INTERSPEECH 2021
30 August – 3 September, 2021, Brno, Czechia

Cross-lingual Speaker Adaptation using Domain Adaptation and Speaker Consistency Loss for Text-To-Speech Synthesis

Detai Xin, Yuki Saito, Shinnosuke Takamichi, Tomoki Koriyama, Hiroshi Saruwatari

Graduate School of Information Science and Technology, The University of Tokyo, Japan.
{detai_xin, shinnosuke_takamichi}@ipc.i.u-tokyo.ac.jp

Abstract

We present a cross-lingual speaker adaptation method based on domain adaptation and a speaker consistency loss for text-to-speech (TTS) synthesis. Existing monolingual speaker adaptation methods based on direct fine-tuning are not applicable for cross-lingual data. The proposed method first trains a language-independent speaker encoder by speaker verification using domain adaption on multilingual data, including the source and the target languages. Then the proposed method trains a monolingual multi-speaker TTS model on the source language's data using the speaker embeddings generated by the speaker encoder. To adapt the TTS model of the source language to new speakers the proposed method uses a speaker consistency loss to maximize the cosine similarity between speaker embeddings generated from the natural speech and the same speaker's synthesized speech. This makes fine-tuning the TTS model of source language on speech data of target language become possible. We conduct experiments on multi-speaker English and Japanese datasets with 207 speakers in total. Results of comprehensive experiments demonstrate that the proposed method can significantly improve speech naturalness compared to the baseline method.

Index Terms: speaker adaptation, cross-lingual, TTS, domain adaptation, speaker verification

1. Introduction

Cross-lingual text-to-speech (TTS) synthesis refers to a task that requires the TTS model to synthesize a source language's speech for a target language's speaker. Previous work about cross-lingual TTS usually trains a multilingual multi-speaker TTS model on multiple monolingual datasets by conditioning the TTS model on speaker and language representations called speaker and language embeddings, respectively [1, 2, 3, 4, 5]. One of the drawbacks of such a method is that it requires a large amount of speech data with transcriptions for speakers of the target language. However, in practice not necessarily all speakers of the target language have such an amount of data. In such a case speaker adaptation can be used, which refers to a technology that can adapt the TTS model to a new speaker whose data is not included in the training set and enable the TTS model to synthesize the target speaker's speech at a relatively lower cost.

Existing monolingual speaker adaptation methods often use a small amount of the target speaker's speech data to fine-tune a pretrained multi-speaker TTS model [6, 7]. However, since the TTS model of the source language never sees the target language's data during the training process, this method is not applicable for cross-lingual speakers, i.e., speakers of different languages. Himawan et al. built a multilingual acoustic model by using a large number of monolingual and a few bilingual speakers and adapted the model by fine-tuning the acoustic model on the target speaker's data [8]. Hemati et al. trained a IPA-based Tacotron [9] instead of using normal text character to support unseen languages [10]. The language-agnostic model could then be fine-tuned on the data of cross-lingual speakers directly. However, since bilingual data and the IPA are not necessarily available for all languages, they are not applicable for all languages. Unlike previous work, the basic idea of our work is inspired by Jia et al. [11], a monolingual speaker adaptation method. It uses the speaker embeddings generated by a pretrained speaker verification model to train a multi-speaker TTS model and synthesizes speech for target speakers with their speaker embeddings. However, our previous work [1, 2] showed that when the speaker recognition model was trained on multilingual data, domain shift of different languages was easy to appear, which would impede extending the monolingual method to multilingual settings.

In this paper, we propose a cross-lingual speaker adaptation method using domain adaptation and speaker consistency loss for TTS synthesis. The proposed method neither needs bilingual data nor phoneme representation but only needs multilingual data without transcriptions to train a speaker verification model and the source language's data to train a TTS model. Also, the proposed method can fine-tune the source language's TTS model on the target language's data by using the speaker embeddings of the target speakers, which only needs up to 3 minutes of speech data of each speaker. Inspired by our previous work [1, 2], the proposed method first trains a language-independent speaker verification model on multilingual data by using domain adaptation. Then the speaker embeddings for source language's speakers are used to train a monolingual multi-speaker TTS model. To adapt the TTS model to cross-lingual target speakers, the proposed method fine-tunes the TTS model under a speaker consistency loss that maximizes the cosine similarity between speaker embeddings of the same speaker generated from the target language's natural speech and the source language's synthesized speech. Since the speaker embeddings are generated by a language-independent speaker verification model, the knowledge of cross-lingual speakers can be well transferred to the TTS model. Experimental results demonstrated that (1) the proposed method can synthesize speech of the source language of a cross-lingual speaker with higher speech naturalness than the conventional method; (2) using speaker consistency loss with a language-dependent speaker verification model will instead causing performance degradation. The audio samples of this work are publicated on our project page: https://aria-k-alethia.github.io/2021clsa/.

