The NTU-AISG Text-to-speech System for Blizzard Challenge 2020

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Abstract

We report our NTU-AISG Text-to-speech (TTS) entry systems for the Blizzard Challenge 2020 in this paper. There are two TTS tasks in this year challenge, one is a Mandarin TTS task, the other is a Shanghai dialect TTS task. We have participated both. One of the main challenges is to build TTS systems with low-resource constraints, particularly for the case of Shanghai dialect, of which about three hours data are available to participants. To overcome the constraint, we adopt an average-speaker-modeling method. That is, we first employ external Mandarin data to train both End-to-end acoustic model and WaveNet vocoder, then we use Shanghai dialect to tune the acoustic model and WaveNet vocoder respectively. Apart from this, we have no Shanghai dialect lexicon despite syllable transcripts are provided for the evaluation data during training stage, we use Mandarin lexicon for Shanghai dialect instead. With the letter, as decomposed from the corresponding Mandarin syllable, as input, though the naturalness and original speaker similarity of the synthesized speech is good, subjective evaluation results indicate the intelligibility of the synthesized speech is deeply undermined for the Shanghai dialect TTS system.

Index Terms: Text-to-speech, speech synthesis, End-to-end, transfer learning

1. Introduction

As Artificial Intelligence (AI) technology is widely applied in human daily life nowadays, human-machine interaction, such as human-machine speech-based dialogue interaction, has become increasingly important. Text-to-speech (TTS) is one of many key components realizing a better human-machine interaction experience. Over decades, TTS technology has been developed significantly, from the earliest hand-crafted wave unit concatenation method ¹ ² to the present machine-learning-based End-to-end method ³ ⁴ ⁵ ⁶, thanks to the advent of the deep neural network technologies ⁷ ⁸ ⁹. Specifically, we use the End-to-end approach to front-end acoustic modeling. It realizes text to acoustic feature estimation. After that, a WaveNet conditioned on the learned acoustic features is employed as vocoder to synthesize the waveform.

The main efforts lie in how to build a TTS system under such a low-resource condition, particularly for the Shanghai dialect case. Since we have no knowledge and resource about Shanghai dialect, except for that it shares the same character sets with the Mandarin language, we leverage both Mandarin speech data and lexicon to solve the problem. In practice, we use Mandarin speech data to train a TTS system, then we tune the TTS system using Shanghai dialect. Since we realized it is obvious wrong to let the two languages share the same lexicon, we use letter instead, which is decomposed from Mandarin syllable. Previously, it is not a trivial work to build a TTS system, since one needs expertise for different components.

Though we have achieved remarkable progress on TTS technology development, we are still far from perfect in many scenarios. For large high quality speech training data that are recorded by professional speaker from sound recording studio, we are almost done with perfect text-to-speech quality ¹⁰. For limited speech data that are recorded with inconsistent acoustic environment, the quality of the synthesised speech are yet to be improved. Besides, for highly expressive speech, such as speech enriched with emotion, present methods still have long way to go for final mature application. Additionally, majority of present TTS systems only perform monolingual speech synthesis. As globalization trends are intensified, code-switching ¹¹ based multilingual speech synthesis is also worth our efforts. Last but not least, state-of-the-art TTS systems are often built with deep neural networks, which can have up to several million parameters that requires big device storage, as well as extensive computational resource. Consequently, how to develop small footprint device-based TTS system is also drawing our attention ¹² ¹³ ¹⁴.

To address the above-mentioned challenges and the beyond, as well as to explore the new frontier of the novel Text-to-speech method, Blizzard Challenge workshop has been initiated since 2005 ¹⁵. It is drawing word-wide attention and participation from both research and industrial communities, expediting the process of research and development for TTS system.

There are two sub-tasks in this year challenge. The first one is a Mandarin TTS task, and the second one is a Shanghai dialect TTS task. Training data are 9.5 and 2.9 hours respectively. We participated both tasks. The main challenge comes from that the second task belongs to a low-resource problem. Our two TTS systems are built with Tacotron2 ⁴ plus WaveNet ⁸. Specifically, we use the End-to-end approach to front-end acoustic modeling. It realizes text to acoustic feature estimation. After that, a WaveNet conditioned on the learned acoustic features is employed as vocoder to synthesize the waveform.

2. TTS system building recipe

In this section, we start with reporting our data preparation. Since it’s the first priority for building a successful TTS system, no matter what kind of methods is employed. After that,
we introduce our efforts on the three components of a typical TTS system. That is, a front-end component for the linguistic feature generation, an End-to-end acoustic models realizing linguistic feature to acoustic feature mapping using Tacotron2, and a WaveNet Vocoder realizing acoustic feature to waveform generation.

