TDASS: Target Domain Adaptation Speech Synthesis Framework for Multi-speaker Low-Resource TTS

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Abstract—Recently, synthesizing personalized speech by text-to-speech (TTS) application is highly demanded. But the previous TTS models require a mass of target speaker speeches for training. It is a high-cost task, and hard to record lots of utterances from the target speaker. Data augmentation of the speeches is a solution but leads to the low-quality synthesis speech problem. Some multi-speaker TTS models are proposed to address the issue. But the quantity of utterances of each speaker imbalance leads to the voice similarity problem. We propose the Target Domain Adaptation Speech Synthesis Network (TDASS) to address these issues. Based on the backbone of the Tacotron2 model, which is the high-quality TTS model, TDASS introduces a self-interested classifier for reducing the non-target influence. Besides, a special gradient reversal layer with different operations for target and non-target is added to the classifier. We evaluate the model on a Chinese speech corpus, the experiments show the proposed method outperforms the baseline method in terms of voice quality and voice similarity.

Index Terms—Text-to-speech, Speech synthesis, Domain adaptation, Low resource.

I. INTRODUCTION

Text-to-speech synthesis (TTS) aims to generate intelligible and natural speech from the input text or phoneme sequence [1]–[5]. It has a long history in the TTS research, from the method of concatenative synthesis, and statistical parametric synthesis to the recent method of deep neural TTS. Concatenative synthesis methods and parametric synthesis methods are two main methods for TTS. Concatenative methods propose to combine each word’s voice into a full-sentence voice. It means the method can make synthesis voice only if the database has all single words’ representatives of the input text. The concatenative synthesis relies on the database of prestored utterance, it can synthesize natural speech nearly the same as the raw speech spoken by the person. But due to it needing a huge amount of utterances to cover different words, it is costly and cannot be used in a general way. Parametric synthesis methods transfer the known words and their voice to vectors and predict the unknown words’ vectors. To use the known voice vectors and predicted vectors, parametric synthesis models can generate voice. While the statistical parametric synthesis method can address the drawbacks of the concatenative method by recovering the speech through limited acoustic parameters. But the quality of the statistical parametric synthesis has lower intelligible and robotic can be easily differentiated from human speech.

Recent advances in TTS models achieved high-quality synthetic speech. Such as Tacotron series [6], [7], FastSpeech series [8] are able to synthesize the approach human naturalness speech. But the challenges remain, these models require a number of clean speeches to train. But it is hard for the industry to collect the hundreds of speeches per person [9]–[11]. Furthermore, training one model for multiple speakers is another challenge (Multi-speaker TTS) to improve the efficiency of TTS models [12]–[14].

Previous researches on multi-speaker TTS remain requires hundreds or thousands of high-quality training speeches per person [15]–[17]. Several studies utilize voice conversion [18]–[20] to augment both speaker and speech databases to address the extensive training data required. But the recent advance of voice conversion is hard to synthesize noise-free speeches. These speeches restrict the outcome quality of downstream TTS tasks [21]–[24].

Most of the previous works utilize the timbre information of speakers for multi-speaker TTS. X-vector, which represents the speaker timbre features, is commonly used in multi-speaker TTS models [25], [26]. By adding the X-vector into Tacotron2 [7], it can synthesize speech for multiple speakers. However, the similarity of synthesis speech to the target speaker is another challenge. Because the synthesis process is easy to be influenced by the other speakers who are not the target. Some previous works believe the problem happens on the alignment, while others believe the network structure is unsuitable. The Light-TTS is a new SOTA model for multi-speaker TTS [27], [28], which modifies the FastSpeech2 [8]. Cai et al. [29] utilize a reconstruct timbre distance loss. Through control of the distance between the timbre embedding of synthesis speech to the original to restrict the voice similarity.

We propose a new framework and training process for the multi-speaker TTS model to apply in the low-resource situation and address the voice similarity. The framework is called as Target Domain Adaptation Speech Synthesis Network (TDASS), the structure is shown in Figure 1. Based on the backbone of Tacotron2, we introduce a self-interested classifier to improve the synthesis of voice similarity. The self-interested classifier identifies and filters all the non-target encoding hidden vectors, which combine the linguistic and

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timbre information. Furthermore, a special gradient reversal layer (GRL) was added to the classifier. The GRL will give gradient reversal for non-target speakers and normal gradient for target speakers. Compared to the [29], [30], rather than the reconstruct timbre distance loss, the classifier is more specific for the target speaker. We applied the TDASS to a database of Chinese speeches. The experiments show the proposed model has improved than the baseline method in terms of naturalness and similarity.

