AdaSpeech 4: Adaptive Text to Speech in Zero-Shot Scenarios

Yihan Wu\textsuperscript{1}, Xu Tan\textsuperscript{2,∗}, Bohan Li\textsuperscript{3}, Lei He\textsuperscript{3}, Sheng Zhao\textsuperscript{3}, Ruizhua Song\textsuperscript{1,∗}, Tao Qin\textsuperscript{2}, Tie-Yan Liu\textsuperscript{2}

\textsuperscript{1} Gaoling School of Artificial Intelligence, Renmin University of China
\textsuperscript{2} Microsoft Research Asia, \textsuperscript{3} Microsoft Azure Speech

\texttt{yihanwu@ruc.edu.cn, \{xuta, bohli, helei, taoqin, szhao, tyliu\}@microsoft.com}

\section*{Abstract}

Adaptive text to speech (TTS) can synthesize new voices in zero-shot scenarios efficiently, by using a well-trained source TTS model without adapting it on the speech data of new speakers. Considering seen and unseen speakers have diverse characteristics, zero-shot adaptive TTS requires strong generalization ability on speaker characteristics, which brings modeling challenges. In this paper, we develop AdaSpeech 4 \textsuperscript{1}, a zero-shot adaptive TTS system for high-quality speech synthesis. We model the speaker characteristics systematically to improve the generalization on new speakers. Generally, the modeling of speaker characteristics can be categorized into three steps: extracting speaker representation, taking this speaker representation as condition, and synthesizing speech/mel-spectrogram given this speaker representation. Accordingly, we improve the modeling in three steps: 1) To extract speaker representation with better generalization, we factorize the speaker characteristics into basis vectors and extract speaker representation by weighted combining of these basis vectors through attention. 2) We leverage conditional layer normalization to integrate the extracted speaker representation to TTS model. 3) We propose a novel supervision loss based on the distribution of basis vectors to maintain the corresponding speaker characteristics in generated mel-spectrograms. Without any fine-tuning, AdaSpeech 4 achieves better voice quality and similarity than baselines in multiple datasets.

\textbf{Index Terms}: Text to Speech, Adaptive TTS, Zero-shot, Multi-speaker, Generalization

\section{Introduction}

Neural text to speech (TTS) \cite{1} models can synthesize high quality human voice when being trained with a large amount of single-speaker or multi-speaker datasets \cite{2, 3, 4, 5, 6, 7, 8, 9}. When synthesizing speech for new speakers, few-shot adaptive TTS \cite{10, 11, 12, 13} is usually adopted by first training a source TTS model on a large multi-speaker dataset and then fine-tuning this model on a few speech data of target speakers. Although few-shot adaptive TTS achieves good similarity and voice quality on target speakers, it has two limitations: 1) it needs some training data of target speakers, which are hard to obtain from consumers; 2) it needs fine-tuning a source TTS model on target data, which incurs much computation cost when serving a lot of new speakers. Such a situation is common for commercialized TTS services (e.g., Microsoft Azure, Google Cloud, Amazon Web Services, etc.).

Zero-shot adaptive TTS \cite{14, 15} can generate a new voice by only modeling the speaker characteristics from a reference speech, without adapting the source TTS model on the speech data of new speakers. Although zero-shot adaptive TTS is both data and computation efficient, it faces big challenges for achieving good voice quality. Specifically, considering target/unseen speakers and source/seen speakers can have many diverse characteristics, it requires the source TTS model to have strong generalization ability on speaker characteristics. In this paper, we first categorize the modeling of speaker characteristics in current TTS systems into several steps, and then propose a new system to improve the generalization ability on speaker characteristics at each step and thus achieve better zero-shot quality.

