Cross-Lingual Text-to-Speech Using Multi-Task Learning and Speaker Classifier Joint Training

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Abstract
In cross-lingual speech synthesis, the speech in various languages can be synthesized for a monoglot speaker. Normally, only the data of monoglot speakers are available for model training, thus the speaker similarity is relatively low between the synthesized cross-lingual speech and the native language recordings. Based on the multilingual transformer text-to-speech model, this paper studies a multi-task learning framework to improve the cross-lingual speaker similarity. To further improve the speaker similarity, joint training with a speaker classifier is proposed. Here, a scheme similar to parallel scheduled sampling is proposed to train the transformer model efficiently to avoid breaking the parallel training mechanism when introducing joint training. By using multi-task learning and speaker classifier joint training, in subjective and objective evaluations, the cross-lingual speaker similarity can be consistently improved for both the seen and unseen speakers in the training set.

Index Terms: cross-lingual, text-to-speech, speaker similarity, multi-task learning, joint training

1. Introduction
In recent years, end-to-end (E2E) models have been widely used in speech synthesis \cite{1,2,3,4,5,6}, where the models can be directly trained on text-speech pairs with minimal engineering efforts. Based on the encoder-decoder E2E framework, various multilingual text-to-speech (TTS) approaches have been proposed \cite{7,8,9,10,11,12,13,14}. In these approaches, the speaker and language embeddings are introduced to characterize the voice of the speaker, and the global prosody of the language. By using different combinations of the input sequence, speaker and language embeddings, cross-lingual synthesis can be achieved.

Normally, only the data from monoglot speakers in different languages are available in multilingual model training. Without using polyglot data or any constrain in training, the generated cross-lingual speech can have low speaker similarity. This phenomenon has been exhibited in the previous work \cite{9,10,12}. However, the approaches to improve cross-lingual speaker similarity are scarcely discussed. In \cite{9}, a speaker classifier is introduced under the domain-adversarial training framework to encourage the encoded phone sequence to be speaker-independent. This approach, to some extent, improves the cross-lingual speaker similarity when there is only one or very few speakers per language in the training data. In \cite{10}, a polyglot loss is introduced to minimize the L1 distance between the speaker embeddings of the original recording and cross-lingual speech for the same speaker. This approach can only be applied to the systems using speaker encoders, which map the input speech sequence to a fixed-dimensional vector. For the systems using lookup tables, only a fixed or trainable embedding vector is associated with one speaker, then the polyglot loss becomes inapplicable.

Our previous work on multilingual TTS \cite{12} shows that the multilingual model can achieve very good speaker similarity in intra-lingual synthesis, which is very close to the original recording. Thus, this paper focuses on improving the speaker similarity in cross-lingual scenarios.

In this work, the multilingual model is based on the transformer TTS \cite{6} by introducing additional speaker and language networks. Based on the multilingual transformer TTS, a multi-task learning (MTL) framework is introduced to encourage the speaker and language embeddings to capture the speaker and language characteristics. Experiments show that MTL enhances the speaker representation and improves speaker similarity in cross-lingual synthesis. To further improve the cross-lingual speaker similarity, an x-vector speaker classifier \cite{15} is introduced to be jointly trained with the multilingual transformer \cite{6}. In joint training, the distance between the x-vectors of the recording and the cross-lingual speech is minimized. As cross-lingual speech needs to be generated in jointing training, the transformer needs to be operated in inference mode, thus the model cannot be trained in parallel. To alleviate this problem, an approximate approach similar to parallel scheduled sampling \cite{16,17} is introduced to train the transformer in parallel.

The paper is organized as follows. In section 2, the general framework of MTL and speaker classifier joint training is introduced. Experiments and corresponding evaluation results are presented in section 3. Finally, conclusions and the future work are discussed in section 4.

