AdaDurIAN: Few-shot Adaptation for Neural Text-to-Speech with DurIAN

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Abstract

This paper investigates how to leverage a DurIAN-based average model to enable a new speaker to have both accurate pronunciation and fluent cross-lingual speaking with very limited monolingual data. A weakness of the recently proposed end-to-end text-to-speech (TTS) systems is that robust alignment is hard to achieve, which hinders it to scale well with very limited data. To cope with this issue, we introduce AdaDurIAN by training an improved DurIAN-based average model and leverage it to few-shot learning with the shared speaker-independent content encoder across different speakers. Several few-shot learning tasks in our experiments show AdaDurIAN can outperform the baseline end-to-end system by a large margin. Subjective evaluations also show that AdaDurIAN yields higher mean opinion score (MOS) of naturalness and more preferences of speaker similarity. In addition, we also apply AdaDurIAN to emotion transfer tasks and demonstrate its promising performance.

Index Terms: few-shot, speaker adaptation, content encoder, DurIAN

1. Introduction

The rise of deep learning has made more complex sequence generation tasks such as speech synthesis and machine translation feasible. Text-based generation of natural speech has been continuously investigated over the past decades. Concatenative synthesis with unit selection and statistical parametric speech synthesis were the state-of-the-art systems for many years. However, such systems require lots of human labour and are unsatisfactory for lacking naturalness. Recently, a sequence-to-sequence architecture, Tacotron, has greatly improved the naturalness and similarity of speech synthesis compared to traditional statistical parametric speech synthesis. Tacotron, usually followed by a traditional or neural vocoder, takes linguistic feature and speaker identity as input and generates mel-spectrogram as output. Unfortunately, when dealing with out-of-domain or abnormal texts inputs, Tacotron-like attention based end-to-end structures could render unacceptable errors, including skipping, repeating, long unexpected pause and attention collapse. More recently, stepwise monotonic attention (SMA) method, which is based on monotonic attention, was proposed to enforce strict constraint to meet the demand of locality, monotonicity and completeness in the speech synthesis process.

As far as we know, building a naturally speaking TTS system requires at least ten hours of recording audio. Moreover, every audio utterance should be recorded in a professional recording studio and the transcribed phonemes should be evenly distributed. Preparing such a large amount of high-quality data with multiple speakers is impractical and extremely expensive. Typically, it’s troublesome and unnecessary to let native Chinese speaker to say English if he knows little about English. Moreover, there is no chance to gather 10 hours training data for a specific person like a pop star. The only resources we can get are the limited talks or shows from TV. Therefore, utilizing a few minutes of audio and synthesizing arbitrary speech in target’s voice remains a very important task.

However, building TTS system with limited data often sacrifices quality and reliability. To scale the capacity for new speakers, we can adapt existing pre-trained multi-speaker system to generate new speakers’ voice, which is a well-studied subject of few-shot learning also known as speaker adaptation. There are mainly two approaches here: the first is to update the new speaker embedding and combine it with the linguistic feature as inputs to a TTS model; the second is to fine-tune the entire multi-speaker network to select a optimal single-speaker model. Although fine-tuning can combine the advantages of multiple speakers and achieve a new speaker’s better performance, as we described before, end-to-end attention models such as Tacotron-like models may meet unpredictable instability and bad cross-lingual speaking in few-shot learning settings. To achieve naturalness and robustness in speech synthesis, FastSpeech and duration informed attention network (DurIAN) have been recently proposed to overcome the unexpected errors of end-to-end systems by combining duration information of traditional statistical parametric speech synthesis system. The former FastSpeech is a non-autoregressive feed-forward framework without attention. The latter DurIAN, originally proposed for multi-modal speech synthesis, is an autoregressive framework which achieves robustness and naturalness by using skip state encoder and combining duration with windowed content-based attention.