Basically, the modeling of speaker characteristics in TTS can be categorized into three steps: 1) extracting speaker representation from target speaker; 2) taking the extracted representation as a condition to TTS model; and 3) generating target mel-spectrogram given this speaker representation. For the first step, previous zero-shot TTS models \cite{16, 17, 18} usually leverage a speaker/reference encoder to extract speaker representation of a target speaker. Most efforts focus on improving the speaker encoder to extract a more adaptable speaker representation. However, speaker representation is hard to be precisely extracted in zero-shot scenarios since various factors such as timbre, speaking style, and prosody need to be considered. For the second step, previous models usually concatenate or add the extracted speaker embedding with the hidden output of phoneme encoder and then take them as the input of the decoder, which causes a mismatched decoder input when the speaker embedding is not precisely extracted in zero-shot scenarios, and affects the generalization ability. In the third step, most previous works have no explicit guarantee that the generated mel-spectrograms follow the same speaker characteristics as the extracted speaker representation, where the situation is even worse in zero-shot scenarios. Some previous works \cite{19, 20} apply speaker classification loss on generated mel-spectrograms as a supervision to ensure the synthesized speech to be more similar to reference speech, which, however, does not bring much improvement in speaker similarity \cite{16}.

Based on the above analyses, in this paper, we develop AdaSpeech 4, an adaptive TTS model for high-quality speech synthesis in zero-shot scenarios. Based on the model structure of AdaSpeech \cite{10}, we improve the generalization ability on new speakers in three steps:

\begin{itemize}
  \item To extract speaker representation with better generalization, we factorize the speaker characteristics into basis vectors and extract speaker representation by weighted combining of these basis vectors through attention, which can ensure good generalization on new speakers in zero-shot scenarios. To
\end{itemize}
2. Proposed Method

The whole architecture of AdaSpeech 4 is shown in Figure 1(a), where the model backbone is based on AdaSpeech [10], a non-autoregressive TTS model with specifically designed acoustic condition modeling for few-shot adaptation. Based on the categorization of the three key steps in speaker characteristics modeling as in Section 1, we further improve the model’s generalization ability to new speakers in zero-shot scenarios correspondingly.

First, we employ a set of basis vectors to represent speaker characteristics and extract more generalized speaker representation through attention, as shown in Figure 1(b). Second, we integrate the extracted speaker representation to TTS model by conditional layer normalization to minimize the generalization difficulty for unseen speakers, as shown in Figure 1(c). Third, we leverage a supervision loss based on the distribution of the above basis vectors to improve the controllability of speaker characteristics in zero-shot scenarios, as shown in Figure 1(d).

2.1. Extracting Speaker Representation by Basis Vectors

Speaker representation is hard to extract precisely in zero-shot scenarios since complicated speaker characteristics need to be captured. A better way is to represent speaker characteristics with a set of basis vectors and extract speaker representation through the weighted combination of these basis vectors. Since these basic vectors are learnt from all speakers during training, they should have enough representation capability for different characteristics. When extracting speaker representation in zero-shot scenarios, we do not need to generate a representation from scratch, but just need to generate new combination weights for these basis vector, which has more generalization capability to unseen speakers. Inspired by [22] which models speech style by global style tokens for expressive speech synthesis, we leverage a similar pipeline to learn basis vectors and extract speaker representations (as shown in Figure 1(b)): we use the speaker embedding \( S \) generated by speaker encoder as query, and attend to the basis vector through Q-K-V attention [23] to extract the speaker embedding:

\[
E = \text{Attention}(SW^Q, BW^K, BW^V),
\]

where \( W^Q, W^K, W^V \) are all trainable matrices, \( B \) denotes basis vectors, \( Q, K, V \) in Equation 2 are attention queries, keys, and values, and \( d \) is the dimension of \( S \).

To ensure the representation capability on seen speakers and generalization capability on unseen speakers, the basis vectors should be dissimilar to spread out to the whole space of speaker characteristics. To this end, we propose two improvements: 1) We initialize the basis vectors with the cluster centers of speaker embeddings extracted by the speaker encoder. 2) We leverage a regularization loss to prevent each basis vector to be similar to each other. Specifically, we extract speaker embeddings from all speech training data by the speaker encoder, and partition them into \( N \) clusters by \( k \)-means clustering. Here, \( N \) is a hyper-parameter and is equal to the number of basis vec-

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Figure 1: The architecture of AdaSpeech 4, where the basic model backbone is based on AdaSpeech [10], but with three systematic designs to improve the generalization ability on speaker characteristics in zero-shot scenarios. Note that we also use phoneme-level acoustic condition modeling as in AdaSpeech, which is not shown for simplicity. Dashed lines in Figure (a) and (d) represent speaker supervision is only used in the training stage, and “speech” refers to mel-spectrograms here.
Table 1: The MOS and SMOS scores with 95% confidence on LibriTTS, VCTK, and LJSpeech.

