Conversational End-to-End TTS for Voice Agent

Haohan Guo\textsuperscript{1+}, Shaofei Zhang\textsuperscript{2+}, Frank K. Soong\textsuperscript{2}, Lei He\textsuperscript{2}, Lei Xie\textsuperscript{1}

\textsuperscript{1}Audio, Speech and Language Processing Group (ASLP@NPU), School of Computer Science, Northwestern Polytechnical University, Xi'an, China

\textsuperscript{2}Microsoft China

\{hhguo, lxie\}@nwpu-aslp.org, \{frankkps, helei, shazh\}@microsoft.com

Abstract

End-to-end neural TTS has achieved superior performance on reading style speech synthesis. However, it's still a challenge to build a high-quality conversational TTS due to the limitations of the corpus and modeling capability. This study aims at building a conversational TTS for a voice agent under sequence-to-sequence framework. We first construct spontaneous conversational speech corpus well designed for the voice agent with a new recording scheme ensuring both recording quality and conversational speaking style. Secondly, we propose a conversation context-aware end-to-end TTS approach which has an auxiliary encoder and a conversational context encoder to reinforce the information about the current utterance and its context in a conversation as well. Experimental results show that the proposed methods produce more natural prosody in accordance with the conversational context, with significant preference gains at both utterance-level and conversation-level. Moreover, we find that the model has the ability to express some spontaneous behaviors, like fillers and repeated words, which makes the conversational speaking style more realistic.

Index Terms: Text-to-Speech, End-to-End, Conversational TTS, Speech Corpus, Voice Agent

1. Introduction

Text to speech (TTS) has been playing an increasingly important role in human-machine conversation, enabling the machine to talk with users. However, the existing TTS technologies still cannot achieve satisfying performance and immersive experience in conversation-oriented tasks, which needs more human-like and more natural speech with conversational speaking style adapting to conversational context. In order to build a high quality conversational TTS system, it is crucial to solve two main problems: 1) an effective method of developing a conversational speech corpus, and 2) a high performance TTS model of capturing rich prosody in conversation.

A standard corpus is usually composed of well-designed transcripts and high-quality recordings. This kind of corpus mostly requires the speaker to speak every single utterance using reading style consistently. Hence it is difficult for the speaker to read context-aware conversational transcripts with natural conversation-style prosody under this recording scheme. In\cite{1}, the corpus is built by letting two speakers freely discuss a topic to present real spontaneous conversational speaking style. But it also brings other problems, such as the unclear pronunciation, over-disfluent prosody and background noise, which may aggravate the difficulty of data annotation and modeling. To alleviate these problems, in this paper, we propose a new scheme for building spontaneous conversational corpus, which consists of three steps: scene and dialogue design, recording in the form of performance and transcribing. By combining reading style recording scheme and the free talk scheme in\cite{1}, it becomes more effective to build a corpus with clear pronunciation, high audio quality and spontaneous conversational speaking style.

Conversational corpus has the characteristics of high variety of prosody, strong context dependency, small corpus size, etc. So it usually needs rich text features and a high-performance model to build a conversational TTS system. Most previous researches are based on HMM-based or DNN-based statistical parametric speech synthesis (SPSS)\cite{2}, which utilize complicated conversation-related labels, e.g. speech or dialog acts\cite{3} and extended context\cite{4}, to directly provide rich textual information to compensate for its poor modeling capability. However, both of expensive labeling cost and insufficient representation of the conversation make it more difficult to build a high-expressive conversational TTS. To avoid these problems, in this paper, we propose a new conversation context-aware TTS approach based on state-of-the-art sequence-to-sequence model. End-to-end TTS\cite{5,6,7} based on seq2seq paradigm has recently shown great modeling capability that can synthesize natural speech directly from a character or phoneme sequence. It makes it possible to abandon complicated labels. Besides, we add an auxiliary encoder to help to produce better prosody by extracting more useful semantic and syntactical features from BERT embedding and statistical features on the syntactic structure. Moreover, different from the conventional conversational TTS, we directly use a conversation context encoder to extract prosody-related information from the chat history, which is represented by a sequence of utterance-level BERT embedding.

This paper will firstly introduce our new recording scheme for spontaneous conversational speech corpus and a Chinese voice agent corpus developed in this way. Then we describe our proposed conversation context-aware end-to-end TTS system in detail, including the end-to-end model, auxiliary encoder and conversation context encoder. Finally, we conduct a CMOS test with a test set containing five typical conversations between customer and agent, to evaluate the performance of our approach in both utterance level and conversation level. Experimental results show that both auxiliary encoder and conversational context encoder can effectively improve naturalness. In addition, we find that the model has the ability to express some spontaneous behaviors, like fillers and repeated words, which leads to more realistic conversation speaking style.