To improve the scalability of TTS in few-shot speaker adaptation, we introduce AdaDurIAN, an adaptive neural TTS system based on DurIAN, with the ability to synthesize natural cross-lingual speech in a new speaker’s voice with just few minutes of monolingual data. We investigate it in three different aspects that have not been fully explored in previous work. First, we employ sequences of phoneme and tone (or stress) to achieve a robust speaker-independent content encoder, and incorporate the concatenated representation of speaker characteristics into the output states of content encoder. Second, instead of fine-tuning weights of the whole architecture, we found a key aspect that only fine-tuning the speaker embedding and decoder network leads to fewer pronunciation errors. Last, to generate the smooth mel spectrograms in a streaming inference manner, we adopt a time-delayed LSTM post-net instead of a global CBHG-like module. Through various evaluations, our proposed AdaDurIAN significantly surpasses the Tacotron-like model in terms of naturalness, speaker similarity and cross-lingual speaking, and also shows its promising performance in few-shot emotion transfer tasks.

The rest of this paper is organized as follows. Section2 introduces...
2. The proposed method

2.1. Architecture of AdaDurIAN

The original DurIAN [24] is a single-speaker TTS system, the model for each speaker should be trained individually with their own voice. We made improvements to support multi-speaker, multi-style and multi-lingual speech synthesis. Figure 1 shows the architecture of proposed AdaDurIAN. It’s composed of (1) a speaker-independent content encoder that encodes the linguistic sequences, (2) an alignment model that predicts the duration of each phoneme and then aligns the output states of content encoder to acoustic frames, (3) a decoder network that generates 5 frames of mel spectrogram autoregressively.

2.1.1. Speaker-independent Content Encoder

It’s hard to ensure that the input tokens (phonemes, tones, stresses and so on) are evenly distributed for a single speaker’s training corpus. To benefit from the knowledge of multi-speaker’s training corpus, different from DurIAN, we take both phoneme and tone (or stress, which appears in English words) sequence with prosodic boundary symbols as the input to content encoder of AdaDurIAN. With state skipping [25], the output of the content encoder is a sequence of hidden states containing speaker-independent global linguistic feature transformation.

2.1.2. Alignment Model

To combine linguistic feature transformation and speaker characteristics representation, we incorporate speaker embedding, emotion embedding and language embedding into the expanded states of content encoder. The language code switching is implemented based on the language to which the current phoneme belongs. Such speaker-dependent concatenated representation makes AdaDurIAN to synthesize speech for different speakers with different styles. Each speaker-dependent frame state is repeated according to the alignment model and then concatenated with relative position encoding [23] inside each phoneme. The detailed structure of alignment model is shown in Figure 1 and the alignment model doesn’t share any trainable embeddings with content encoder for stable training.

2.1.3. Decoder

Different from DurIAN, we adopt the residual LSTM [26] layers for its efficient training which is of great importance in few-shot learning. Instead of CBHG [3] module, we adopt a vanilla LSTM layer with a time delay of 5 frames as post-net. Practically, such structure of post-net can significantly improve the quality of mel spectrogram predicted by the decoder, and also achieve the streaming synthesis to be deployed in production environment. As a result, the inference of AdaDurIAN is 17 times faster than real-time with two CPU cores.

2.2. Speaker Adaptation Strategy

Few-shot speaker adaptation is an intractable task for that there are very few training samples. The insoluble dilemma lying in few-shot speaker adaptation is that the distribution of linguistic tokens is hardly even. Following the general training procedure, the model of new speaker would soon be unable to synthesize out-of-domain words, let alone the naturalness and speaker similarity. Fortunately, the speaker-independent content encoder of AdaDurIAN can absorb the knowledge across different speakers, so a pre-trained content encoder can also be borrowed to transform linguistic feature for any new speaker.

Straightforwardly, the training procedure of AdaDurIAN for few-shot speaker adaptation is to transfer the linguistic feature transformation of a multi-speaker system to a new speaker with limited training data without losing naturalness, speaker similarity and cross-lingual speaking. Inspired by [27], modules in the light red dotted rectangle in Figure 1 will be fixed and shared for any new speaker. To achieve this, we first fully shuffle the training data to ensure that each mini-batch contains the data of different speakers and then train AdaDurIAN to get an average multi-speaker TTS model. At the stage of few-shot speaker adaptation, modules including phone embedding, tone (or stress) embedding, language embedding, emotion embedding and encoder in average model will be fixed. With such proposed speaker adaptation strategy, AdaDurIAN can be applied to speakers who have very limited data. We will validate that, by borrowing knowledge from other speakers and only optimizing speaker embedding and decoder, AdaDurIAN has a better performance in terms of naturalness, speaker similarity and cross-lingual speaking.