2. Baseline Method

In this section we introduce a baseline method for cross-lingual speaker adaptation based on previous work [11] used in the experiments. The baseline method contains two components: (1) a speaker encoder based on multilingual speaker verification, (2) a monolingual multi-speaker TTS model based on Tacotron2.

http://dx.doi.org/10.21437/Interspeech.2021-897

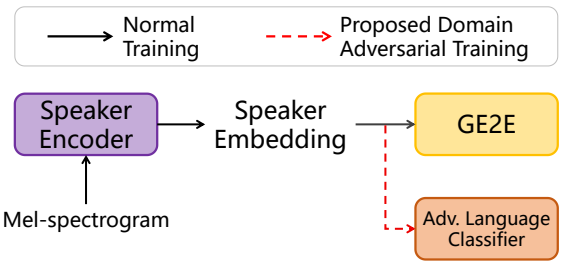


Figure 1: *Architecture of the speaker encoder. The adversarial language classifier is not used in the conventional method.*

2.1. Speaker Encoder based on Speaker Verification

Recent work has shown that speaker verification/recognition is an appropriate pretext task to learn speaker embeddings for multi-speaker TTS [1, 12]. This is because learning a representative and distinct speaker embedding for each speaker is a common requirement for speaker verification and multi-speaker TTS. Thus in this stage we train the speaker encoder based on speaker verification using multilingual data.

The general architecture of the speaker encoder is illustrated in Figure 1. Basically it is similar to the architecture mentioned in Jia et al. [11]. The only difference here is that we use a more powerful model called ResCNN [13] as the speaker encoder's implementation instead of simple long short-term memory to encode the mel-spectrograms to cope with the complexity of multilingual data. We use generalized end-to-end (GE2E) loss $\mathcal{L}_{ge2e}$ [14] as the speaker verification loss. Minimizing this loss will increase the cosine similarity between speaker embeddings of the same speaker while decreasing the similarity between different speakers' embeddings.

2.2. Multi-speaker Tacotron

After we get the trained speaker encoder, we train a monolingual multi-speaker TTS model by conditioning a Tacotron2-based TTS model [9] on the speaker embedding generated by the speaker encoder (Figure 2). Specifically, following previous work [10, 11] we concatenate the speaker embedding to the output states of the text encoder and use this as the input of the attention module to let the decoder attend over them. In this stage we only use the source language's data and keep the parameters of the speaker encoder fixed.

Formally, denote the mel-spectrogram of the jth utterance of the ith speaker as x_{ij}, the embedding generated by speaker encoder $f_s(\cdot)$ is defined as: $e_{ij} = f_s(x_{ij})$. Denote the Tacotron2 model and the text sequence of the mel-spectrogram x_{ij} as $f_t(\cdot)$ and y_{ij}, respectively, the loss function of the TTS model is defined as the L1 distance between the natural mel-spectrogram x_{ij} and the synthesized one $\tilde{x}_{ij} = f_t(y_{ij}, e_{ij})$: $\mathcal{L}_{tts} = \sum_{i,j} |\tilde{x}_{ij} - x_{ij}|$. After training, to adapt to a new speaker, we first average speaker embeddings generated from the speaker's k utterances and use the averaged speaker embedding to synthesize the source language's speech.

3. Proposed Method

In this section we describe the proposed method by extending the baseline method described in Section 2. The proposed method first trains a speaker encoder based on speaker verification using GE2E loss and domain adaptation to construct a language-independent speaker space. This makes it easy to transfer knowledge to the TTS model for cross-lingual speakers. To fine-tune the TTS model on cross-lingual speech, the proposed method then uses a speaker consistency loss to maximize the cosine similarity between the speaker embeddings of the natural and the same speaker's synthesized mel-spectrograms, which can benefit from the language-independent speaker space learned by the domain adaptation.

