FCTalker: Fine and Coarse Grained Context Modeling for Expressive Conversational Speech Synthesis

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Abstract

Conversational Text-to-Speech (TTS) aims to synthesize an utterance with the right linguistic and affective prosody in a conversational context. The correlation between the current utterance and the dialogue history at the utterance level was used to improve the expressiveness of synthesized speech. However, the fine-grained information in the dialogue history at the word level also has an important impact on the prosodic expression of an utterance, which has not been well studied in the prior work. Therefore, we propose a novel expressive conversational TTS model, termed as FCTalker, that learns the fine and coarse-grained context dependency at the same time during speech generation. Specifically, the FCTalker includes fine and coarse-grained encoders to exploit the word and utterance-level context dependency. To model the word-level dependencies between an utterance and its dialogue history, the fine-grained dialogue encoder is built on top of a dialogue BERT model. The subjective and objective evaluation results show that the proposed model achieves remarkable results compared to the baseline model and generates contextually appropriate expressive speech. We release the source code at: https://github.com/AI-S2-Lab/FCTalker.

Index Terms: Conversational Text-to-Speech (TTS), Fine and Coarse Grained, Context, Expressive

1. Introduction

In conversational Text-to-Speech (TTS), we take the speaker interaction history between two speakers into account and generate expressive speech for a target speaker [1, 2]. This technique is highly demanded in the deployment of intelligent agents [3, 4]. With the advent of deep learning, neural TTS [5–8], i.e. Tacotron [5, 6], FastSpeech [7, 8] based models, has gained remarkable performance over the traditional statistical parametric speech synthesis methods [9, 10] in terms of speech quality. However, the prosodic rendering of neural TTS in a conversational context remains a challenge.

The attempts at conversational TTS can be traced back to the HMM era [11–14]. They make use of rich textual information, such as dialog acts [12] and extended context [14] for expressive speech generation. However, these approaches are limited by the need of manual annotation and inadequate dialogue representation of the model. In the context of neural TTS, Guo et al. [1] proposed a conversation context encoder based on Tacotron2 model to extract utterance-level prosody-related information from the dialogue history. Cong et al. [2] proposed a context-aware acoustic model which predicts the utterance-level acoustic embedding according to the dialogue history. Mitsui et al. [15] exploited utterance-level BERT encoding to predict conversational speaking styles with spontaneous behavior during TTS synthesis. These studies have advanced the state-of-the-art in conversational TTS. However, they didn’t exploit the word-level information in the dialogue history for the prosody rendering of the current utterance.

Speech prosody is rendered at various segmental level from syllable, lexical word, to sentence [16, 17]. As shown in Fig.1, the blue words “trophy” and “won” are strong indicators that determine the prosodic expression of the final response. We also find that fine-grained token-level information has played a significant role in conversation-related studies, such as multturn dialog generation [17], conversational emotion recognition [16], dialogue state tracking [18, 19], conversation intent classification [20] etc. They simultaneously model the hierarchical contextual semantic dependencies, i.e. word and sentence, between the current utterances and its conversational history, and achieve performance gains.

Inspired by this, we design a novel dialogue BERT [21] based fine-grained encoder in addition to the traditional coarse-grained context encoder. Pre-training a fine-grained encoder, we take the word-level sequences of dialogue history and current utterance as input to learn their fine-grained dependency. At last, the outputs of the fine and coarse-grained context encoders are combined with the phoneme encoding of the input text for expressive speech generation. In addition, we note a study [22] that used ChatGPT-derived embeddings of contextual words as conditional features for expressive speech synthesis. However, their subjective evaluation results show that the actual results are only close to [1]. While the Large Language Model (LLM) can understand dialogue content, it predicts the utterance-level acoustic embedding according to the dialogue history. Therefore, it would be more effective to use pre-trained dialogue models to extract contextual feature information directly.