Table 1: Results of word error rate (WER) with different modules to be fixed during few-shot speaker adaptation.

| Freeze Modules                      | WER   |
|-------------------------------------|-------|
| nothing                             | 5.48% |
| +phone embedding                    | 4.00% |
| +tone/stress, language embedding    | 3.36% |
| +encoder                            | 2.28% |

Figure 1: Detailed architecture of AdaDurIAN. Modules in the light red dotted rectangle will be fixed in few-shot speaker adaptation. For simplification, the windowed content-based attention is not shown.
Table 2: Robust mean opinion score (MOS) as a function of the amount of training data and different speakers. CN speaker denotes a native Chinese speaker, while EN speaker denotes a native English speaker. All audios are converted by Griffin-Lim algorithm \[9\] from mel spectrogram.

| System    | Chinese sentences | English sentences | Recordings |
|-----------|-------------------|-------------------|------------|
|           | CN speaker | EN speaker | CN speaker | EN speaker | CN speaker | EN speaker |
| SMA 1m    | 3.85 ± 0.07 | 3.29 ± 0.07 | 3.80 ± 0.20 | 3.55 ± 0.21 | 4.13 ± 0.22 | 3.98 ± 0.18 |
| AdaDurIAN 1m | 4.14 ± 0.06 | 3.90 ± 0.06 | 4.03 ± 0.21 | 3.95 ± 0.18 | 4.21 ± 0.16 | 3.96 ± 0.16 |
| SMA 3m    | 3.84 ± 0.07 | 3.29 ± 0.08 | 3.69 ± 0.23 | 3.18 ± 0.24 | 4.45 ± 0.05 | 4.14 ± 0.06 |
| AdaDurIAN 3m | 4.21 ± 0.05 | 3.73 ± 0.07 | 4.06 ± 0.18 | 2.98 ± 0.28 |
| SMA 20m   | 4.10 ± 0.06 | 2.97 ± 0.09 | 3.80 ± 0.20 | 3.55 ± 0.21 | 4.13 ± 0.22 | 3.98 ± 0.18 |
| AdaDurIAN 20m | 4.10 ± 0.06 | 3.57 ± 0.07 | 4.21 ± 0.16 | 3.96 ± 0.16 |

3. Experiments

We take SMA \[10\] as our baseline model, an optimal variant of Tacotron 2 \[4\], in which the memory at each decoding step is computed by a stepwise monotonous attention \[10\] instead of an alignment model. We find that, compared with original Tacotron 2, SMA performs much better in terms of accurate pronunciation and synthesizing long or abnormal utterances.

We performed three sets of experiments for adaptive TTS to show the performance of the proposed AdaDurIAN system. First, we investigate the stability of pronunciation under different adaptation strategies on AdaDurIAN. Second, we compare the performances of SMA and AdaDurIAN with a random subset of the audio with total duration of 1, 3 and 20 minutes, respectively. Finally, we perform the few-shot emotion transfer tasks on two unseen speakers with limited neutral speech data. We highly recommend readers to go listen to the generated audio.

3.1. Experiment Setup

The data we used is our internal carefully annotated 200-hour speech corpus which is collected from around 55 speakers with different genders and nations. All audios are sampled by 24kHz with mono channel, windowed with 45 ms and shifted every 10 ms. The 80-th order mel spectrograms are extracted to represent the spectral envelope.

Two neural TTS systems are implemented for comparison. For AdaDurIAN, as shown in Figure 1, sequences of linguistic tokens are passed through a pre-net that contains three fully-connected layers followed by a CBHG module. The same group of two BLSTM layers with 512 units, excluding the speakers to be evaluated in this paper. To eliminate the influence of WaveRNN, in MOS test, audios including recording audios are all converted by Griffin-Lim algorithm \[4\]. Audios of other tests are converted by such speaker-independent WaveRNN.

3.2. Objective Evaluation

We performed pronunciation error statistical task by using 1-minute data of several speakers to compare the performances of AdaDurIAN under different few-shot speaker adaptation strategies. We randomly selected 30 long and abnormal sentences with a total of 4000 words for synthesis. Such pronunciation error statistical task was performed with 50-80 anonymous and untrained subjects participating in several evaluation sessions, constructed so that each sentence was evaluated by 10 distinct subjects. Each participant was asked to count the number of errors in each sentence, including wrong pronunciation, unclearness and incorrect tone. Although we can use automatic speech recognition (ASR) system, we find that ASR system is too robust to spot minor pronunciation errors.