II. RELATED WORK

Hidden Markov Model (HMM) based TTS model is a statistic method of traditional parametric synthesis method [31], [32]. Using statistical results from the training dataset to reason and predict a possible voice used in the next state. HMM is a popular model used in synthesis voice [33]–[38]. Because the HMM assumes the next state is only related to the current state. This is in line with the characteristics of human speech. However, the HMM-based synthesis methods predict accuracy is low to lead the generated voice worse than concatenative synthesis methods. Furthermore, the methods also required many databases to learn the relation between every single word.

WaveNet is an autoregressive generative model, that predicts the next sampling point by learning the previous points [39]. WaveNet is similar to the HMM used in traditional parametric synthesis methods. It can not directly synthesize voice from the input text and require a preprocessing model to transfer text to features. The performance of TTS by using WaveNet is improved, but the result is influenced by the preprocessing. If the error occurs in the previous steps, the WaveNet is hard to fix it. Furthermore, WaveNet is slow to synthesize voice as it can only predict a sampling point per time.

With the development of deep model on many tasks [40]–[42]. Tacotron is the first end-to-end TTS model [6]. Instead of using another model to preprocess the input text, the Tacotron can encode text and generate voice. The Tacotron consists of five parts, encoder, attention, decoder, and post-processing. It improves the performance in terms of WaveNet, which is the end-to-end model benefits. But the improvement is limited, as the output of Tacotron is mel-spectrogram and requires a model to transfer the mel-spectrogram to voice. Previous research uses the Griffin-Lim reconstruction algorithm, a simple model to generate voice but with little noise.

To address the problem of Tacotron, Tacotron2 is proposed, which is also an end-to-end model [7]. Tacotron2 uses WaveNet vocoder to replace Griffin-Lim to synthesize voice from mel-spectrogram. Besides, Tacotron2 only generates one frame per step in the decoder and uses another post-net part to adjust the generated mel-spectrogram.

Fastspeech [43] is not like the previous neural TTS, it firstly generated mel spectrum in a parallel way. FastSpeech is built up a feed-forward network based on Transformer, the attention alignments between encoder and decoder are achieved with phoneme duration prediction based on a teacher model. Through a length regulator to expand the source phoneme sequence to match the length of the target mel-spectrogram sequence for a parallel generation. Due to mel spectrum was relied on the distilling of the teacher-student model, there exists information loss. The Fastspeech2 [44] was proposed to do a enhance of the Fastspeech, it introduces variance adaptor to enhance the variation information such as pitch, energy, and duration. The training avoids two-stage teacher-student distillation, it directly uses the groundtruth mel spectrum.

While the previous neural TTS modes need two-stage, one is the acoustic model to generate mel spectrum from linguistic information, and the other is the vocoder to generate audio way from mel spectrum. Several recent neural TTS models enabling single-stage training and parallel sampling have been proposed. VITS [45] adopts normalizing flows and an adversarial training process for variational inference augmentation, which improves the expressive of the generator. A stochastic duration predictor to synthesize speech with diverse rhythms from input text was added in VITS, it could encode the same input text in multiple ways for speaking.

But training the high-quality TTS systems needs a large amount of paired text and speech data. Most languages lack training data for developing TTS systems. The low resources TTS works often utilize self-supervised training, cross-lingual transfer, cross speaker transfer, and dataset augmentation in the wild.

III. PROPOSED METHOD

A. Backbone Modules

The processing network consists of an encoder and attention mechanism. The primary purpose of the processing network is to encode the input embedding of the phoneme sequence and decode the high-level feature added with speakers’ timbre feature to each frame of mel-spectrogram.

Given the phoneme sequences $x$, the output $z$ of encoder is calculated as $z = \phi(x, \theta_p)$, where $\phi(\cdot)$ is the mapping function of encoder. $\theta_p$ is the parameter of encoder. Then, we concatenate the phoneme embedding $z$ and timbre $x$-vector to get the embedded features, $Z$.