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The main contributions of this paper include: 1) We propose a novel conversational TTS model FCTalker to synthesis expressive speech; 2) We design a novel fine and coarse grained context modeling scheme to incorporate word and utterance level context; and 3) The proposed model outperforms all state-of-the-art baselines in terms of expressiveness rendering. To our best knowledge, this is the first study of conversational TTS that combines fine-grained and coarse-grained contextual information about text modalities in conversational history for prosodic rendering.

2. FCTalker: Methodology

As shown in Fig.2, our FCTalker adopts the non-autoregressive Fastspeech2 [8] as the backbone, which includes fine-grained context encoder, coarse-grained context encoder, text encoder, speaker encoder, duration predictor, length regulator, variance adaptor and the mel-spectrum decoder.

2.1. Overall Architecture

Given a conversation of $T$ dialogue turns, $L = \{L_1, L_2, ..., L_T\}$, where $L_{his} = \{L_1, L_2, ..., L_{T-1}\}$ is seen as the dialogue history, while $L_T$ is the current utterance to be synthesized. For each utterance $L_i$ ($i \in [1, T]$), $W_i$ indicates the word-level sequence. Therefore, $W_{his} = \{W_1, W_2, ..., W_{T-1}\}$ is used to indicate the word-level sequence of dialogue history while $W_T$ represents the word-level sequence of current utterance.

The fine-grained context encoder $Enc_{FG}$ takes the $W_{his}$ and $W_T$ as input to generate the fine-grained context embedding $H_F$. The coarse-grained context encoder $Enc_{CG}$ leads the dialogue history and current utterance in utterance, that are $L_{his}$ and $L_T$, to extract the coarse-grained context embedding $H_C$. The text encoder, consists of 4 layers of Feed-Forward Transformer (FFF) blocks, seeks to extract the phoneme embedding $H_P$ for the current input utterance. The speaker encoder is a learnable lookup table, that encodes the speaker information into a speaker code $H_{SPK}$ [23, 24] to represent the speaker of current utterance. Similar with the [8], the remaining module, acoustic decoder, consists of duration predictor, length regulator, variance adaptor and the mel-spectrum decoder. Variance adaptor aims to estimate different variance information such as duration, pitch and energy and add them into the hidden sequence to predict the mel-spectrum features. For duration predictor, we replace the external aligner section of the FastSpeech2 framework with a CTC-based aligner [25] since external aligners show a risk of an out-of-distribution problem and perform misalignment for some data. Note that the fine and coarse grained context embeddings $H_F$, $H_C$ seek to modulate the input phoneme embedding $H_P$ with the word and utterance level context information, which enables all variance information (including pitch, energy and duration) to be affected to express the prosodic in conversation scenario. As shown in Fig.2, fine- and coarse-grained context embeddings $H_{F}$, $H_{C}$, phoneme embedding $H_{P}$ and the speaker code $H_{SPK}$ are concatenated together and feed to the acoustic decoder to predict the mel-spectrum feature. We employ HiFi-GAN [26] to convert the generated mel-spectrum into speech waveform.

We follow [1] to implement the coarse-grained context encoder structure. Each utterance $L_i$ ($i \in [1, T]$) is embedded using a pre-trained BERT model to obtain the sentence embedding. Each sentence embedding is appended with a one-hot vector as a speaker ID to distinguish different speakers. Then the GRU layer is used to encode the sentence embedding sequence of dialogue history as a prosody feature, which is then concatenated with the sentence embedding of the current utterance. The following linear layer is used to convert the concatenated feature to the final utterance-level context embedding $H_C$ [1]. For fine-grained context encoder, to model deep contextual dependencies at the word level, we build its structure with the dialogue BERT model [21]. The parameters of the fine-grained context encoder are initialized by a pre-training step, termed as “Fine-Grained Context Modeling with Dialogue BERT Pre-training”. We will demonstrate the details of pre-training and fine-grained context embedding extraction in the following subsections.