| Metric              | SMOS (↑) | MOS (↑) |
|---------------------|----------|---------|
| Dataset             | LibriTTS | VCTK    | LJSpeech | LibriTTS | VCTK    | LJSpeech |
| GT                  | 4.09 ± 0.11 | 4.17 ± 0.10 | 4.08 ± 0.10 | 3.45 ± 0.12 | 3.69 ± 0.13 | 3.67 ± 0.13 |
| GT mel + Vocoder     | 3.97 ± 0.10 | 4.13 ± 0.09 | 4.03 ± 0.09 | 3.42 ± 0.12 | 3.68 ± 0.14 | 3.62 ± 0.12 |
| FastSpeech 2 (vanilla) [5] | 3.33 ± 0.13 | 3.23 ± 0.12 | 3.26 ± 0.13 | 3.12 ± 0.14 | 3.54 ± 0.14 | 3.16 ± 0.12 |
| FastSpeech 2 (d-vector) [5] | 3.12 ± 0.14 | 2.98 ± 0.12 | 2.80 ± 0.12 | 3.08 ± 0.14 | 2.63 ± 0.13 | 3.53 ± 0.14 |
| StyleSpeech [14]    | 3.64 ± 0.13 | 3.81 ± 0.11 | 3.58 ± 0.13 | 3.24 ± 0.13 | 3.58 ± 0.14 | 3.30 ± 0.18 |
| AdaSpeech (zero-shot) [10] | 3.62 ± 0.14 | 3.79 ± 0.10 | 3.54 ± 0.12 | 3.22 ± 0.13 | 3.63 ± 0.14 | 3.35 ± 0.17 |
| AdaSpeech 4          | 3.88 ± 0.11 | 3.86 ± 0.10 | 3.68 ± 0.10 | 3.34 ± 0.12 | 3.66 ± 0.13 | 3.37 ± 0.11 |

2.3. Supervising Speaker Representation in Synthesized Speech with Distribution Loss

There is no explicit guarantee that the generated mel-spectrograms follow the same speaker characteristics as the extracted speaker representation, which could affect the similarity of the generated speech, especially in zero-shot scenarios. Thus, we propose a novel supervision loss based on the distribution of basis vectors to minimize the difference of speaker characteristics between reference mel-spectrograms and synthesized mel-spectrograms (as shown in Figure 1(d)). Specifically, we employ KL divergence loss to minimize the distance between the attention weights of the reference speech (calculated by the attention module in Equation 2) and that of the generated speech:

\[ \mathcal{L}_{dist} = \sum_{i=1}^{N} w_i \log \frac{w_i}{w_{i}} \]  

where \( w_i = softmax(\text{SW}^{T}h_{i}W_{F}^{E}) \) according to Equation 1 and 2, which denotes the attention weights of speaker embedding \( S \) from reference speech to the basis vector \( b_i \). \( w_i \) follows the same calculation method but from generated speech instead.

Unlike previous work which maximizes the similarity score based on speech embedding, our proposed distribution-level loss requires the reference speaker representation and the generated speaker representation to have the similar distribution over the shared basis vectors. It maintains speaker representation in synthesized speech in a more controllable way, which benefits zero-shot scenarios.

3. Experiments and Results

3.1. Datasets and Experiments Settings

Datasets. We train AdaSpeech 4 on LibriTTS dataset [25], which is a multi-speaker TTS corpus derived from LibriSpeech [26]. We split the dataset into training, validation, and test sets. All speakers in the test set are unseen during training. To evaluate generalization abilities in various acoustic conditions, we also conduct zero-shot synthesis in VCTK [27] (a multi-speaker dataset) and LJSpeech [28] (a single-speaker dataset). We randomly sample ten speakers (including five men and five women) from multi-speaker datasets (i.e., LibriTTS and VCTK) and the one speaker from single-speaker dataset (i.e., LJSpeech). Then we randomly select one audio from each speaker as reference and synthesize 15 sentences for human evaluation. The way of preprocessing on the speech and text data follows AdaSpeech [10].