2.1. Data Processing

In Blizzard Challenge, the data released by the organizer is normally far from clean. Typical issues include: 1) the acoustic utterances are rather long, and some of utterances have poor acoustic conditions; 2) the transcription are not exactly transcribed and yet to be normalized; 3) the linguistic unit for acoustic model training should be obtained with the help of language specific lexicon

2.1.1. Data preparation

For this year data preparation, we first cut the longer utterance into smaller segments according to the silence indication. This is crucial for End-to-end system training, since we found longer utterance with limited training data can lead to poor acoustic models (fail to align in the end of utterance, that is, unstoppable repetition or word missing). Figure 1 reveals our data length distribution before and after utterance segmentation.

![Utterance length distribution before and after utterance re-segmentation](Image)

(a) Original Mandarin (b) Original Shanghai dialect

(c) Resegmented Mandarin (d) Resegmented Shanghai dialect

Figure 1: Utterance length distribution before and after utterance re-segmentation for the ease of training.

As shown in Figure 1, we restrict the maximal utterance length around 7 second for both tasks. After re-segmentation, the length variation of the overall utterance are reduced a lot. Besides, when segmenting the longer utterance into shorter utterance, we also correct/normalize the transcription simultaneously. After that, we train a Mandarin ASR system with the processed Mandarin data, using Kaldi toolkit \[16\], and employ such an ASR system to align the training data. We remove those utterances that fails to align.

2.1.2. Feature preparation

We have both input and output features to prepare. That is, the front-end linguistic features that are generated from the normalized text transcription or the phonetic sequence with the help of the lexicon, and the output acoustic features. We choose 80-dimensional Mel scale filter-bank features as our acoustic feature. For the front-end linguistic features, we use the character/letter that is from corresponding Mandarin initial-final-based syllables. Usually, one can embed other linguistic knowledge, such as word features, prosodic features to improve the prosodic expressive capability, as well as intelligibility of the synthesized waveform.

2.2. End-to-end acoustic Model

We use Tacotron2 \[4\] as the acoustic model to map syllable-based letter sequence to 80-dimensional Mel filter-bank sequence. The model architecture and the training method are similar to what are proposed in \[4\]. We use Tacotron2 as our acoustic model because it is much simpler compared with the WaveNet-based TTS method.

Unlike WaveNet-based TTS method \[3, 8, 4\], Tacotron cannot generate time-domain-based waveform directly, it’s output is a low-level acoustic features, such as short-time Fourier transform (STFT) features, or Mel filter-bank features as employed in our work. The output features can be employed to generate waveform with different means, such as algorithm-based Griff-Lim method, or conditional WaveNet-vocoder-based method. Besides, the input of the Tacotron method is much simpler than the WaveNet-based TTS method. It only uses pure linguistic features, while the input of the WaveNet-based method not only contains and context-dependent linguistic features, but also contains acoustic features, such as F0, which can not be reliably obtained.

2.3. WaveNet Vocoder

We use conditional WaveNet \[3\] as our vocoder to synthesize the waveform once we obtain the estimated acoustic features from Tacotron2 model. The conditional features are 80-dimensional Mel filter-bank features as mentioned in Section 2.2 which are actually dependent on the output of the front-end Tacotron model. Compared with the original work \[8\], we have the following specific configuration. We use 24 causal convolutional layers, which means our WaveNet have an intermediate receptive field. In \[4\], it is shown decent results can be obtained even using 12 causal convolutional layers (versus original 30 layers of network) that are also conditioned on the 80-dimensional Mel filter-bank features. Besides, the output distribution of the WaveNet is modelled with 10-mixture of discretized logistic distributions. The output of the WaveNet is 16kHz 16-bit waveform.

To train the WaveNet vocoder, we are using the estimated acoustic features, instead of using the ground-truth features. In \[4\], it is shown using ground-truth features yield worse synthesized results due to that the WaveNet trained with the fast variational features cannot generalize.

2.4. Model Training

As mentioned above, our TTS system pipeline contains two main components, namely, a Tacotron2-based acoustic model, and a WaveNet-based vocoder. We use ESPNet toolkit \[18\] to
train Tacotron2 model, and another open source r9y9 to train WavNet vocoder respectively.

One of the main challenges comes from low-resource issue, since we have only about 3 hours of Shanghai dialect data for the Shanghai dialect TTS task. Even for the Mandarin task, the organizer only released about 8 hours of training data, it is not enough to train a robust and higher-quality TTS system. As a result, we think of using more external data to train an initial average speaker TTS system. After that we are using the target Mandarin and Shanghai dialect data to fine-tune the average speaker models respectively. The whole framework is illustrated in Figure 2. Since we cannot get Shanghai dialect data, here we use the Biaobei data set that is public available for Mandarin text-to-speech research work.

Figure 2: A simple average speaker modeling approach to low-resource text-to-speech synthesis using Tacotron + WaveNet pipeline

From Figure 2, we merge the Biaobei and the 8-hour Mandarin data to train both Tacotron2 and WaveNet networks. What we are doing is actually a simplified speaker average modeling approach. We use 2 speakers to train the average models, however no speaker dependent embedding is considered.