2.2. Fine-Grained Context Encoder

2.2.1. Dialogue BERT Pretraining

We use BERT’s deep bidirectional context modeling capability [21] to model the word-level dependencies of dialogue history and current utterance. We use multiple turns of a conversation involving different speakers for the BERT pretraining in this work. As shown in Fig.3(a), the input sequence of dialogue BERT based $Enc_{FG}$ consists of [CLS] token, $W_{his}$ and $W_T$ sequence, and the [SEP] token. To capture speaker information and the underlying interaction behavior in conversation, the speaker token [SPK] for each utterance is prefixed to each word-level sequence $W_i$. At last, the input of the dialogue BERT pre-training model is processed as “[CLS] [SPK] $W_1$ [SPK] $W_2$ ... [SPK] $W_{T-1}$ [SPK] $W_T$ [SEP]” with standard positional embeddings and segmentation embeddings. With the help of global context modeling capacity of self-attention [27], the multi-layer Transformer blocks are stacked to learn the deep context for the word-level input sequence. We follow [28] and build the dialogue BERT model with BERT-based uncased model [28], which includes 12-layers Transformer blocks with 12 attention heads with hidden sizes $h_n = 768$ in each layer.

We conduct the pre-training using two loss functions: 1) Masked Language Modeling Loss ($L_{mlm}$) and 2) Dialogue Contrastive Loss ($L_{dc}$). $L_{mlm}$ is a common objective function for BERT-like architectures. Note that unlike the BERT model that mask and replace the token once before training [21], inspired by [28], we conduct token masking dynamically during batch training. The $L_{mlm}$ is defined as: $L_{mlm} = \sum_{m=1}^{M} \log P(x_m)$, where $M$ is the total number of masked tokens and $P(x_m)$ is the predicted probability of the token...
is that Wow that's including MAE-M, MAE-P, MAE-E and MAE-D for three features. We select 1000 test samples from the test set randomly over the vocabulary size. \( L_{M} \) learns the word-level contextual information, etc. Suppose that there are \( T' \) conversations, each consisting of multiple turns of dialogue. The \( L_{dc} \) is defined as: \( L_{dc} = - \sum_{t=1}^{T'} \log \hat{M}_{h,k}, \) where \( M = \text{Softmax}(CR) \in \mathbb{R}^{T' \times T}. \) \( C \in \mathbb{R}^{T' \times s_{h}} \) and \( R \in \mathbb{R}^{T' \times s_{h}} \) are history and current matrices respectively by taking the output \([CLS]\) representations from the \( T' \) dialogues. For more details, please refer to [28]. At last, we sum them up as the total loss: \( \mathcal{L} = L_{m+n} + L_{dc}. \)

2.2.2. Fine-Grained Context Embedding Extraction

During the FCTalker training, the \( \text{Enc}_{FC} \) learns the word-level context information to extract the context embedding for current utterance. As shown in Fig.3(b), we add a linear layer on the top of the neurons for \( \mathcal{W}_{T} \) to extract the fine-grained context embedding \( \mathcal{H}_{FC}. \) The neurons for dialogue history and other special tokens are discarded.

There was a study [29] of a local attention module to learn the fine-grained context in a conversation. For clarity, we would like to highlight two differences of our work: 1) [29] is focused on the multimodal conversation while this work is only on textual modality; 2) the simple attention mechanism in [29] only learns the interaction and ignores the deep semantic dependency between the dialogue history and the current utterance, that we learn via a BERT model in this study. Unlike the original dialogue BERT model [28], the pre-trained dialogue BERT model trained under large-scale dialogue data is used as a contextual feature extractor to obtain a more meaningful contextual representation for the current utterance in our methodology.

