Cross-lingual Multispeaker Text-to-Speech under Limited-Data Scenario

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1. Introduction

Recently, the combination of an encoder-decoder based text-to-spectrogram network and a neural vocoder has allowed machines to synthesize high-fidelity speech that is as natural as human. This technique can well equip text-to-speech (TTS) applications (e.g., audiobook reader, virtual assistants, navigation systems, etc.) in our daily life. However, these models, like Tacotron2 [1], keep a certain level of limitations in controllability regarding latent speech attributes. Thus the models’ robustness is limited and may be incapable of synthesizing speech with various speech characteristics. Then extensions on Tacotron2 have been proposed to address these problems: Yuxuan Wang et al. modeled the latent speech attributes by global style tokens (GSTs) while there are no explicit labels provided [2]. Ye Jia et al. extend the Tacotron2 with conditioned features extracted from a speaker verification system to achieve speaker identity cloning and multispeaker TTS [3].

However, as linguists and multilingualists are commonly seen in today’s world, the speech communication scenario becomes complicated. It is essential for speech analysis tools, including speech recognition and speech synthesis, to adapt this change for maintaining their current performance. The challenge is that languages, mostly, have different grapheme set and pronunciations between each other. This challenge motivates researchers to find and investigate shared representations between languages for speech analysis [4][5][6].

Even with appropriate representations for multiple languages, the model architecture needs to be upgraded in order to achieve multilingual processing for all speech analysis systems. For TTS, approaches are proposed for multilingual synthesis, even cross-lingual synthesis, based on classical statistical parametric speech synthesis (SPSS) [7][8]. Since the end-to-end TTS models can generate speech with higher quality compared with classical methods, extensions on the end-to-end TTS frameworks also have been explored for multilingual modeling [9][10][11][12]. Normally, the voices of the multilingual TTS training datasets are different. Therefore, most TTS multilingual systems also support multispeaker synthesis. But the cross-lingual synthesis, where we can generate speech with foreign text for a monolingual speaker, is challenging. Yu Zhang et al. had achieved high-quality cross-lingual synthesis in a sufficient-data scenario [10]. Zhaoyu Liu et al. investigated cross-lingual synthesis with limited data for each speaker. But the synthesized speech has moderate quality due to the data sparsity issue [13].

Motivated by the aforementioned works, in this paper, our focus is to achieve cross-lingual multispeaker TTS with limited data form two languages, English and Mandarin. We propose a model that incorporates speaker embedding and language embedding as the conditioned features for multilingual multispeaker TTS. The proposed model can generate high-quality speech for all speakers with respect to their own language. In addition, we investigate cross-lingual synthesis with the same model in a limited-data scenario by involving a bilingual TTS dataset. Results show that language-related knowledge can be transferred from the bilingual speaker to monolingual speakers, which enables us to generate fluent, high-fidelity, and intelligible speech in both Mandarin and English using monolingual speakers’ voices.

2. Related works

Developing a multilingual multispeaker (MLMS) TTS model can relieve the efforts of training multiple TTS models used for several voices with different languages. While the voice can be controlled by a text-independent speaker embedding in a multispeaker TTS system [3][14]. TTS regarding multiple languages is more complicated due to different grapheme representations across languages. However, similar pronunciations between different languages can help reduce the gap of cross-lingual text-to-speech. Previously, Huaiping Ming et al. presents a light-weighted bilingual synthesis system that adopts concatenated vectors in the linguistic-feature level to manage two languages in one model [8]. Bo Li et al. proposed an MLMS TTS approach based on conventional statistical parametric speech
3. Method

3.1. Input representation

Code-switching is defined as more than one language occurring in one sentence or between sentences, either orally or in written form. With the world’s globalization, code-switching patterns in speech become a common case in many countries and regions. The language environment in the globalization inspires more and more bilingualists and multilingualists, which motivates researchers to develop speech processing systems that can handle multilingual challenges. Furthermore, code-switching corpora have been collected and released for research related to speech communication in the recent decade [16][17], followed with various approaches proposed to address complicated speech analysis, including multilingual automatic speech recognition (ASR), language identification and language diarization with respect to multilingual scenario [18][19][20][21]. Likewise, TTS systems need to be improved for synthesizing natural speech for code-switching sentences [11].