Model configurations. The model configurations of AdaSpeech 4 follow AdaSpeech [10] unless otherwise stated. The speaker encoder [2, 22] is a 6-layer convolution network,
Table 2: The SMOS and CMOS scores with 95% confidence on LibriTTS for ablation study.

| Ablation Modules | ID   | Settings       | SMOS (↑) | CMOS (↑) |
|------------------|------|----------------|----------|----------|
| Speaker Extraction | #1   | AdaSpeech 4    | 3.88 ± 0.11 | 0        |
|                   | #2   | k-means init   | 3.84 ± 0.11 | -0.36    |
|                   | #3   | $L_{tvg}$      | 3.67 ± 0.11 | -0.46    |
|                   | #4   | basis vectors  | 3.62 ± 0.12 | -0.17    |
| Speaker Condition | #5   | encoder CLN    | 3.72 ± 0.12 | -0.21    |
|                   | #6   | decoder CLN    | 3.70 ± 0.11 | -0.36    |
| Speaker Supervision | #7   | $L_{dist}$     | 3.64 ± 0.12 | -0.06    |
|                   | #8   | $L_{cos}$      | 3.69 ± 0.13 | -0.08    |
|                   | #9   | $L_{cos}$      | 3.71 ± 0.12 | -0.06    |

where each layer is composed of 3 × 3 filters with 2 × 2 strides, using “same” padding and ReLU activations. Batch normalization [29] is applied to every layer. Output channels for 6 convolutional layers are 32, 32, 64, 64, 128, 128. The number of phoneme encoder’s output; 5) FastSpeech 2 (d-vector): similar to 4), except for leveraging d-vector as speaker embedding; 6) AdaSpeech (zero-shot): the implementation of AdaSpeech in zero-shot scenarios, i.e., without fine-tuning. All the above baselines use HiFi-GAN as the vocoder to generate waveforms. The MOS and SMOS results are shown in Table 1 respectively. We observe that AdaSpeech 4 achieves good improvements in SMOS in both three datasets while maintaining good or achieving slightly better voice quality in terms of MOS.

3.3. Ablation Studies

In this section, we conduct ablation studies to verify the effectiveness of each component in AdaSpeech 4. As shown in Table 2, we can have following observations:

- **Speaker extraction.** When removing the initialization op-

- **Speaker condition.** Discarding conditional layer normalization (CLN) in phoneme encoder (#5) or both in mel decoder and phoneme encoder (#6) impairs voice quality and speaker similarity, which verifies the effectiveness of conditional layer normalization in AdaSpeech 4.

- **Speaker supervision.** Discarding distribution loss (#7) leads to a voice similarity drop in terms of SMOS. Besides, we apply a cosine similarity loss (denoted as $L_{cos}$) between reference speaker embedding and generated speaker embedding as supervision loss, which is applied in many previous works [16, 31]. However, employing this embedding-level supervision loss alone (#8) or jointly (#9) does not bring obvious gain.

- **The number of basis vectors.** As the number of basis vectors determines the variety of speaker characteristics, we further investigate the zero-shot quality under different number of basis vectors on LibriTTS test set. As shown in Figure 2, the voice quality and similarity continuously drops when the number of basis vectors decreases from 2000, while there is no obvious gain when the number of basis vectors is greater than 2000. Thus, we choose 2000 in our experiments.

4. Conclusion

In this paper, we develop AdaSpeech 4, an adaptive TTS system for high-quality speech synthesis in zero-shot scenarios. We categorize the modeling of speaker characteristics into three steps and improve its generalization ability in a systematic way. Specifically, we extract speaker representation by basis vectors, integrate the extracted speaker representation to TTS model by conditional layer normalization, and maintain speaker representation in synthesized speech with a novel distribution-level supervision loss. Experiment results demonstrate that AdaSpeech 4 can synthesize speech with high quality and similarity in zero-shot scenarios. For future work, we will evaluate AdaSpeech 4 in more diverse speaker characteristics and explore advanced techniques to improve the prosody and expressiveness of synthesized speech in zero-shot scenarios.
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