3. Experiments and Results

3.1. Dataset

We validate the FCTalker on a recently public dataset for conversational TTS called DailyTalk [30], which is a subset of the open-domain conversation dataset DailyDialog [31]. DailyTalk consists of 23,773 audio clips representing 20 hours in total, in which 2,541 conversations were sampled, modified, and recorded. All dialogues are long enough to represent the context of each conversation. The dataset was recorded by a male and a female simultaneously. All speech samples are sampled at 44.10 kHz and coded in 16 bits. We partition the data into training, validation, and test sets at a ratio of 8:1:1. The dialogue BERT pretraining is conducted on a set of dialogue corpora [28] consisting of nine different task-oriented datasets, such as MetaLWOZ [32] and Schema [33]. There are about 100 thousand dialogues covering more than 60 different domains.

3.2. Experimental Setup

The fine-grained encoder consists of 12-layers Transformer blocks and 12 attention heads with hidden size \( s_{h} = 768. \) Note that the additional linear layer of Fig.3(b) reduces the output dimension from 768 to 256. The coarse-grained encoder is implemented by following [1]. The text encoder takes 256-dimensions phoneme sequence as input. We extract 80-channel mel-spectrum features with a frame size of 50ms and 12.5ms frame shift as the reference target. The dimensions of \( \mathcal{H}_{T}, \mathcal{H}_{C}, \mathcal{H}_{F} \) and \( \mathcal{H}_{S} \) are all 256. The detailed setup of acoustic decoder can be found in [30]. We set the value of dialogue turns \( T \) to range from 1 to 14 for comparison. For FCTalker training, we use Adam optimizer with \( \beta_{1} = 0.9, \beta_{2} = 0.98. \) All speech samples are re-sampled to 22.05 kHz. The model is trained on a Tesla V100 GPU with a batch size of 32 and 900k steps. We follow [28] to pretrain the fine-grained dialogue BERT with 900k steps.

3.3. Comparative Study

We develop four neural TTS systems for a comparative study, that include the 1) FastSpeech2 [8] (or \( \text{FCTalker w/o fine-and coarse} \)): the state-of-the-art neural TTS model that takes the single utterance as input, without any conversational context modeling; 2) DailyTalk [30] (or \( \text{FCTalker w/o fine} \)): the latest neural conversational TTS model with coarse-grained context encoder; 3) \( \text{FCTalker} \): the proposed model with fine-and coarse-grained context modeling strategy; 4) \( \text{FCTalker w/o coarse} \): we take the coarse-grained encoder module out of the proposed FCTalker model and 5) \( \text{Ground Truth} \) speech under conversation scenario. Note that systems 1, 2, and 4 can be seen as ablation experiments of \( \text{FCTalker} \) in terms of coarse-grained and fine-grained encoders.

3.4. Objective Evaluations

We first conduct objective evaluations to validate our \( \text{FCTalker} \) for expressiveness in terms of acoustic features, that are frame-level mel-spectrogram, pitch, energy and phoneme-level duration. We set the dialogue turns \( T \) to 2 and report the performance in terms of mean square absolute (MAE) error between predicted and ground-truth features, including MAE-M, MAE-P, MAE-E and MAE-D for three features.

We select 1000 test samples from the test set randomly

| System          | Utterance-level | Dialogue-level |
|-----------------|-----------------|----------------|
| FastSpeech2 [8] | 3.80 ± 0.025    | 3.90 ± 0.046   |
| DailyTalk [30]  | 3.86 ± 0.042    | 3.96 ± 0.056   |
| FCTalker w/o coarse [T=2] | 3.94 ± 0.061 | 4.11 ± 0.047   |
| FCTalker [T=2]  | 4.07 ± 0.040    | 4.15 ± 0.031   |
| Ground Truth    | 4.46 ± 0.031    | 4.52 ± 0.034   |

Table 1: The MOS results for all comparative systems, with 95% confidence interval.
Table 2: Objective evaluations for all comparative systems. (* means the metric value achieved the suboptimal result among all values.)

