residual encoder are presented in Figure 11. The results demonstrate that using the residual encoder can achieve better naturalness than the additional context vector for three languages.
For speaker consistency, the residual encoder and the additional context vector achieve almost the same preference. Furthermore, we compare the performance of using residual encoder or not. The results, shown in Figure 9, demonstrate that using residual encoder brings better naturalness for three languages, or not. The results, shown in Figure 11, demonstrate that using more, we compare the performance of using residual encoder and the additional context vector.

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