We evaluate the performance of each adaptation strategy by calculating the word error rate (WER). Table 1 shows each WER of different adaptation strategies. We find that fixing phone embedding, tone (or stress) embedding, language embedding and encoder could achieve the least pronunciation error. Which is reasonable because these fixed parameters still stay in the same distribution space even given very limited unbalanced data. With extremely imbalanced 1-min data, a much lower WER indicates that such fine-tuning strategy is reliable in few-shot speaker adaptation.

3.3. Subjective Evaluation

3.3.1. Speaker Adaptation

We selected one native Chinese speaker (denoted as ‘CN speaker’) without English speech corpus, and one native English speaker (denoted as ‘EN speaker’) without Chinese speech corpus to perform few-shot speaker adaptation tasks. We constructed three datasets for each test speaker with a total dura-
The result of speaker similarity preference test is shown in Table 5. For CN speaker, AdaDurIAN gains much more preferences than SMA in all experiments. For EN speaker, AdaDurIAN outperforms SMA with a significant margin on English sentences, and AdaDurIAN still has a comparable performance with SMA on Chinese sentences. Such promising evaluation results motivate us to apply AdaDurIAN in further tasks that have a high requirement of speaker similarity.

| Target  | Selected | Acc. |
|---------|----------|------|
| neutral | 224      | 9    | 53 | 14 | 0.75 |
| anger   | 80       | 168  | 32 | 20 | 0.56 |
| happiness | 90    | 33   | 169| 8  | 0.56 |
| sadness | 194      | 26   | 21 | 59 | 0.20 |
| Average |          |      |    |    | 0.52 |

Table 3: The ABX test of speaker similarity.

| System     | Chinese sentences | English sentences |
|------------|------------------|------------------|
|            | CN speaker       | EN speaker       |
| SMA 1m     | 17.78%           | 7.22%            |
| AdaDurIAN 1m | 62.96%       | 46.30%           |
| No preference | 19.26%     | 46.48%           |
| SMA 3m     | 16.85%           | 22.78%           |
| AdaDurIAN 3m | 70.56%       | 44.07%           |
| No preference | 12.59%     | 33.15%           |
| SMA 20m    | 23.89%           | 16.48%           |
| AdaDurIAN 20m | 56.85%      | 36.11%           |
| No preference | 19.26%     | 47.41%           |

3.3.2. Emotion Transfer

To explore the ability of AdaDurIAN on transferring different emotions with few neutral data, we used an available female corpus with four annotated emotion styles: neutral, anger, happiness and sadness. We first trained such a base emotional model on the previous AdaDurIAN average model, then we fine-tuned such female emotional model with a 1 minute male speech corpus and a 1 minute female speech corpus with already described strategy. We evaluate the performances of two female-to-male (F2M) and female-to-female (F2F) few-shot emotion transfer tasks by subjective emotion classification. As shown in Table 4 and Table 5, emotion transfer of F2F task is less difficult than that of F2M. The mean emotion classification accuracy of F2F is 64% while that of F2M is only 52%. Specifically, we find that the emotion transfer of neutral and happiness is the easiest, emotion transfer of sadness is the second, while emotion transfer of anger is the hardest. This discovery provides an important reference for future few-shot emotion transfer research.

4. Conclusions

In summary, we proposed AdaDurIAN, a few-shot adaptive neural TTS system for higher naturalness and speaker similarity. We described the improvements of AdaDurIAN over original DurIAN and demonstrated the adaptation strategy when the speaker’s data is very limited. Based on AdaDurIAN, we performed several few-shot speaker adaptation tasks to evaluate the stability, naturalness, speaker similarity and emotion transfer ability. The evaluations show that, compared with Tacotron-like model, AdaDurIAN has both higher MOS of naturalness, more preferences of speaker similarity and especially fluent cross-lingual speaking. Furthermore, we also applied AdaDurIAN in emotion transfer tasks and showed its promising performance.
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