2. The general framework
The multilingual transformer TTS \cite{12} is an extension of the transformer TTS \cite{6} by introducing the speaker and language conditions to the model. These conditions represent the speaker and language global characteristics, and play key roles in multilingual modeling. However, without using polyglot data or any constrain in training, such model cannot guarantee a good speaker similarity in cross-lingual synthesis. To improve the cross-lingual speaker similarity, MTL and speaker classifier joint training are discussed in this section.

2.1. Multi-task learning
Multi-task learning can be viewed as a form of inductive transfer. Inductive transfer can help improve a model by introducing

\textsuperscript{1}The language embedding is optional for some systems.

\textsuperscript{2}Although the transformer-based model is discussed, the general MTL and joint training frameworks can also be applied to other E2E multilingual models.
2.2. Joint training with the speaker classifier

The most direct way to improve the cross-lingual speaker similarity is to introduce a constraint on the generated cross-lingual speech. In this work, the x-vector speaker classifier system is introduced. By minimizing the distance between the x-vectors of the recording and the cross-lingual speech for the same speaker, the multilingual model can be updated towards generating cross-lingual speech with high speaker similarity. The x-vector system introduces an additional learning bias to the multilingual model, thus joint training with the speaker classifier can also be viewed as an MTL approach.

The joint training framework can be summarized in Fig. 2. In this figure, the multilingual model can be the vanilla multilingual transformer TTS or the MTL framework illustrated in Fig. 1. The speaker system can be any network which predicts the speaker identity given the input speech. The x-vector system is used in this work. Compared with the vanilla multilingual model, in joint training with the speaker classifier, two additional losses are introduced. One is the CE loss for the speaker classifier. Another one is the cross-lingual loss targets to minimize the speaker distance between the ground-truth and the predicted Mels is a strong constraint, which can lead to good speaker similarity for the predicted intra-lingual speech.

To minimize the cross-lingual loss described in equation (1), the multilingual model needs to be operated in inference mode to generate the cross-lingual speech. Therefore, teacher forcing cannot be used in training, and the transformer model cannot be trained in parallel. Moreover, it is impractical to apply back-propagation to an auto-regressive loop for an audio sequence, which usually is long. To alleviate this problem, the cross-lingual audio samples can be generated on the fly, then the generated samples can be treated as the ground truth in the teacher forcing mode. This approximation is similar to the operation used in parallel scheduled sampling.  

3. Experiments

The training corpus is comprised of around 700 hours professional recordings from 14 language locales. In each locale, there are at least 3 speakers. In this work, the same language from different locales is treated independently, i.e. different phone sets and language identities are used. The amount of training data is unbalanced for different locales, and the data distribution over 14 language locales is illustrated in Fig. 3. Thus, the language-balanced training strategy discussed in [12] is used throughout this work. In training, all the audio samples are down-sampled to 16 kHz, and the beginning and ending silences are trimmed to a fixed length, i.e. 30 ms. The Adam optimizer is used with initial

\[
\mathcal{L}_{\text{cross}} = \sum_{l} \sum_{l' \neq l} \sum_{o_l} f_{\text{dist}}(f_{\text{xvec}}(o'_l), f_{\text{xvec}}(o_l')) \tag{1}
\]

where \(o'_l\) is the training audio sample for speaker \(s\) in language \(l\), and \(o'_l\) is the synthesized cross-lingual sample for speaker \(s\) in language \(l'\). In training, the input phone sequence used to generate the cross-lingual sample \(o'_l\) is randomly chosen from the training set of language \(l'\). \(f_{\text{xvec}}(\cdot)\) is the x-vector system, which maps variable-length audio samples to fixed-dimensional vectors. \(f_{\text{dist}}(\cdot)\) is a distance function, e.g. the cosine distance or L2 norm. In this work, L2 norm is used. It is worth noting that, when minimizing the cross-lingual loss \(\mathcal{L}_{\text{cross}}\), only the parameters of the multilingual model are updated. Although this cross-lingual loss targets to minimize the speaker distance between the recordings and the cross-lingual samples, the multilingual model can still keep good speaker similarity in intralingual synthesis, as the original mean squared error (MSE) loss between the ground-truth and the predicted Mels is a strong constraint, which can lead to good speaker similarity for the predicted intra-lingual speech.