2. Spontaneous Conversational Corpus

Conversational TTS requires not only high-quality recording and well-designed text, but also natural and realistic conversation scenes. In the paper, we adopt a new recording approach.
to meet these requirements.

2.1. Performing Recording

For the standard TTS corpus, the speaker is often required to read an utterance fluently and accurately according to the well-designed transcripts, as shown in the most left part of Figure 1. This method can ensure the pre-designed text and high-quality recording quality [8], but lacks the variation of the speaking style to a certain extent, and it is not suitable for dialogue scene in which context-aware prosody is highly desired. Another approach for conversational recording (the middle one in Figure 1) is to make the speakers have task-oriented conversations [9, 10]. The transcripts of the free-talking are not pre-designed which may lead to incomplete phoneme context coverage, and also the recording has lower pronunciation clarity and over-disfluent prosody. All of these factors will aggravate the difficulty of data annotation and modeling.

To balance the relationship between natural conversational speaking style and high-quality recording, we propose a performing recording approach (the most right one in Figure 1), including three steps:

• Design conversational scenarios and transcripts. Most conversations are designed for voice agent, like scheduling. Then we can design transcripts with a high coverage in phoneme context, sentence pattern and dialogue context based on these scenarios.

• Speakers perform according to the transcripts. They are allowed to modify part of the content and insert appropriate spontaneous behaviors for more natural conversational speaking style, such as fillers, repeated word, etc.

• Transcribing. We will transcribe the speaker’s actual speech content to have correct pronunciation.

By allowing the speakers to perform freely within the well-designed conversational transcripts and then transcribing the speech according to the actual speech content, we can effectively control a good recording quality, context coverage and sufficient context-aware speaking style. Finally, we collect 45 conversations between two female native Chinese speakers, an agent and a customer (totally 6 hours, 3 hours per speaker).

2.2. The Spontaneous Behaviors in Corpus

There have been a lot of studies for the spontaneous behavior, such as [11] [12]. Usually, we focus on the most salient features of it, disfluency. In our corpus, we include the following behaviors:

• Fillers. Such as “um”, “oh”, “Aha”, “uh”, etc.

• Repeated word or phrase. The word or phrase is spoken twice because of anxious or stammer.

• False start. The speaker sometimes interrupts the current sentence, then begins a new sentence.

• Reduced speech rate or pause due to the non-verbal behavior.

Different from using complex labels for the spontaneous behavior in SPSS, in this paper, we propose to use a conversation context-aware end-to-end TTS model to learn to express these behaviors by itself.

3. Conversational Context-Aware End-to-End TTS

The prosody in a conversation is highly dependent on both of the current text and its context. So a powerful model is desired to learn to extract rich prosody-related information from them. In this section, we introduce a conversational context-aware end-to-end TTS approach which can produce better conversational speech with the help of an auxiliary encoder and a conversational context encoder.

3.1. End-to-End TTS

Our end-to-end TTS system is based on Tacotron2 [6], which has shown excellent performance on naturalness and sound quality. It is an attention-based seq2seq mapping model containing three modules, an encoder, an attention module, and an auto-regressive decoder.

The encoder consists of an embedding layer that embeds the discrete phoneme to continuous space, three 1-D convolution layers followed by batch normalization and ReLU activations that add neighboring context information and a BLSTM layer that adds sequential information. To deal with exposure bias [14], we use Pre-net with two feedforward layers followed by dropout with a probability 0.5 to reduce the dependency on historical information. In each decoding step, we pass the output of the second LSTM layer to the attention module to get the corresponding vector from the encoder based on the weight calculated by the attention module. Finally, we use the attention output and the second LSTM layer to the attention module to get the corresponding vector from the encoder based on the weight calculated by the attention module. Finally, we use the attention output and the second LSTM output to predict the acoustic feature and the stop token. PostNet is a post-filter with five 1-D convolution layers to further improve the output quality. Conversational TTS often needs to synthesize long utterances which are easy to cause stability problems using location sensitive attention, so we adopt stepwise monotonic attention [15], which shows great effect and stability on the long utterance.
To reconstruct speech with high sound quality from the acoustic feature, we use neural vocoder \[16, 17\] to generate waveform. In this work, we adopt Parallel Wavenet \[18\] as our neural vocoder.