However, one of the main challenges of code-switching TTS is that the grapheme set or the phoneme set between languages are different. Regarding that some phonetic pronunciations between different languages are close. Thus exploring a multilingual TTS model with minimum data requirement, including textual and vocal data, is possible and essential. Previous approaches, which are proposed for addressing multilingual issues in TTS, indicate that shared input representation across languages is one of the keys to realize cross-lingual synthesis [6][7][9]. The shared representations include shared phoneme set, international pronunciation alphabet (IPA), and the Bytes coding [6], where the phoneme representation can obtain better performance [10].

In our work, we choose to use a shared phoneme set from CMU dictionary [22] to investigate bilingual multispeaker TTS and cross-lingual synthesis between Mandarin and English. As for Mandarin, the pronunciation representation called pinyin can be converted to CMU phoneme by the pinyin-to-cmu mapping table [23]. Since Mandarin is a tone-language, digits 1 to 6 are used to denote different tones, while ’0’, ’1’, ’2’ are used to mark the lexical stress for English. Although the tone and stress share the same annotations in our input, which may cause ambiguity, we have language identification tokens as another input stream. Moreover, language identification tokens are used to
generate language-dependent encoding features while preserving the shared information between languages, like close pronunciations. Similarly, ‘0’, ‘1’, ‘2’ are used for language identification in our input representations, where ‘0’ represents the corresponding phoneme or stress annotation is from English, ‘1’ is for Mandarin and ‘2’ for language-unrelated symbols like punctuation marks. Take the phrase ‘speech 合成,’ (speech synthesis.) as an example, two input sequences are obtained after the front-end text processing. One is the phoneme sequence ‘S P I Y 1 CH HH ER 2 CH AH 2 NG 2 .’, and the other is the corresponding language identification tokens ‘0 0 0 0 0 1 1 1 1 1 2’ which has the same length as the phoneme sequence. We break up phonemes with its corresponding tones, e.g., ‘AH2’ is converted to ‘AH 2’, to allow our proposed model to share close pronunciations between Mandarin and English.

3.2. Proposed model

Our proposed bilingual multispeaker TTS model is illustrated in figure 1. The input text is converted into phoneme sequence and language token sequence, as introduced in section 3.1. The phoneme sequence is converted to phoneme embedding sequence by a learnable lookup table. Correspondingly, the language tokens are converted to a 64-dimensional language embedding sequence through another learnable embedding table. Two embedding sequences are concatenated together as the input of the Tacotron encoder, which accumulates the linguistic and context characteristics of the input vector sequence with layers of convolutional layers and a bi-directional long short-term memory (BLSTM) layer. 256-dimensional speaker embedding is concatenated with the encoder outputs for conditioning the network to synthesize expected voices. For the speaker embedding, we use the mean embedding derived from all embeddings extracted with a pretrained speaker verification model [24] by feeding all training utterances of each speaker. We believe that it can induce the same performance as using a trainable lookup table yet costs less training time. Mel-spectrogram is used as the predicted output of the Tacotron encoder, which accumulates the linguistic and context characteristics of the input vector sequence with layers of convolutional layers and a bi-directional long short-term memory (BLSTM) layer.

4. Experiments

4.1. Datasets

Our experiments are conducted with three TTS datasets, including the publicly available LJ Speech (LJS) dataset [26] and two Chinese female voice datasets, DB-1 and DB-4, from Data Baker [27]. LJS, DB-1 and DB-4 are used as representations for cross-lingual TTS model trained with DB-1 and LJS. The other system, notated by CLMS, is the system trained with all datasets, including the bi-lingual dataset DB-4. Although the latter system also can be used for bilingual multispeaker synthesis, we focus on its capability of cross-lingual

Table 1: Phonemes (without tone and stress) and their corresponding frequencies in LJ-Speech, DB-1 and DB-4

