Exploiting Deep Sentential Context for Expressive End-to-End Speech Synthesis

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Abstract

Attention-based seq2seq text-to-speech systems, especially those use self-attention networks (SAN), have achieved state-of-art performance. But an expressive corpus with rich prosody is still challenging to model as 1) prosodic aspects, which span across different sentential granularities and mainly determine acoustic expressiveness, are difficult to quantize and label and 2) the current seq2seq framework extracts prosodic information solely from a text encoder, which is easily collapsed to an averaged expression for expressive contents. To better make use of the sentential context in an E2E framework, one way is feature engineering as the previous generation of TTS does. For example, recent study has shown that exploiting syntactic features in a parsed tree is beneficial to the richness of the prosodic outcomes, leading to more natural synthesized speech [5].

However, modeling expressiveness in text-to-speech is still challenging as it refers to different levels of syntactic and semantic information reflected in intensity, rhythm, intonation and other prosody related factors. However, it is difficult to define the relations explicitly between the syntactic/semantic factors and the prosodic factors. To model expressivity, the global style tokens (GST) family [6,7] learns style embeddings from a reference audio in an unsupervised way, which lets the synthesized speech imitate the style of reference audio. Although the style embeddings from a reference audio is helpful to control the style of synthesized speech, it is hard to choose an appropriate reference audio for each input sentence. Likewise, the variational autoencoder (VAE) models styles or expressivity in a similar way [8].

Recent studies have revealed that self-attention based networks (SAN) [9,10,11,12] have strong ability in capturing global prosodic information, leading to more natural synthesized speech. And unveiled by recent NLP tasks, different SAN encoder layers can capture latent syntactic and semantic properties of the input sentence at different levels [3,4]. But current SAN-based TTS systems only leverage the highly aggregated representation can be treated as a global description of the sentential context, it is not enough to generate expressive content according to our experiments as it may disperse the contribution of sentential context in an unsupervised way, which is easily collapsed to an averaged expression for expressive contents. To better make use of the sentential context in an E2E framework, one way is feature engineering as the previous generation of TTS does. For example, recent study has shown that exploiting syntactic features in a parsed tree is beneficial to the richness of the prosodic outcomes, leading to more natural synthesized speech [5].

In this paper, to excavate the sentential context for expressive speech synthesis, we propose a context extractor to sufficiently exploit sentential context over an expressive corpus for seq2seq-based TTS. Specifically, we utilize different levels of representations from the SAN-based text encoder to build a context extractor, which is helpful to extract different levels of syntactic and semantic information [14]. In details, our context extractor first collects the prosodic-related sentential context information from different SAN-based encoder layers, and then aggregates them to learn a comprehensive sentence representation to enhance the expressiveness of the final generated

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Figure 1: Proposed architecture with context aggregation based on Tacotron2 and SAN encoder.

To fully make use of the contexts extracted from each block, we propose a context extractor to aggregate the different levels of contexts to form a comprehensive sentence representation. For the $l$th self-attention block, we extract the intermediate content from the output $H^l$ through:

$$g^l = g(H^l) = \text{MeanPool}(\text{Conv1d}(H^l)), \quad (4)$$

where Conv1d means 1d-convolution, MeanPool represents mean pooling $\text{Conv1d}$, $g(\cdot)$ denotes the function to summarize the outputs of self-attention layers, and $g^l$ represents the sentential context from $l$th block. A straightforward and intuitive choice to aggregate the different levels of contexts is through a concatenation operation, with residual connection and layer normalization $\text{[9]}$:

$$C_g = \text{LN} \left( \text{Concat}(g^0, \ldots, g^L) + g^L \right), \quad (5)$$

where $g^0$ represents the inputs of the first self-attention layer through Eq. (3). To further integrate the information concatenated from all sentential contexts, we use another round of feedforward network and layer normalization as the final aggregation function $\text{[19]}$ $\text{[20]}$:

$$g = \text{LN} \left( \text{FFN}(C_g) + C_y \right). \quad (6)$$

Here, $g$ is the final sentential context.

2. Proposed Model

Figure 1 illustrates our proposed approach on exploiting deep sentential contexts for expressive speech synthesis. It contains a modified self-attention based text encoder, an auto-regressive decoder and a GMM-based attention [15] to bridge the encoder and the decoder. WaveGlow [16] is adopted to reconstruct waveforms from mel spectrogram. We augment the encoder with a context aggregation module, which will be described in detail.