The abbreviation for each locale consists of the language code and the locale ID, e.g. en is English, US is the United States.
learning rate $10^{-3}$, and exponential decay after 100k steps. The minimum learning rate is set to $10^{-5}$. The baseline multilingual transformer model has the same model structure as [12], with encoder model dimension 512, and decoder model dimension 768. Both the speaker and language embedding dimensions are 128. The universal WaveNet vocoder described in [12] is used in waveform generation. Once the vocoder is trained, it can be applied to the spectrogram from any speaker in any language without additional adaptation or fine-tuning procedure. In the speaker classifier joint training experiments, the x-vector system is used, which has the same structure as [15], but with a smaller hidden size 256.

When calculating the cross-lingual loss $L_{\text{cross}}$, it is very computationally expensive to generate the cross-lingual speech $s'_{\lambda}$, as transformer inference cannot be parallelized. The sum over all cross-lingual languages $l$ will make it even worse. In order to make training more efficient, an approximation is made in the experiments. Rather than summing over $l'$, $l'$ is randomly chosen from the training language set except $l$. In experiments, we found the cross-lingual loss is a very strong constrain on the model and it is still slow to train. To avoid overfitting and improve training efficiency, the cross-lingual loss is introduced when both the multilingual model and speaker classifier model (x-vector system) are fully converged, then jointly update the whole model with the cross-lingual loss.

In evaluation, the synthesized audio samples are evaluated by the crowd-sourced subjective listening tests and the objective tests from a speaker classifier. In subjective tests, the mean opinion score (MOS) is used to rate the cross-lingual naturalness and similarity to the target speakers, with range from 1 to 5. In each similarity evaluation, 15 crowd-sourcing judges are from the source language, and 15 are from the target. Whereas, in each naturalness evaluation, 20 crowd-sourcing judges are all from the target language. In objective tests, an independently trained ResNet x-vector speaker classifier system [19] is used to score the speaker similarity. Cosine distance is used in evaluations, with range from 0 to 2. Smaller value indicates better speaker similarity. This x-vector system is trained with VoxCeleb 1 and 2 data sets [20, 21] from 7363 speakers with 2794 hours of speech in total. The detail model architecture can be found in [19]. The audio samples associated with this work are available on this web page.

### 3.1. Multi-task learning and joint training

In cross-lingual synthesis, without using polyglot data or any constrain in training, the speaker similarity of the generated speech cannot be guaranteed. By using MTL and speaker classifier joint training, a learning bias can be introduced to improve the speaker representations of the model. In this section, these modified systems are compared with the baseline model. The baseline multilingual transformer model has the same model architecture as [12]. This system is denoted as “Baseline” in the experiments. The MTL system is based on this multilingual transformer by introducing additional classification tasks as discussed in section 2.1. This system is indicated by “+MTL”. The system using speaker classifier joint training is based on the MTL system, and an additional x-vector system is introduced to be jointly trained with the MTL multilingual system as described in section 2.2. This system is represented by “+MTL+Joint”. The cross-lingual experiments on the seen speakers during training are tabulated in Table 1 and Table 2. In the tables, “Cos.” denotes the average cosine distance between the recordings and the synthesized cross-lingual speech. “Sim.” and “Nat.” are the similarity and naturalness MOS respectively. This type of notation is used throughout this paper. The best subjective and objective similarity values are marked in bold.

In Table 1, the cross-lingual evaluations of the zh-CN (Chinese) speaker are evaluated in languages en-US (American English) and de-DE (German). By using MTL, the speaker similarity can be improved in both languages. This improvement can be reflected in both the cosine distance and the similarity MOS. The smaller cosine distance represents better speaker similarity. By introducing speaker classifier joint training, the speaker similarity can be further improved, with smaller cosine distance and greater similarity MOS.