### 3.2. Auxiliary Encoder

In addition to phonetic information, the text also contains rich information affecting prosody, including semantics and syntax aspects. Auxiliary encoder is proposed to extract rich text features from these information to help produce more natural prosody. Word embedding is a kind of text representation, which has been widely used in SPSS \[19\] and end-to-end TTS \[20\] to help improve prosody by providing latent semantic and syntactic information. As the state-of-the-art word/sentence representation, BERT embedding \[21\] can provide more effective features to the TTS model.

![Figure 3: An example of extracting statistical features](image)

Considering the fact that an utterance may be composed of more than one sentence, we also design a simplified group of statistical features to further improve the understanding of the syntactic structure. As shown in Figure 3, the features include the following items:

- $F_1$: the number of characters in the current sentence.
- $F_2$: the relative-position of the current character in the current sentence.
- $F_3$: the number of characters in the current utterance.
- $F_4$: the relative-position of the current character in the current utterance.
- $F_5$: the number of sentences in the current utterance.
- $F_6$: the relative-position of the current sentence in the current utterance.

Auxiliary encoder uses BERT embeddings and the proposed statistical features to represent each character in a sentence. The encoder consists of a pre-net and a CBHG module, which has shown good modeling capability in Tacotron1 \[5\] (see the middle part of Figure 2). The CBHG, composed of a group of CNN layers, highway network and GRU layer, can extract effective high-level sequential information to the TTS model. The features will be encoded by it, and up-sampled from character-level features to phoneme-level by replication, finally combined with the encoder outputs using the addition operation.

### 3.3. Conversation Context Encoder

In conventional conversational TTS, speech or dialogue act is often used as the conversation-related feature, which is either labeled manually, or predicted \[22\]. However, this approach apparently has some problems. Firstly, the prediction error may lead to unnatural prosody when the wrong label is tagged as the input feature of the TTS model. Secondly, although the simple classification of sentences can represent various sentence patterns, it also results in the loss of important semantic and syntactic information.

Therefore, we propose a conversational context encoder to directly extract prosody-related features from sentence embeddings with richer information rather than using sentence tags. As BERT can be used to extract both word embedding and sentence embedding, we thus use the sentence embedding in BERT as the sentence representation. And each embedding is attached by a one-hot vector representing speaker ID.

The right part of Figure 2 shows the structure of the conversational context encoder. The conversational context encoder firstly obtains embeddings $E_{t-c}t$ through a linear layer. We assume that text-related prosody is influenced by the current text and the cumulative state vector only determined by the past. So the chat history is divided into two parts, the current part $E_t$ and the past $E_{t-c-1}$. The GRU layer is used to encode the sequence $E_{t-c-1}$ to a state vector $G_{t-1}$ as the representation of the past. Then we concatenate $G_{t-1}$ and $E_t$, and feed them to the linear output layer to get the embedding vector of the sen-
tence in a conversation. In this work, we set capacity $c$ for the chat history to abandon the utterances earlier than $t - c$ which have less effect on the prosody of the current utterance.

4. Experiments

4.1. Training strategy & setup

Our conversational corpus is recorded by two native Chinese female speakers who play the customer and the agent respectively. In this work, we only use the agent speech data containing about 2,000 utterances (3 hours) to train the TTS model for the voice agent. This corpus has rich conversational speaking styles and the wide phoneme context coverage by the new recording scheme, but such a small amount of data still cannot satisfy our requirement on intelligibility and stability when we use this corpus to train the end-to-end model from scratch. Hence our model are trained based on a pre-trained end-to-end model which is built with a standard TTS corpus to guarantee the stability of voice agent. More specifically, we build the end-to-end model using about 6 hours standard TTS corpus recorded by a native Chinese female speaker. We select the pre-trained model with stable attention alignment as the initialization model for our subsequent model training.

To evaluate the performance of our approaches on conversational TTS, we train three models:

- $M_1$: baseline mentioned in Section 3.1
- $M_2$: $M_1$ plus auxiliary encoder.
- $M_3$: $M_2$ plus conversational context encoder.