2.1. Self-attention based Encoder

Self-attention based sequence-to-sequence framework has been successfully applied to speech synthesis [9] [10] [17]. In the basic SAN-based text encoder, there is a stack of $L$ blocks, each of which has two sub-networks: a multi-head attention and a feed forward network. The residual connection and layer normalization are applied to both of the sub-networks. Formally, from the previous encoder block output $H^{l-1}$, the first sub-network $C_l$ and the second sub-network $H^l$ are calculated as:

$$C_l = \text{LN} \left( \text{MultiHead}(\text{head}_l^0, \ldots, \text{head}_l^d) + H^{l-1} \right), \quad (1)$$

$$H^l = \text{LN} \left( \text{FFN}(C_l^d) + C_l^l \right), \quad (2)$$

where MultiHead(·), FFN(·) and LN(·) are multi-head attention, feed forward network and layer normalization respectively. And each head in multi-head attention split from the previous encoder block output is computed by:

$$\text{head}_l^h = \alpha \cdot V = \text{softmax} \left( \frac{QK^T}{\sqrt{d}} \cdot V \right), \quad (3)$$

where $\{Q, K, V\}$ represent queries, keys and values, $d$ is the dimension of the hidden state and $\alpha$ represents the weight matrix for each head.

2.2. Direct Aggregation

Although the SANs have the ability of directly capturing global dependencies among whole input sequence [18], it may not appropriately exploit the sentential context because it calculates the relevance between the characters without considering the contextual information [9] [14]. Besides, the weighted sum option from the lower layers in SANs has only aggregated the global contextual information, which may weaken the contribution of sequential context extracted in each block.

To fully make use of the contexts extracted from each block, we propose a context extractor to aggregate the different levels of contexts to form a comprehensive sentence representation. For the $l$th self-attention block, we extract the intermediate context from the output $H^l$ through:

$$g^l = g(H^l) = \text{MeanPool}(\text{Conv1d}(H^l)), \quad (4)$$

where Conv1d means 1d-convolution, MeanPool represents mean pooling $\text{Conv1d}$, $g(\cdot)$ denotes the function to summarize the outputs of self-attention layers, and $g^l$ represents the sentential context from $l$th block. A straightforward and intuitive choice to aggregate the different levels of contexts is through a concatenation operation, with residual connection and layer normalization [9]:

$$C_g = \text{LN} \left( \text{Concat}(g^0, \ldots, g^L) + g^L \right), \quad (5)$$

where $g^0$ represents the inputs of the first self-attention layer through Eq. (3). To further integrate the information concatenated from all sentential contexts, we use another round of feedforward network and layer normalization as the final aggregation function [19] [20]:

$$g = \text{LN} \left( \text{FFN}(C_g) + C_y \right). \quad (6)$$

Here, $g$ is the final sentential context.

2.3. Weighted Aggregation

With direct aggregation, the sequential contexts of each block are simply concatenated to guide the auto-regressive generation, which does not consider the varying importance of each $g^l$. Assuming the sequential contexts in each block may have different contribution to the expressiveness of the synthesized speech, we utilize a self-learned weighted aggregation module across layers to catch the different levels of contribution.

In detail, we employ a multi-head attention to learn the contribution of each block. The individual sentential contexts $\{g^0, g^1, \ldots, g^L\}$ are treated as attention memory for the attention based weighted aggregation. Specifically, we transpose the dimension of sequential length with the number of heads in the multi-head attention to combine the contextual information across layers. Therefore, we modify Eq. (5) to obtain the weighted contexts:

$$C_g = \text{LN} \left( \text{MultiHead}(g^0, \ldots, g^L) + g^L \right), \quad (7)$$

where the modified $C_g$ offers a more precise control of aggregation for each $g^l$.

3. Experiments

3.1. Basic setups

To investigate the effectiveness of modeling expressiveness, we carried out experiments on two expressive Mandarin corpora – the publicly-available Blizzard Challenge 2019 corpus [21] from a male talk-show speaker and an internal voice assistant corpus from a female speaker. The talk-show (TS) corpus contains about 8 hours speech of, and the voice assistant (VA) corpus contains about 40 hours of speech. Both corpora are
Table 1: MCD scores over the two expressive corpora.

| Corpus | BASE | SA | SA-DA | SA-WA |
|--------|------|----|-------|-------|
| TS     | 8.01 | 7.48 | 7.42  | 7.32  |
| VA     | 7.60 | 7.37 | 7.32  | 7.23  |

Table 2: The MOS over the two expressive corpora with confidence intervals of 95%.

| Corpus | BASE | SA | SA-DA |
|--------|------|----|-------|
| TS     | 3.84±0.05 | 3.97±0.06 | 4.04±0.06 |
| VA     | 4.11±0.06 | 4.20±0.06 | 4.24±0.06 |

Figure 2: AB Preference results on TS with confidence intervals of 95% and p-value < 0.0001 from t-test.