The attention mechanism takes the embedded features, $Z$, as input. The output features of the processing network, $\delta$, is calculated as $\delta = f(Z, \theta_d)$, where $f(\cdot)$ is the mapping function of the attention mechanism. $\theta_d$ is the parameter of the attention mechanism.

The Generative network is composed of a self-interest classifier and supervised generator. The generator is the same as the decoder of Tacotron2 [7]. It aims to synthesize the mel-spectrogram for the input feature information, $\delta$.

B. Self-interested Classifier

We introduce the self-interested classifier $C$ takes the feature information $\delta$ and passes it through three fully connected layers and a Softmax function. The Softmax function identifies whether the voice is spoken by the target or non-target. The
though back-propagation.

\[ \theta \]

\[ \text{rogram and ground truth. Parameters} \]

\[ L \]

\[ \text{task learning framework, jointly with the self-interest classifier} \ C \]

\[ C \]

\[ \text{identified by the classifier.} \]

\[ \text{Finally, the non-target speaker could not be} \]

\[ \text{generation, it will be converged when the output is similar to} \]

\[ \text{minimization of classification and maximization of network} \]

\[ L \]

\[ \text{denotes the target speaker’s classification loss.} \]

\[ P \]

\[ \text{output is two probabilities} \ P_0, P_1 \text{ for non-target and target} \]

speakers.

\[ (P_0, P_1) = C(\delta; \theta_C) = C(P(x, x - \text{vector}; \theta_P; \theta_C) \]

\[ (1) \]

where \( C \) denotes the self-interest classifier, and the parameters of the self-classifier is labeled as \( \theta_C \). The parameter of the processing network is \( \theta_P \), which equal with \( (\theta_p, \theta_d) \). The self-interest classifier \( C \) and the generate network are trained together with the cross entropy loss on speaker classification:

\[ L_{\text{CLS}}(\theta_P, \theta_C) = L_{\text{non-target}} + L_{\text{target}}, \]

\[ L_{\text{non-target}} = -\Pi(y_{\text{speaker}} == 0) \log P_0, \]

\[ L_{\text{target}} = -\Pi(y_{\text{speaker}} == 1) \log P_1. \]

where the indicator function is labeled as \( \Pi(\cdot) \), speech \( x \) is spoken by the speaker of \( y_{\text{speaker}}, \) for non-target speakers the classification loss is labeled as \( L_{\text{non-target}}, \) and \( L_{\text{target}} \) denotes the target speaker’s classification loss.

During training, parameters \( \theta_C \) are used to discriminate the target and non-target speaker by minimizing the classification loss, whereas gradient reversal is used to update \( \theta_P \). During the minimization of classification and maximization of network generation, it will be converged when the output is similar to the target speaker. Finally, the non-target speaker could not be identified by the classifier.

The supervised generator \( G \) and the processing network are jointly with the self-interest classifier \( C \) for training a multi-task learning framework,

\[ L(\theta_P, \theta_G, \theta_C) = L_{\text{GLS}}(\theta_P, \theta_G) \]

\[ - \lambda L_{\text{non-target}}(\theta_P, \theta_C) \]

\[ + L_{\text{target}}(\theta_P, \theta_C) \]

where \( \theta_G \) is the parameters of the supervised generator, \( L_{\text{GLS}}(\theta_P, \theta_G) \) is the distance between generated mel spectrogram and ground truth. Parameters \( \theta_P, \theta_C, \theta_G \) are updated though back-propagation.

C. Target Domain Adaptation: Special Gradient Reversal Layer

For synthesis voice similarity and target domain adaptation, in self-interest classifier. For target and non-target, we process a different way of gradient reversal \cite{46, 47}. The self-interest classifier has a specific designed gradient back propagated method as follow:

\[ F(\frac{\partial L_{\text{CLS}}}{\partial \theta_P}) = -\lambda \frac{\partial L_{\text{non-target}}}{\partial \theta_P} + \frac{\partial L_{\text{target}}}{\partial \theta_P} \]

\[ (4) \]

where \( F(\cdot) \) is the mapping function of gradient reversal layer. \( \lambda \) is the weight adjustment parameters. The processing network parameters \( \theta_P \) are updated based on the gradient back-propagation loss function.