$M_1$ is the baseline model which has the same structure and model parameter as Tacotron2 [6], except for the attention module, which adopts stepwise monotonic attention (soft version) [15] to improve stability on the long utterance. The input is phoneme sequence which contains phonemes, punctuation, inter-word and inter-syllable symbols. The output is 80-dim Mel spectrum with 12.5ms frameshift and 50ms frame length. $M_2$ is to verify the effect of introducing the auxiliary encoder, the pre-net and CBHG in the auxiliary encoder are the same as the corresponding modules in Tacotron1 [5]. The wordpiece-level 768-dim BERT embedding and 6-dim statistical features are replicated to phoneme level, and encoded to 512-dim features by the auxiliary encoder, then combined with the encoder outputs using the addition operation. $M_3$ introduces the conversational context encoder which encodes the 768-dim utterance-level BERT embedding and 1-dim speaker ID of $C_{t-c:t}$ mentioned in Section 2.3 to a 512-dim vector using a 64-dim linear layer with LeakyReLU activation, a 64-dim GRU layer, and a 512-dim linear output layer, and then combined with the above encoder outputs. $c$ is set as 10 in our experiments.

All of the three models are trained on a single GPU with a batch size of 32. We use Adam optimizer with $\beta_1 = 0.9, \beta_2 = 0.999$ and the learning rate exponentially decayed from $10^{-3}$ to $10^{-4}$ after 50,000 iterations to update these models.

4.2. Subjective Evaluations

The test set is composed of five complete conversations between customer and agent (totally 31 conversation turns). The voice of the customer is synthesized by an high-quality end-to-end TTS system trained with a male Chinese reading-style corpus and the agent part is synthesized using our models. A group of 14 Chinese native speakers takes part in CMOS listening test, and they need to compare the prosodic performance according to the conversational context (Is prosodic expression more suitable and more natural with the current context??). Then rate on a scale from -3 to 3 with 1 point discrete increments. Firstly, these conversation turns are played one by one, and listeners rate every audio from the agent. Then we play the complete conversations again uninterruptedly, and listeners rate them based on the overall performance of the agent. Note that the customer voice is not subject to human scoring.

|            | CMOS | Preference (%) |
|------------|------|----------------|
| $M_1$      |      | Neutral        |
| $M_2$      |      | Neutral        |
| $M_3$      |      | Neutral        |

Experimental results in Table 1 show that auxiliary encoder significantly improves the performance over the baseline model by CMOS score 0.55 and preference 50% on the utterance level. On the conversation level, it also achieves superior performance with CMOS score 0.46 and preference 45.7%. Compared with $M_2$, conversation context encoder can further improve the prosody expression by CMOS score 0.35 and preference 43.5% on the utterance level, and CMOS score 0.48 and preference rate 51.4% on the conversation level. By analyzing the test details, adding the auxiliary encoder can enhance the prosody expressiveness in term of stress, pause, and intonation by introducing semantic and structure features, and the conversation context encoder can make the agent response more natural and more consistent with the context.

In our corpus, most of spontaneous behaviors are about hesitation as mentioned in Section 2.2. Note that, we don’t need any extra-label of them, and just make conversation end-to-end TTS model learn to express these behaviors by itself. By inserting the appropriate spontaneous behaviors to the synthesized content, we find that our models have the ability to express them, such as fillers, repeated word, properly, which can make the conversational speaking style more realistic to listeners.

5. Conclusion

In this work, we firstly design a well-recorded spontaneous conversational TTS corpus for voice agent. This corpus adopts a new recording approach, recorded in three steps: scene and dialogue design, recording in the form of performance and transcribing. To produce high-quality conversational speech for voice agent, we then propose a conversational context-aware end-to-end TTS approach. We add an auxiliary encoder to help better understand the current utterance, and a conversational context encoder to improve awareness on the contextual information. Experimental results show that both of these two encoders are effective to help the voice agent to produce better prosody in the conversation, and some spontaneous behaviors can be well expressed by the proposed end-to-end models.

|            | CMOS | Preference (%) |
|------------|------|----------------|
| $M_1$      |      | Neutral        |
| $M_2$      |      | Neutral        |
| $M_3$      |      | Neutral        |

**Table 1: The results of CMOS tests**

|            | CMOS | Preference (%) |
|------------|------|----------------|
| $M_1$      |      | Neutral        |
| $M_2$      |      | Neutral        |
| $M_3$      |      | Neutral        |

CMOS: much worse (-3); worse (-2); slightly worse (-1); same (0); slightly better (1); better (2); much better (3).
6. References

[1] M. Husin, D. Stewart, and J. Ming, “Creating a spontaneous conversational speech corpus,” *Data Science Journal*, 2011.