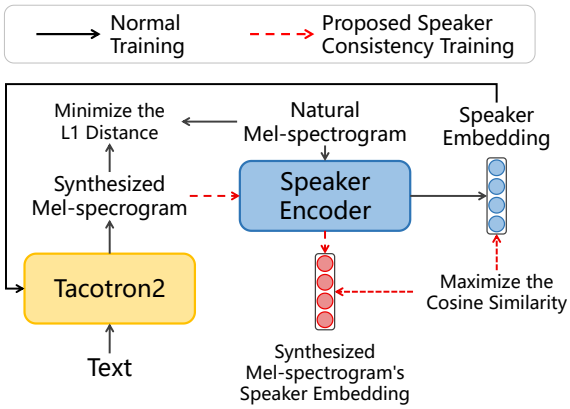


Figure 2: *Diagram of the proposed TTS model and the speaker consistency loss.*

3.1. Language-independent Speaker Verification based on Domain Adaptation

The baseline speaker verification method introduced previously (Section 2.1) is suitable for monolingual settings. However, when training the model on multiple datasets of different languages, the language-dependent speakers cause a domain shift between the speakers of different languages [15]. This impedes the knowledge transferring from the speaker encoder to the TTS model for cross-lingual speakers. Therefore to make it possible to fine-tune the TTS model on cross-lingual data, following our previous work [1, 2] we use a domain adaptation algorithm to eliminate the domain shift.

Specifically, we use domain adversarial neural network (DANN) [16]. As illustrated in Figure 1, the proposed method extends the baseline method by adding an adversarial language classifier. During training the classifier tries to learn the language label from the speaker embedding. Meanwhile, the adversarial training forces the model to exclude information relating to language from the speaker embedding, which finally makes the speaker encoder become language-independent. This is accomplished by a gradient reversal layer (GRL) to reverse the gradient back-propagated from the classifier to the speaker embedding.

Formally, denote the GRL operator, the adversarial language classifier and the language label of x_{ij} as $\triangle$, $f_l(\cdot)$ and l_{ij}, respectively, the loss of DANN is defined as:

$$\mathcal{L}_{da} = \sum_{i,j} -l_{ij} \log \sigma(f_l(\triangle e_{ij})) - (1-l_i) \log (1 - \sigma(f_l(\triangle e_{ij}))), \tag{1}$$

where $\sigma(\cdot)$ is the sigmoid function. The final loss function of the proposed speaker encoder is defined as: $\mathcal{L}_s = \mathcal{L}_{ge2e} + \mathcal{L}_{da}$. This loss makes the speaker space generated by the speaker encoder not only reflect the speaker characteristics but also not depend on language.

3.2. Speaker Adaptation based on Consistency Loss

As mentioned previously cross-lingual speech data can not be used to fine-tune a monolingual TTS model of source language directly. However, the knowledge learned by the pretrained speaker encoder can be utilized. Thus we propose a speaker consistency loss (SCL) to maximize the cosine similarity between speaker embeddings extracted from the natural and the

Table 1: *Accuracy (%) on train and test set of a new language classifier trained on the embeddings generated by each speaker encoder.*

	Base.	DA	Random Model
Train	98.13	**66.75**	83.13
Test	93.95	**66.10**	79.20

same speaker's synthesized mel-spectrogram. The core idea is inspired by Nachmani et al. [3], which has shown a possible way to apply such loss to the cross-lingual TTS task. While their work only used the gradient of the loss to update the speaker encoder's parameters, which has little influence on the speech synthesis process, in this work we used the gradient to update the parameters of the decoder in the Tacotron2 model.