| Phoneme | LJS | DB-1 | DB-4 | Phoneme | LJS | DB-1 | DB-4 | Phoneme | LJS | DB-1 | DB-4 |
|---------|-----|------|------|---------|-----|------|------|---------|-----|------|------|
| J       | 12088 | 12720 | 12949 | X       | 8050 | 11895 | 11791 | Q       | 5435 | 7489 |
| IY      | 28587 | 54859 | 85601 | EH      | 26397 | 3598 | 11791 | AA      | 16976 | 11173 | 23205 |
| L       | 23893 | 9420  | 23510 | AY      | 12079 | 7479 | 15619 | UW      | 15345 | 30630 | 44593 |
| SH      | 7957  | 11456 | 17804 | OW      | 10201 | 6921 | 13698 | Y       | 4426  | 16540 | 27793 |
| N       | 68392 | 33006 | 56339 | T       | 65657 | 8969 | 26654 | JH      | 4824  | 8994  | 13821 |
| AE      | 21502 | 27640 | 42203 | NG      | 7229  | 25895 | 36286 | AH      | 102042 | 12558 | 33953 |
| G       | 5901  | 69600 | 12298 | AW      | 4248  | 9654 | 15397 | Z       | 27845 | 5749  | 14135 |
| M       | 23778 | 5967  | 14833 | AO      | 16035 | 6970 | 14496 | S       | 43700 | 5485  | 17965 |
| UH      | 2856  | 7567  | 11253 | W       | 20352 | 7151 | 15411 | CH      | 4751  | 5118  | 7940 |
| D       | 43601 | 14192 | 30390 | ER      | 23525 | 15131 | 30264 | B       | 15608 | 7577  | 15252 |
| F       | 17018 | 4111  | 8890  | R       | 40428 | 5025 | 16386 | K       | 27866 | 3325  | 12650 |
| HH      | 13785 | 7915  | 14745 | EY      | 14095 | 4891 | 10838 | F       | 20122 | 2496  | 8607 |
| V       | 19628 | 4089  | 12311 | DH      | 29311 | 4716 | 11895 | IH      | 53904 | 33953 | 13687 |
| TH      | 3604  | 1250  | 831   | OY      | 331   | 11895 | 11253 | 5957    | 23205 | 607   | 237 |
| AX      | 156   | 418   | 11253 | Q       | 5395  | 11253 | 11253 | Z       | 607   | 237   | 237 |

2https://www.data-baker.com/us.html
4.3. Objective evaluations

The objective evaluation is done by speech synthesis MOS-scale rating, a categorical score from 1 to 5, with 0.5 increments. We ask 16 native Mandarin speakers (all speakers are familiar with English) to rate the synthesized speech concerning naturalness, similarity, and intelligibility. The naturalness is related to the quality of synthesized audios regardless of the content. The speaker similarity score is to measure how close is the synthesized voice to the expected speaker, while the intelligibility evaluates the clarity level of the speech content. We have three types of synthesized text for evaluating the performance, which are Mandarin sentences, English sentences, and code-switching sentences that contain both Mandarin and English content in each sentence. Each type of text has 15 sentences.

The naturalness mean opinion scores (MOS) are shown in Table 2. As shown in the table, the quality of synthesized audios reaches around 4.0. While the performance degrades when generating cross-lingual speech for monolingual speakers. For example, DB-1 obtains MOS with 4.12 when synthesizing Mandarin sentences but degrades to 3.64 for English sentences. As shown in Table 3, the speech synthesized by our proposed model can well preserve the speaker identity according to the speaker embedding. Most speaker similarity MOS are above 4, while scores lower than 4 can be observed in cross-lingual cases.

The code-switching performance can be clearly observed from Table 4. Although BLMS can achieve bilingual multi-speaker synthesis, the cross-lingual synthesis performance is poor, which matches the result in [10]. The cross-lingual synthesized speech is unintelligible as the intelligibility MOS are below 2. However, while involving a bilingual dataset, CLMS is able to generate cross-lingual speech, even in code-switching cases, with intelligible pronunciations. Raters said that the synthesized speech is exactly like a foreign speaker speak another language with the accent from their native language. This indicates that, with our proposed model, using a bilingual dataset can significantly improve cross-lingual speech synthesis, although we only have limited data for each language.

4.4. Alignments

In addition, the cross-lingual synthesis performance also can be seen from the attention alignments in Figure 2. The synthesized content is a code-switching sentence. For system BLMS, we can observe clear breaks when the language switches in the sentence for monolingual speakers DB-1 and DB-4 in Figure 2(a) and (b). However, the attention alignments obtained from CLMS are smooth even for monolingual speakers. This also implies that language-related knowledge can be transferred from the bilingual speaker to monolingual speakers with our proposed model.

5. Conclusion

We present a bilingual multispeaker TTS approach based on shared phonemic representations. Our proposed model is able to achieve high-fidelity bilingual multispeaker TTS. In addition, results show that, by involving a bilingual dataset, the model is capable of cross-lingual synthesis, even for code-switching synthesis, under the limited-data scenario. We are able to obtain fluent, accented, and intelligible cross-lingual speech as monolingual speakers speak a foreign language.

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