| System       | MAE-M  | MAE-P  | MAE-E  | MAE-D  |
|--------------|--------|--------|--------|--------|
| FastSpeech2  | 0.681  | 0.506  | 0.346  | 0.300  |
| DailyTalk    | 0.675  | 0.506  | 0.352  | 0.296  |
| FCTalker w/o coarse | 0.656  | 0.497  | 0.329  | 0.276  |
| FCTalker     | 0.655  | 0.498* | 0.333* | 0.275  |

and report the results in Table 2. We observed that FCTalker performs best in terms of the mel-spectrogram quality and phoneme duration alignment. For pitch and energy, FCTalker w/o coarse and our FCTalker outperform FastSpeech2 and DailyTalk, and achieved optimal and suboptimal performance respectively. The above observations can demonstrate that our fine-grained encoder shows a strong ability in contextual fine-grained prosodic expression learning.

3.5. Subjective Evaluations

Note that objective metrics do not fully reflect the human perception [34]. Furthermore, we conduct 5-point Likert scale mean opinion score (MOS) [35] listening experiments 1 to validate the FCTalker model in terms of prosodic expressiveness and context modeling.

Note that the prosodic expressiveness of conversational speech is related to its adjacent dialogue. Therefore, we design two kinds of experiments, including Utterance-level and Dialogue-level MOS tests, to test the prosodic performance of synthesized speech in a conversation scenario. Specifically, Utterance-level MOS means the volunteers only rated single sentences from different systems, without reference to the dialogue history. Dialogue-level MOS indicates that volunteers rate a multi-turn conversation that includes several audios, some of which are synthesized from the TTS model.

In this section, each audio is listened by 30 volunteers, each of which listens to 80 speech samples. There is a 1:1 ratio of men to women among the volunteers, who are all studying at university and are between 20 and 25 years old. Prior to the subjective test, we had a training to ensure they understood their tasks and the rules. For DailyTalk and FCTalker, we set the dialogue turns $T$ to 2 and report the results in Table 1.

It’s observed that our FCTalker outperforms all baselines and performs the smallest gap with the ground truth speech, in both the utterance and dialogue scenarios. FastSpeech2 achieves the lowest performance due to the lack of prosodic information in context during speech generation. DailyTalk can produce more prosodic speech than FastSpeech2 since it incorporates utterance-level contextual information. The difference between the FCTalker w/o coarse and FCTalker is small and proves the effectiveness of the fine-grained encoder. As expected, FCTalker achieves the best performance by considering both word-level and sentence-level contextual information, which is remarkable.

3.6. Analysis for Dialogue Turns

Contextual information is important for the prosodic expression of the current statement, but how the length of a dialogue turn is chosen to achieve the optimal effect needs to be further verified. In this section, considering the average number 9.3 of dialogue turn in the DailyTalk, we set the dialogue turn $T$ range from 2 to 14 to compare the utterance-and dialogue-level MOS scores.

Figure 4: The MOS results of various dialogue turn number $T$ (range from 2 to 14) for FCTalker, with 95% confidence interval.

We also invite 30 volunteers and follow the settings of Sec.3.5 to conduct the listening test.

As shown in Fig.4, when the value of dialogue turn $T$ increases from 2 to 12, the utterance-and dialogue-level MOS scores show an overall upward trend, while they show a certain downward trend when it increases from 12 to 14. We also found that when the number of $T$ ranged from 9 to 12, the MOS scores remained above 4.0 steadily. Given that the average dialogue turn of DailyTalk is 9.3, we concluded that it might be a good choice to set the optimal $T$ according to the average dialogue turn.

4. Conclusions

This work proposed a novel expressive conversational TTS model, termed as FCTalker, which includes both fine- and coarse-grained encoders. The fine-grained encoder is implemented on a pre-trained dialogue BERT model and can learn the deep fine-grained context dependencies of the dialogue history and the current utterance. Experimental results show that our model outperforms all baselines and generates expressive speech that is more in line with the conversational context. We also give suggestions on the selection of the optimal dialogue turns through further analysis. To further optimize the context modeling mechanism will be our future focus.

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