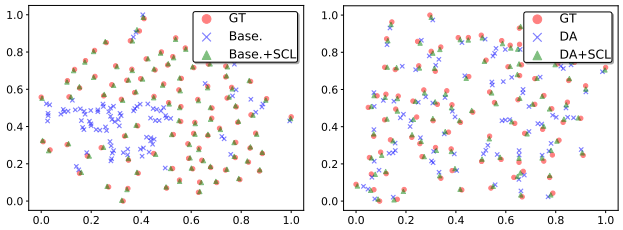
As illustrated in Figure 2, to compute the SCL the proposed method first feeds the text and the speaker embedding extracted from a target speaker's natural mel-spectrogram to the multi-speaker Tacotron2 model to synthesize a mel-spectrogram of the source language. The synthesized mel-spectrogram is then fed to the speaker encoder to get the speaker embedding of the synthesized mel-spectrogram of the same speaker. Finally the cosine similarity between the two embeddings of the same speaker is maximized. In the fine-tuning stage we froze the parameters of the speaker encoder and the Tacotron2 model except for the mel-spectrogram decoder. Formally, the SCL is defined as:$\mathcal{L}_{scl} = -\sum_{i,j} \cos\left(f_s(\tilde{x}_{ij}), e_{ij}\right)$. In addition, during experiments we found only using cross-lingual data to fine-tune would decrease the speech quality. We then computed SCL for both intra-lingual and cross-lingual speakers to fine-tune the TTS model and saw improvements in this case. To stabilize the fine-tuning, we still include the L1 loss in this process. Thus the loss function for fine-tuning is defined as: $\mathcal{L}_{ft} = \mathcal{L}_{tts} + \alpha\mathcal{L}_{scl}$, where α is a hyperparameter.

One may consider using SCL directly without domain adaptation. However, because of the domain shift, in the experiments (Section 4) we show that using the baseline speaker encoder to fine-tune the TTS model will instead cause significant performance degradation when adapting the model to cross-lingual speakers.

4. Experiments

4.1. Experimental Setup

In our experiments, English is regarded as the source language, and Japanese is regarded as the target language. We used English multi-speaker dataset VCTK [17] and Japanese multi-speaker dataset JVS [18] to train the speaker verification model. The total number of speakers was 207 in which 107 were English speakers and 100 were Japanese speakers. We randomly picked up 8 English speakers and 8 Japanese speakers (both contained 4 female and 4 male speakers) as unseen speakers and excluded their data from the training and fine-tuning process. All audios were downsampled to 16 kHz and converted to 80-dimensional mel-spectrograms. The frame number of the mel-spectrogram was segmented to $[120, 150]$ for training the speaker verification model. After training the speaker encoder we trained the TTS model by the L1 loss $\mathcal{L}_{tts}$ using the VCTK dataset. After the TTS model converged, we fine-tuned the TTS model using the fine-tuning loss $\mathcal{L}_{ft}$ with both English and Japanese data. We segmented the synthesized mel-spectrogram to 130 frames to compute the SCL $\mathcal{L}_{scl}$. Note that we don't need text transcription for the speech data of the target language (Japanese), though JVS has it. Finally we used WaveRNN [19] to convert the synthesized mel-spectrogram to the time-domain waveform.



(a) Base. (b) DA

Figure 3: *t-SNE visualization of embeddings of cross-lingual speakers generated by (a) Base. (b) DA speaker encoder from the natural Japanese speech and the synthesized English speech. GT represents the embedding generated from the natural mel-spectrogram by the corresponding speaker encoder.*

In all experiments, the dimension of the speaker embedding was set to 64. The adversarial language classifier was implemented as a 2-layer multi-layer perceptron with 64 hidden units. The number of utterances k for computing speaker embedding and the weight hyperparameter α of SCL were empirically set to 5 and 0.1, respectively.

We used Adam [20] as an optimizer. The initial learning rate was set to 10^{-3} for training both the speaker encoder and the TTS model. We halved the learning rate when the loss on the validation set did not decrease until reaching a minimal value 10^{-5}. All models were trained until converged. For fine-tuning we trained the TTS model for 20 epochs and fixed the learning rate to 10^{-4}. We multiplied the gradient back-propagated from language classifier to the embedding by a factor $\lambda_p = \frac{2}{1+\exp(-10 \cdot p)} - 1$, where p represents the training progress ranging from 0 to 1. This made the speaker encoder less sensitive to the adversarial training at the initial stage.

We trained four models for comparison. The first two models were trained using the baseline and the proposed methods (Section 2, 3), which are denoted by Base. and DA+SCL, respectively. For ablation experiments we additionally trained two models Base.+SCL and DA. The Base.+SCL model was trained by using SCL with baseline speaker encoder without domain adaptation. The DA model was trained by the proposed method without SCL. Note that we didn't fine-tune the TTS model for the two models without using SCL (Base. and DA).