[2] T. Koriyama, T. Nose, and T. Kobayashi, “Conversational spontaneous speech synthesis using average voice model,” in *INTERSPEECH*, 2010.

[3] A. K. Syrdal and Y.-J. Kim, “Dialog speech acts and prosody: Considerations for tts,” in *Proceedings of speech prosody*, 2008, pp. 661–665.

[4] T. Koriyama, T. Nose, and T. Kobayashi, “On the use of extended context for hmm-based spontaneous conversational speech synthesis,” in *INTERSPEECH*, 2011.

[5] Y. Wang, R. Skerry-Ryan, D. Stanton, Y. Wu, R. J. Weiss, N. Jaitly, Z. Yang, Y. Xiao, Z. Chen, S. Bengio et al., “Tacotron: Towards end-to-end speech synthesis,” in *INTERSPEECH*, 2017.

[6] 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 *ICASSP*, 2018, pp. 4779–4783.

[7] N. Li, S. Liu, Y. Liu, S. Zhao, M. Liu, and M. Zhou, “Close to human quality TTS with transformer,” in *AAAI*, 2019.

[8] A. K. Syrdal, A. Conkie, Y.-J. Kim, and M. C. Beutnagel, “Speech acts and dialog tts,” in *SSW*, 2010.

[9] K. Maekawa, “Corpus of spontaneous japanese: Its design and evaluation,” in *ISCA & IEEE Workshop on Spontaneous Speech Processing and Recognition*, 2003.

[10] H. Mori, T. Satake, M. Nakamura, and H. Kasuya, “Constructing a spoken dialogue corpus for studying paralinguistic information in expressive conversation and analyzing its statistical/acoustic characteristics,” *Speech Communication*, vol. 53, no. 1, pp. 36–50, 2011.

[11] É. Székely, G. E. Henter, and J. Gustafson, “Casting to corpus: Segmenting and selecting spontaneous dialogue for tts with a lstm-speaker-dependent breath detector,” in *ICASSP*, 2019, pp. 6925–6929.

[12] R. Qader, G. Lecorvé, D. Lolive, and P. Sébillot, “Disfluency insertion for spontaneous tts: Formalization and proof of concept,” in *International Conference on Statistical Language and Speech Processing*. Springer, 2018, pp. 32–44.

[13] D. Krueger, T. Maharaj, J. Kramár, M. Pezeshkhi, N. Dallas, N. R. Ke, A. Goyal, Y. Bengio, H. Larochelle, A. C. Courville, and C. J. Pal, “Zoneout: Regularizing rnns by randomly preserving hidden activations,” *ArXiv*, vol. abs/1606.01305, 2016.

[14] H. Guo, F. K. Soong, L. He, and L. Xie, “A new gan-based end-to-end tts training algorithm,” in *INTERSPEECH*, 2019.

[15] M. He, Y. Deng, and L. He, “Robust sequence-to-sequence acoustic modeling with stepwise monotonic attention for neural tts,” in *INTERSPEECH*, 2019.

[16] N. Kalchbrenner, E. Elsen, K. Simonyan, S. Noury, N. Casagrande, E. Lockhart, F. Stemberg, A. v. d. Oord, S. Dieleman, and K. Kavukcuoglu, “Efficient neural audio synthesis,” in *ICML*, 2018.

[17] A. Van Den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. W. Senior, and K. Kavukcuoglu, “WaveNet: A generative model for raw audio.” in *SSW*, 2016, p. 125.

[18] A. v. d. Oord, Y. Li, I. Babuschkin, K. Simonyan, O. Vinyals, K. Kavukcuoglu, G. v. d. Driessche, E. Lockhart, L. C. Coho, F. Stemberg et al., “Parallel wavenet: Fast high-fidelity speech synthesis,” *arXiv preprint arXiv:1711.10433*, 2017.

[19] P. Wang, Y. Qian, F. K. Soong, L. He, and H. Zhao, “Word embedding for recurrent neural network based tts synthesis,” *ICASSP*, pp. 4879–4883, 2015.

[20] H. Ming, L. He, H. Guo, and F. K. Soong, “Feature reinforcement with word embedding and parsing information in neural tts,” *ArXiv*, vol. abs/1901.00707, 2019.

[21] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” in *NAACL-HLT*, 2018.

[22] V. K. R. Sridhar, A. Syrdal, A. D. Conkie, and S. Bangalore, “Enriching text-to-speech synthesis using automatic dialog act tags,” in *INTERSPEECH*, 2011.