Besides, we are forcing the Shanghai dialect and the Mandarin acoustic models to share the same phonetic set. As a result, our acoustic model belong to a monolingual acoustic model. Additionally, we are even not including the Shanghai dialect data to train the average models, for fear of our Mandarin text-to-speech synthesis quality being affected. However, after results submission, we are aware of such defects as mentioned. Shanghai dialect is greatly different from Mandarin, consequently their phone sets cannot be shared, and the acoustic models should be multilingual if we want to sufficiently exploit all the data of what we have.

3. Evaluation results

We report the evaluation results for our Mandarin and Shanghai Dialect text-to-speech systems in this section. The organizer has adopted three main subjective measures to evaluate the overall performance of a submitted system. That is, score of Mean Opinion Score (MOS), score of similarity to the original speaker, and score of intelligibility for the synthesized speech.

Figure 3 reports the MOS performance of the overall Shanghai dialect systems, of which our entry system is also represented as K. From Figure 3, our Shanghai dialect MOS score is about 3, which are worse than the one that is obtained for our Mandarin system in Figure 2. Overall speaking, the MOS score of system K are ranked at middle level. However, compared with Figure 3, what is reflected in Figure 2 suggests there are fewer participants (or valid entry systems) for the Shanghai Dialect text-to-speech task, and the MOS performance for the overall entry systems are worse. Such a performance degradation might attribute to less training data being available.

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Figure 4 shows the scores of the similarity to the original speaker for all the participants in Shanghai dialect text-to-
speech task. the score of the system is around 3+, and is again positioned at middle level in the overall participants.

Figure 5: Similarity to original speaker for Shanghai Dialect task (SS1)

Figure 6 presents intelligibility scores of all the participants. Our intelligibility score is almost the worst. This is not surprising. Since we assume we have zero knowledge about Shanghai dialect in terms of word pronunciation, we take Mandarin word pronunciation instead. This pronunciation sharing contradicts the fact that Shanghai dialect has completely different pronunciation from Mandarin pronunciation. After system submission, we are aware we have two choices for better results. One is to let Mandarin and Shanghai dialect share the same formality of pronunciation rules, but with different phone sets. That is, we append the letter from the same syllable with different language identifiers. This should make a difference but not make too much sense. The other choice is to directly use Shanghai-dialect-based syllable as provided by the organizer. Either choice belongs to a multilingual acoustic modeling approach if we merge the two data sets to train the system.

Figure 6: All Intelligibility Scores for Shanghai Dialect task (SS1)

4. Discussion

As is shown in Section 3, our performance are left behind by the top tiers. In this section, we are meant to analyze what remains to be done in ahead of time.

First, we think it is important to train a multilingual acoustic model in future. This is especially important for low-resource language. The effectiveness of multilingual training has already proved in automatic speech recognition area [19]. As is revealed in Figure 6, the intelligibility of the Shanghai Dialect is much worse than that of other competing systems. This is because we made a mistake by using Mandarin phone set for Shanghai Dialect, which is obviously different from the former in terms of word pronunciation though the written form of the two languages are the same. Actually, if we use letter-based context-independent unit, multilingual acoustic model training is completely feasible. This is because a given language usually contains only dozens of language-dependent letters/characters that are from its phone set which itself is also far below 100.

Secondly, our front-end linguistic features are too simple; we only have letter embedding features as input. This might not be a severe issue if one has enough training data. However, for a low-resource text-to-speech system development. High-level features, such as word and prosodic features [20], could benefit a lot. For instance, we can employ off-the-shelf BERT system to generate word embedding features to boost our encoder for the Tacotron models. Similarly, we can also add prosodic features by means of using Conditional Random Fields (CRF) [21] to label the input text utterance. All these are worth our efforts in future.

Thirdly, although using WaveNet as neural vocoder can yield very desirable synthesized speech, it’s computational cost is huge, and not applicable in real case. During system training, we also attempted to use other neural vocoders. Particularly, we tried LPCNet [14]. We found LPCNet can also synthesize good voice, however it seems to yield lower-quality speech compared with WaveNet.

5. Conclusions

We reported our work for the NTU-AISG text-to-speech entry system in Blizzard Challenge 2020. We have participated two tasks. One is a Mandarin TTS task and the other is a Shanghai Dialect TTS task. To address the low-resource issue, we employed a simplified average speaker modeling method for both Tacotron2-based acoustic model and WaveNet-based vocoder. However, we forced Mandarin and Shanghai dialect to share the same syllable set, such an assumption contradicts the real linguistic facts. As a result, our text-to-speech system for the Shanghai dialect task yields poor intelligibility. In future, we are conducting real average speaker modeling method, as well as multilingual training research.
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