4.2. Objective Evaluation

4.2.1. Language-dependence of Speaker Encoder

We evaluate the language-dependence of each speaker encoder. For each speaker encoder, we trained a new language classifier on the embeddings generated by the speaker encoder and computed the average accuracy on the train and the test sets. We also used a randomly initialized speaker encoder as a control model. The result is shown in Table 1. As one can expect, the speaker encoder DA has the lowest accuracy, which shows the effectiveness of the proposed domain adaptation method to learn the language-independent speaker encoder. On the other hand the embeddings of Base. and random model both show high language-dependence, which demonstrates that the domain shift originally exists in the data and the baseline speaker encoder magnifies it.

4.2.2. Visualization of Speaker Embedding

We visualized the speaker embeddings of cross-lingual speakers generated by each speaker encoder. In addition to the speaker embeddings of Japanese natural speech, we also generated the

Table 2: *Results of XAB tests on speaker similarity.* ***Bold*** *scores indicate preferred method has* p *value less than* 0.05

Task	Speaker	Base. vs. DA	Base.+SCL vs. DA+SCL	DA vs. DA+SCL	Base.+SCL vs. DA
Intra-lingual	Seen	0.464 - **0.536**	0.473 - **0.527**	0.500 - 0.500	0.468 - **0.532**
	Unseen	0.450 - **0.550**	0.448 - **0.552**	0.479 - **0.521**	0.504 - 0.496
Cross-lingual	Seen	0.440 - **0.560**	0.408 - **0.592**	0.492 - 0.508	0.408 - **0.592**
	Unseen	**0.524** - 0.476	**0.531** - 0.469	0.488 - 0.512	0.496 - 0.504

Table 3: *Results of MOS evaluation on naturalness.* ***Bold*** *indicates better method comparing to Base. without overlapping* 95% *confidence interval*

Task	Spkr.	Base.	Base.+SCL	DA	DA+SCL	GT
Intra	Seen	3.51	**3.65**	3.58	**3.67**	4.04
	Unseen	3.62	**3.73**	3.61	**3.77**	4.15
Cross	Seen	3.39	2.84	**3.60**	**3.61**	4.04
	Unseen	3.54	3.07	3.48	**3.55**	4.06

speaker embeddings for the synthesized cross-lingual English speech of each model. We averaged all embeddings generated from 5 utterances of each speaker as the speaker embedding. We first divided the four models into two groups based on the speaker encoder they used. Then the embeddings were visualized by the t-SNE algorithm [21] for each group. The result is shown in Figure 3. First, the speaker embeddings of the two models without using SCL (blue cross) have relatively lower similarity with their GT counterparts (red circle) compared to the two models with SCL (green triangle), which demonstrates the effect of SCL. Second, the domain shift existing in the embeddings of Base. can be easily observed from the left side of the figure, which implies that the speaker encoder of Base. cannot well recognize the same speaker if the two embeddings are generated from the speech of different languages. Therefore, although in the view of the language-dependent speaker encoder of Base., the embeddings of Base.+SCL have high similarity with their GT counterparts, combing this result with the poor cross-lingual performance of Base.+SCL in the subjective evaluation (Table 3) we can say that the knowledge saved in the speaker encoder of Base. is not suitable for cross-lingual speaker adaptation.

4.3. Subjective Evaluation

We evaluated the synthesized speech from two aspects: speech naturalness and speaker similarity. In addition to the 16 unseen speakers, we randomly picked 16 speakers from the training set as seen speakers. Note that, since models without using SCL have no fine-tuning step, the 8 Japanese seen speakers are seen by the speaker encoder but completely unseen by the TTS model of Base. and DA. For each speaker we synthesized 20 utterances. All of these utterances were not included in the training process. We used Amazon Mechanical Turk[1] to conduct the subjective evaluation.