\[ \theta_P \leftarrow \theta_P - \mu \left( \frac{\partial L_{\text{GLS}}}{\partial \theta_P} - \lambda \frac{\partial L_{\text{non-target}}}{\partial \theta_P} + \frac{\partial L_{\text{target}}}{\partial \theta_P} \right) \]

\[ (5) \]

When the training sample is target, the back-propagation of \( \theta_P \) is calculated as follow:

\[ \theta_P \leftarrow \theta_P - \mu \left( \frac{\partial L_{\text{GLS}}}{\partial \theta_P} + \frac{\partial L_{\text{target}}}{\partial \theta_P} \right). \]

\[ (6) \]

When the training sample belongs to a non-target, the \( \lambda \frac{\partial L_{\text{non-target}}}{\partial \theta_P} \) equal to zero. It aims to gradually removed the style influence from the non-target speakers under adversarial training. The \( \frac{\partial L_{\text{target}}}{\partial \theta_P} \) is zero, when the training sample comes from the target speaker. The operation optimize towards the style information of the target speaker under supervised training.

In the TDASS, we set the loss of the self-interest classifier as the style loss, representing that the timbre information of embedded feature information is target or non-target. Besides, the loss of supervised generator is primarily composed of the style loss and the content loss, which aim the pronunciation of input text similar to the real. Therefore, the style information of the non-target speakers, in Equation (5), is gradually removed under adversarial training. In Equation (6), the feature information, \( \theta \), is optimized towards the style information of
the target speaker under supervised training. The proposed training process makes the processing network remove the non-target information, and the generated network generates the mel-spectrogram for target speakers.

IV. EXPERIMENTS

To validate the performance of our proposed method, we design an ablation study on a small-capacity target speaker dataset of 30, 100, 300, 500. In the experiment, we compare the TDASS with the baseline model of Tacotron2, and the baseline model with adding timbre feature of x-vector and TDASS without timbre feature in detail.

A. Datasets

We evaluate the proposed framework on a dataset of Chinese speech corpus. There are three speakers with 4019, 20257, 8915 records, respectively, in the database. The sampling rate of the audios is 22050 Hz. We set speaker1 and speaker2 as non-target speakers and used them for training the TDASS without the self-interested classifier. The total 24276 speeches of the two speakers are split into 24000 training records and 276 validation records. Then, we utilize speaker3’s speeches and the previous speakers to fine-tune the TDASS with the self-interest classifier. To show the low-resource performance of the proposed model, we set four experiments that randomly select 30, 100, 300, 500 utterances from speaker3, respectively. The test database of the four experiments uses the same 100 samples.

B. Configuration

The backbone configuration are following the Tacotron2. To specifically specify is that, the self-interest classifier contains three fully connected layers, of which the set are (1536,1024), (1024,64), and (64,2), respectively. The timbre feature x-vector is a one-dimensional vector obtained from each training sample and the length of the vector is 512.

Our proposed model was trained on a single NVIDIA V100 GPU. To begin with, we pre-train the TDASS without a self-interested classifier on the non-target speakers, speaker1 and speaker2, utterances. Then we load the parameter into the TDASS with a self-interested classifier to synthesize the target voice on the multi-speakers, all three speakers. Following [46], we gradually changed the parameter $\lambda$ in the self-interest classifier from 0 to 1 as follow

$$\lambda = \frac{2}{1 + exp(-10 \cdot k)} - 1$$

(7)

where, $k$ is the percentage of the training process. We train our model with batch size of 24 samples, and use the default Adam optimizer with $\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$. We adopt the learning rate of $10^{-4}$ and apply $L_2$ regularization with weight $10^{-6}$ [7], [48].

C. Evaluation Metrics

We utilize subjective and objective well-known metrics to evaluate the Tacotron2 w/o X-vector, Tacotron2, TDASS w/o X-vector, and TDASS.

Objective metrics Mel cepstral distortion (MCD) is one of the objective metrics widely used to compare two speeches’ similarities. It represents the distance between the Mel-scale Frequency Cepstral Coefficients (MFCC) of synthesis speech and the original speech’s MFCC. Besides, we also provide an example of mel-spectrograms comparison, shown in Fig. 2. The more similar mel-spectrogram, the more similar voice. Because the mel-spectrogram is obtained by passing the spectrogram, which is transferred from voice by short-time Fourier transformation (STFT), through the mel-scale filter banks. It means the mel-spectrogram can be seen as the voice shown in two-dimensional visualization.