### Table 1: Cross-lingual evaluations on a zh-CN speaker.

| Systems         | Baseline | +MTL | +MTL+Joint |
|-----------------|----------|------|------------|
| Cos.            | 0.173    | 0.197| 0.067      |
| en-US Sim.      | 3.96±0.08| 4.02±0.08| 4.05±0.07 |
| Nat.            | 3.60±0.09| 3.52±0.08| 3.56±0.09 |
| Cos.            | 0.246    | 0.113| 0.076      |
| de-DE Sim.      | 3.16±0.10| 3.84±0.07| 3.91±0.08 |
| Nat.            | 2.91±0.13| 3.24±0.12| 3.16±0.11 |

### Table 2: Cross-lingual evaluations on an en-US speaker.

| Systems         | Baseline | +MTL | +MTL+Joint |
|-----------------|----------|------|------------|
| Cos.            | 0.291    | 0.234| 0.188      |
| zh-CN Sim.      | 3.62±0.09| 3.67±0.09| 3.72±0.09 |
| Nat.            | 3.32±0.08| 3.20±0.09| 3.19±0.09 |
| Cos.            | 0.255    | 0.231| 0.227      |
| de-DE Sim.      | 3.41±0.11| 3.47±0.11| 3.64±0.10 |
| Nat.            | 3.77±0.09| 3.74±0.09| 3.89±0.08 |

### Table 3: Objective similarity evaluations in different languages.

| Languages | en-GB | es-ES | ja-JP | fr-FR |
|-----------|-------|-------|-------|-------|
| Baseline  | 0.134 | 0.091 | 0.142 | 0.115 |
| +MTL      | 0.126 | 0.084 | 0.124 | 0.118 |
| +MTL+Joint| 0.125 | 0.080 | 0.117 | 0.102 |
| Cross     | 0.241 | 0.163 | 0.183 | 0.152 |
| +MTL+Joint| 0.185 | 0.146 | 0.134 | 0.125 |

| Audio samples: [https://jingy308.github.io/JointSpk](https://jingy308.github.io/JointSpk) |
3.2. Experiments on new speakers

The multilingual model is trained with a limited number of speakers. Therefore, it is common to extend the model to a new speaker, which is unseen in the training set, with a limited amount of data. When extending to new speakers, the whole multilingual model is refined. To avoid overfitting to the target speaker, the data from the new speaker and the existing speakers are used in model refining. Normally, the amount of data from the new speaker is very limited, whereas the data amount from other speakers is very huge. Thus, language-balanced training described in [12] is also used in speaker extension. The effect of MTL can be clearly observed from previous experiments, thus in the following experiments, only the final “+MTL+Joint” model is compared with the baseline model.

Table 4 tabulates the cross-lingual evaluation results of a new zh-CN speaker. There are around 9 minutes of data available for training. By using MTL and speaker classifier joint training, smaller cosine distance and greater similarity MOS can be achieved. This means an increase in the speaker similarity between the cross-lingual speech and the original native recordings of this new speaker. More objective evaluation results are given in Table 5. The proposed model yields consistent similarity gains in each language, and in general the gains in cross-lingual synthesis are much greater than that in intra-lingual. Similar experiment is carried on a new en-GB (British English) speaker, with around 5 minutes of data. The experimental results are tabulated in Table 6 and 7. The same conclusion can be drawn on this speaker in both subjective and objective evaluations. By using MTL and speaker classifier joint training, the speaker similarity to this new speaker can be improved, with greater similarity MOS and smaller cosine distance in each language.

4. Conclusions and the future work

This paper studies the approaches to improve the speaker similarity for the multilingual transformer TTS model. By using multi-task learning, the overall speaker similarity for the model can be improved. Joint training with an x-vector system, the speaker similarity can be further improved. These techniques can also be easily extended to model new speakers, and the speaker similarity to new speakers can be improved as well. Moreover, our experiments show that the cosine distances from the x-vector system are consistent with the similarity MOS, and this objective score can be easily computed. The naturalness of the cross-lingual speech is still a drawback for the multilingual model. The future work will focus on the improvement in the voice quality and naturalness of the cross-lingual speech.

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6. References

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