4.3.1. Speech Naturalness

We conducted 5-scale mean opinion score (MOS) tests to evaluate the speech naturalness of the synthesized speech. We categorized all utterances into four groups by their speaker (seen/unseen) and task (intra-lingual/cross-lingual); the MOS was calculated separately for each group. Totally 720 English listeners joined in the evaluation; each test had 90 listeners with 25 answers per listener. The result is shown in Table 3, in which ground truth (GT) represents the natural speech. It can be observed that the proposed DA+SCL model obtains the best performance in all tasks. For the intra-lingual task, Base.+SCL also obtains significant improvements compared to Base. and DA, demonstrating that the SCL can improve the intra-lingual speaker adaptation. In contrast, for the cross-lingual tasks the performance of Base.+SCL degrades significantly while the DA+SCL model still maintained similar performance compared to their performance on the intra-lingual tasks. This demonstrates that the domain shift makes it difficult to apply SCL directly for adapting the TTS model to cross-lingual speakers. Finally the DA model also has comparable performance to the DA+SCL model, which shows the effectiveness of removing the domain shift for the cross-lingual tasks.

4.3.2. Speaker Similarity

We then conducted preference XAB tests to evaluate the speaker similarity of the synthesized speech. Here X is the natural speech, which is English for VCTK speakers and Japanese for JVS speakers. We chose four pairs among all six combinations of the four models. Two pairs (Base., DA) and (Base.+SCL, DA+SCL) were chosen to show the effect of the proposed method. In addition, we compared DA to DA+SCL to evaluate the effect of SCL. We also compared Base.+SCL to DA to evaluate DA and SCL separately. Totally 800 listeners joined in the evaluation; each test had 25 listeners with 10 answers per listener. The result is shown in Table 2. The DA and DA+SCL models both obtain relatively better performance than the Base. and Base.+SCL models, respectively, which shows the effectiveness of the proposed method. Surprisingly, the performance of DA and DA+SCL are almost the same, which implies the SCL has relatively little influence on speaker similarity. Finally the DA model obtains more improvements on the cross-lingual tasks than the Base.+SCL model compared to the intra-lingual tasks, which shows the effectiveness of eliminating domain shift for the cross-lingual tasks. Note that, for the cross-lingual unseen task the performance of Base. (+SCL) is slightly better than DA. (+SCL). After a preliminary analysis, we find that the speaker similarity between different models in this task has small differences, which may because of the relatively low generalization ability of the proposed model since the speaker number of the speaker verification model (207) is very small compared to normal speaker verification systems which have thousands of speakers. Therefore we additionally trained some models with more speakers in the speaker verification model. One can find audio samples of these models on our project page.

5. Conclusions

This paper described a method for cross-lingual speaker adaptation for TTS synthesis based on a language-independent speaker encoder using domain adaption and a speaker consistency loss which makes it possible to fine-tune the TTS model of source language on the target language's data. Experimental results demonstrated that the proposed model could significantly improve speech naturalness compared to the baseline method. Future work will be extending this method to more languages.

Acknowledgements: Part of this research and development work was supported by JSPS KAKENHI 18K18100 and 17H06101. JSPS and CAS under the Japan–People's Republic of China Research Cooperative Program.

[1] `https://www.mturk.com/`

6. References

[1] D. Xin, Y. Saito, S. Takamichi, T. Koriyama, and H. Saruwatari, "Cross-lingual text-to-speech synthesis via domain adaptation and perceptual similarity regression in speaker space," in *Proc. Interspeech*, Shanghai, China, Oct. 2020.

[2] D. Xin, T. Komatsu, S. Takamichi, and H. Saruwatari, "Disentangled speaker and language representations using mutual information minimization and domain adaptation for cross-lingual TTS," in *Proc. ICASSP*, Toronto, Canada, Jun. 2021.

[3] E. Nachmani and L. Wolf, "Unsupervised polyglot text-to-speech," in *Proc. ICASSP*, Brighton, United Kingdom, May 2019, pp. 7055–7059.

[4] S. Maiti, E. Marchi, and A. Conkie, "Generating multilingual voices using speaker space translation based on bilingual speaker data," in *Proc. ICASSP*, Barcelona, Spain, May 2020, pp. 7624–7628.

[5] Y. Zhang, R. J. Weiss, H. Zen, Y. Wu, Z. Chen, R. Skerry-Ryan, Y. Jia, A. Rosenberg, and B. Ramabhadran, "Learning to speak fluently in a foreign language: multilingual speech synthesis and cross-language voice cloning," in *Proc. Interspeech*, Graz, Austria, Sep. 2019, pp. 2080–2084.