3.2. Model details

We use the standard encoder-decoder structure in Tacotron2 as the baseline, but GMM attention is adopted instead because it can bring superior naturalness and stability. For networks using SAN based encoder, a 3-layer CNN is firstly applied to the input text embeddings with positional information. Each self-attention block includes an 8-head self-attention and a feed forward sub-network consisting of two linear transformations with 2048 and 512 hidden units. Residual connection and layer normalization are applied to these two sub-networks. There are totally 6 self-attention blocks. In the aggregation module, we double feed $g^f$ into aggregation attention function for the convenience of implementation, where the number of heads in multi-head attention are length and the dimension of weighted matrix are [batch, length, 8, 8]. For the remaining part, we adopt the auto-regressive decoder described in [2]. We use WaveGlow as vocoder which follows the structure in [15], trained using the same training set. We built the following systems for comparison:

- **Base**: Baseline system following Tacotron2 with slightly modified GMMv2 attention.
- **SA**: Another baseline system with SAN based encoder described in Section 2.1.
- **SA-DA**: SAN based encoder with the direct aggregation module fusing all sentential contexts described in Section 2.2.
- **SA-WA**: SAN based encoder with the weighted aggregation module fusing all sentential contexts described in Section 2.3.

3.3. Objective Evaluation

Table 1 shows the MCD results of different systems. It demonstrates that SAN based encoder has lower MCD than the RNN based encoder for both expressive corpora. It also shows that modeling sentential context can further improve the performance of SAN based encoder. Besides, weighted aggregation is a better way than direct aggregation to extract the deep sentential context.

3.5. Performance on less-expressive corpus

We also quickly examine the performance of our approach on a less-expressive reading-style corpus – DB1, to see how our sentential context extractor perform. Here, we only compare the above best-performed SA-WA system with the BASE system. The MCD scores for BASE and SA-WA are 5.78 and 5.72, respectively. The AB preference is illustrated in Figure 4.

Samples can be found from: https://fyyang1996.github.io/context/
Table 3: Correlation in relative energy, duration and F0 within a phoneme computed from different models on TS.

|       | BASE | SA  | SA-DA | SA-WA |        |
|-------|------|-----|-------|-------|--------|
| E     | 0.755| 0.776| 0.781 | 0.799 |        |
| Dur.  | 0.617| 0.638| 0.641 | 0.654 |        |
| F0    | 0.42 | 0.426| 0.437 | 0.501 |        |

Table 4: Diversity values using average standard deviation computed across 100 samples on TS.

|       | BASE | SA  | SA-DA | SA-WA |        |
|-------|------|-----|-------|-------|--------|
| E     | 0.238| 0.277| 0.285 | 0.304 | 0.321  |
| Dur.  | 33.374| 34.337| 34.955| 37.003| 41.866 |
| F0    | 32.302| 33.405| 35.161| 35.766| 36.824 |

4. Conclusion

Seq2seq-based TTS directly maps the character/phoneme sequence to the acoustic feature sequence using an encoder-decoder paradigm. The encoder functions as a sentential context extractor which aggregates latent semantic and syntactic information that highly correlates with the expressiveness of the synthesized speech by the decoder. In this paper, we propose a context extractor, which is built upon the SAN-based text encoder, to sufficiently exploit the text-side sentential context to produce more expressive speech. With the belief that different self-attention layers may capture different levels of latent syntactic and semantic information, which was discovered by recent NLP researches, we proposed two context aggregation strategies: 1) direct aggregation which directly concatenates the outputs of different SAN layers, and 2) weighted aggregation which uses multi-head attention to automatically learn contributions for different SAN layers. Experiments on two expressive corpora show that the two strategies can produce more natural and expressive speech, and weighted aggregation is more superior. Comprehensive analysis on the synthesized speech demonstrates that our sentential context extractor has better ability in reconstruction of prosody related acoustic features and modeling prosody diversity.
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