Subjective metrics Mean Opinion Score (MOS) and Voice Similarity Score (VSS) [49], [50] are used in this experiment. MOS means to identify whether the converted voice is clear or not. VSS aims to determine the most similar to the real voice.

Both MOS and VSS are obtained by inviting native speakers to rate for the synthesis audio. We have 30 testers with an equal number of men and women. Respondents in the test have various knowledge backgrounds, such as Nature Language Processing, Product Manager, Psychology, etc.

For MOS evaluation, we give the testers a total of 140 utterances, 40 speeches per experiment, and eight samples per model of each experiment. Testers score zero to five for given samples, and higher marks mean close to naturalness. For VSS evaluation, we categorize the speeches with the same content into a group. Each group has one ground truth voice and four synthesis samples. Testers need to give zero to five marks for the synthesis speech too.

D. Result and Discussion

The MOS and MCD results for each model are shown in Table I. The VSS result is shown in Figure 3.

Overall The proposed TDASS has better performance whether the low-resource situation and in terms of the different evaluation metrics. The TDASS shows the improvement in the low-resource condition. Furthermore, Fig. 2 shows the proposed model has most similar to the mel-spectrogram of the ground truth speech.

Low-resource analysis The training sample number of target speaker utterances was tested using 30, 100, 300, and 500 in experiments to fine-tune the pretrained model for the low-resource tests. The TDASS improves about 0.2 on MCD, 0.7 on MOS, and 0.6 on VSS on comparison of baseline method in these tests. The higher marks prove the TDASS improves the synthesis voice similarity and the naturalness and is listenable in low-resource. Besides, when the number of target speeches in fine-tune increases, all four models improve the synthesis speech performance. Table I and Figure 3 show the Tacotron2 improved about 0.8 points on both MOS and VSS from 30 utterances used to 500 samples, which satisfies
the instinct. When there are 500 target speeches in fine-tune, the Tacotron2 approaches the normal performance with the 3.8 MOS scores. But in the meantime, the proposed model has better performance than Tacotron2. It proves whether the speaker utterances are limited, the proposed model has outperformance.

But one of the interesting findings is that when the number of target speaker utterances increases, the MCD value is higher. Besides, the TDASS w/o X-vector has better performance on the MCD in the 300 and 500 utterances tests. Nevertheless, MOS and VSS still show the synthesis speech of TDASS is more clear and similar. Because the MCD is an objective metric for comparing the MFCC. The differences of MFCC may not lead the synthesis speeches unclear and unlike voice of the target speaker.

**Self-interested classifier analysis** The difference between Tacotron2 w/o X-vector and TDASS w/o X-vector is the self-interested classifier. But the experiments show there is an average of 0.5 points on the MOS and 0.6 points on the VSS improvements. It means even without the speaker timbre features, the self-interested classifier also improves the quality of Tacotron2 synthesized speeches. TDASS w/o X-vector 0.3 points higher on MOS in the low-resource situation than Tacotron2 and 0.1 points larger in the normal condition. The comparison shows the different abilities based on the self-interested classifier and x-vector to enhance the synthesis speech quality. Because the Tacotron2 utilizes x-vector, TDASS w/o X-vector did not. But TDASS w/o X-vector uses the proposed self-interested classifier. Two comparisons prove the self-interested classifier has significant help for the multi-speaker TTS task.

**Ablation Experiment about X-vector.** The training process is the same. Table I shows whether X-vector uses or not, the TDASS has certain improvements for traditional Tacotron2 under different conditions. But both the TDASS with x-vector and Tacotron2 with x-vector enhance the performance for each condition than without it. It means the X-vector is useful to improve the performance of models.

In a word, the proposed framework, TDASS, and self-interested classifier are positive for synthesizing high-quality and high-similarity speeches. The x-vector, also has little significance on the generated speech.

**V. Conclusions**

To address the low-resource and synthesis speech similarity of the multi-speaker TTS task, we propose the TDASS framework. The TDASS mainly contains a backbone of an acoustic module based on Tacotron2, a self-interested classifier, and a timbre embedding of X-vector. It could reduce the non-target speaker influence and adapt to the target speaker domain, which benefits from the proposed self-interested classifier. The X-vector is used for the speaker embedding during the encoder to a latent variable, and TDASS first is trained based on the
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