[6] H. B. Moss, V. Aggarwal, N. Prateek, J. González, and R. Barra-Chicote, "Boffin TTS: Few-shot speaker adaptation by bayesian optimization," in *Proc. ICASSP*, Barcelona, Spain, May 2020, pp. 7639–7643.

[7] K. Inoue, S. Hara, M. Abe, T. Hayashi, R. Yamamoto, and S. Watanabe, "Semi-supervised speaker adaptation for end-to-end speech synthesis with pretrained models," in *Proc. ICASSP*, Barcelona, Spain, May 2020, pp. 7634–7638.

[8] I. Himawan, S. Aryal, I. Ouyang, S. Kang, P. Lanchantin, and S. King, "Speaker adaptation of a multilingual acoustic model for cross-language synthesis," in *Proc. ICASSP*, Barcelona, Spain, May 2020, pp. 7629–7633.

[9] J. Shen, R. Pang, R. J. Weiss, M. Schuster, N. Jaitly, Z. Yang, Z. Chen, Y. Zhang, Y. Wang, R. Skerrv-Ryan *et al.*, "Natural TTS synthesis by conditioning WaveNet on mel spectrogram predictions," in *Proc. ICASSP*, Calgary, Alberta, Canada, Apr. 2018, pp. 4779–4783.

[10] H. Hemati and D. Borth, "Using IPA-based tacotron for data efficient cross-lingual speaker adaptation and pronunciation enhancement," *arXiv preprint arXiv:2011.06392*, 2020.

[11] Y. Jia, Y. Zhang, R. J. Weiss, Q. Wang, J. Shen, F. Ren, Z. Chen, P. Nguyen, R. Pang, I. L. Moreno *et al.*, "Transfer learning from speaker verification to multispeaker text-to-speech synthesis," *arXiv preprint arXiv:1806.04558*, 2018.

[12] J. Cho, P. Żelasko, J. Villalba, S. Watanabe, and N. Dehak, "Learning speaker embedding from text-to-speech," in *Proc. Interspeech*, Shanghai, China, Oct. 2020, pp. 3256–3260.

[13] C. Li, X. Ma, B. Jiang, X. Li, X. Zhang, X. Liu, Y. Cao, A. Kannan, and Z. Zhu, "Deep speaker: an end-to-end neural speaker embedding system," *arXiv preprint arXiv:1705.02304*, May 2017.

[14] L. Wan, Q. Wang, A. Papir, and I. L. Moreno, "Generalized end-to-end loss for speaker verification," in *Proc. ICASSP*, Calgary, Alberta, Canada, Apr. 2018, pp. 4879–4883.

[15] W. Xia, J. Huang, and J. H. Hansen, "Cross-lingual text-independent speaker verification using unsupervised adversarial discriminative domain adaptation," in *Proc. ICASSP*, Brighton, United Kingdom, May 2019, pp. 5816–5820.

[16] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. Marchand, and V. Lempitsky, "Domain-adversarial training of neural networks," *The Journal of Machine Learning Research*, vol. 17, no. 1, pp. 2096–2030, 2016.

[17] C. Veaux, J. Yamagishi, K. MacDonald *et al.*, "Superseded-CSTR VCTK corpus: English multi-speaker corpus for cstr voice cloning toolkit," 2016.

[18] S. Takamichi, K. Mitsui, Y. Saito, T. Koriyama, N. Tanji, and H. Saruwatari, "JVS corpus: free Japanese multi-speaker voice corpus," *arXiv preprint arXiv:1908.06248*, 2019.

[19] N. Kalchbrenner, E. Elsen, K. Simonyan, S. Noury, N. Casagrande, E. Lockhart, F. Stimberg, A. Oord, S. Dieleman, and K. Kavukcuoglu, "Efficient neural audio synthesis," in *Proc. ICML*, Stockholm, Sweden, Jul. 2018, pp. 2410–2419.

[20] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. ICLR*, San Diego, USA, May 2015.

[21] L. van der Maaten and G. Hinton, "Visualizing data using t-SNE," *Journal of machine learning research*, vol. 9, no. Nov, pp. 2579–2605, 2008.