Triple M: A Practical Neural Text-to-speech System With Multi-guidance Attention And Multi-band Multi-time LPCNet

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Abstract

In this work, a robust and efficient text-to-speech system, named Triple M, is proposed for large-scale online application. The key components of Triple M are: 1) A seq2seq model with multi-guidance attention which obtains stable feature generation and robust long sentence synthesis ability by learning from the guidance attention mechanisms. Multi-guidance attention improves the robustness and the robustness to loss of long-sentence synthesis without any in-domain performance loss or online service modification. Compared with the other results obtained by using single attention mechanism (GMM-based attention), the word error rate of long sentence synthesis decreases by 23.5% when multi-guidance attention mechanism is applied. 2) A efficient multi-band multi-time LPCNet, which reduces the computational complexity of LPCNet by combining multi-band and multi-time strategies (from 2.8 to 1.0 GFLOP). Due to these strategies, the vocoder speed is increased by 2.75x on a single CPU without much MOS degradation (4.57 vs. 4.45).

Index Terms: Speech synthesis, sequence-to-sequence models, attention, vocoder, LPCNet

1. Introduction

In the past few years, speech synthesis becomes one of the most extensively researched fields. Sequence-to-sequence neural network [1] with attention mechanism is one of the most popular text-to-feature methods [2][3]. Attention mechanism is applied to align the input and output sequences. Therefore, the training is no longer fragmented. Content-based attention [4], which is applied in the original Tacotron [2], does not exploit the monotonicity and locality between the text and the acoustic features. Tacotron2 [5] attempts to enhance the robustness of attention by introducing location-related information. However, there are still some problems in this hybrid attention mechanism such as no explicit monotonicity restriction and weak robustness of long sentence synthesis. To tackle these problems, we come up with a novel multi-guidance attention mechanism, which enables the basic attention mechanism (location-sensitive attention) to learn different strengths from multiple guidance sources (forward attention [5] and GMM-based attention [6]). Thanks to the multi-guidance attention mechanism, the alignment speed during training and the robustness to long sentence synthesis have been significantly improved without affecting perceptual quality (MOS score slightly increased). More importantly, experiments show that through a reasonable combination, the advantages of different guidance attention can be transferred to the basic attention.

For large-scale online custom speech synthesis system, the calculation speed and cost of neural vocoder also need to be considered. The flow based neural vocoders, such as Parallel WaveNet [7] and Clarinet [8], reduce the computational overhead of WaveNet [9] by learning from the teacher WaveNet and realize real-time synthesis on the GPU. Recently, autoregressive models with simple structures like WaveRNN [10] and LPCNet [11] have been proposed for real-time synthesis on CPU by introducing sparse GRU. In this work, we propose a multi-band multi-time LPCNet that can simultaneously calculate the excitation of different subbands at adjacent moments in each forward process. Due to this novel generation architecture, the main computational complexity of the LPCNet is reduced from 2.8 to 1.0 GFLOPS and the generation speed on a single CPU core is accelerated by 2.75x.

2. Proposed Method

In this section, we describe the main components in the triple M text-to-speech system (As shown in Figure 1). First, a novel text-to-feature module with multi-guidance attention will be introduced. The basic attention mechanism (location-sensitive attention) learns different strengths (fast convergence, stable feature generation and robust long sentence synthesis) from multiple guidance sources (forward attention and GMM-based attention) in the process of training. In this way, new attention properties which make the system more robust can be integrated without modifying the inference framework of the online system. Next, a novel multi-band multi-time LPCNet which can significantly improve the efficiency of the system, will be described. Compared with the original LPCNet, the speed of the proposed vocoder is increased by 2.75 times without affecting the MOS significantly.

2.1. Multi-guidance attention

The elaboration of multi-guidance attention will be divided into three parts. First, the basic text-to-feature module will be described, which will learn from the guidance attention mechanisms and serve as the final inference model. Then, we will explain why forward attention and GMM-based attention are chosen as the guidance attention mechanisms. Finally, the details of guidance training will be given.

2.1.1. Basic setup

The basic text-to-feature module we use in the work is based on the original Tacotron [2]. The improved hybrid location sensitive attention proposed in Tacotron2 [3] is applied as the basic attention. We use CBHG encoder to transform Chinese Pinyin sequences with tone and prosody information \( \{x_i\}_{i=1}^L \) into hidden text representations \( \{h_i\}_{i=1}^L \) that are more suitable for attention mechanism (Eq.1). An attention RNN uses the last state, context vector and decoding result of the previous time step as input, and outputs the current state \( s_t \) for computing.
the attention score (Eq.4). The hybrid location-sensitive attention module takes the current state, hidden representations and location-related information as input to get the attention score $a_t$. Then and the context vector $c_t$ at the current moment is calculated (Eq.3). Finally, current attention RNN state and the context vector are input to the decoder RNN. Then the current state of the decoder $d_t$ is obtained and passed through an affine function to obtain the final decoding result $o_t$ (Eq.4).

\[
\{h_i\}_{i=1}^L = CBHGEncoder(\{x_i\}_{i=1}^L) \tag{1}
\]

\[
s_t = AttentionRNN(s_{t-1}, c_{t-1}, a_{t-1}) \tag{2}
\]

\[
a_t = LSA(s_t, h_t, l_t) \quad c_t = \sum_{i} a_{t,i} h_i \tag{3}
\]

\[
d_t = DecoderRNN(d_{t-1}, a_t, s_t) \quad o_t = Affine(d_t) \tag{4}
\]

2.1.3. Guidance training

The guidance attention mechanism affects the learning of basic attention mechanism through the loss function in the process of training. The training loss function consists of the first part contains $L_1$ distances between all decoder outputs ($o,o_f,o_g$ represent the output of basic decoder, forward attention decoder and GMM-based attention decoder respectively) and the real acoustic feature $r$. Then there is the $L_1$ distance between the output of CBHG postnet $\hat{p}$ and the real acoustic feature $r$. The last part $ga\_loss$ (Eq.6) includes $L_1$ distances between the basic alignment score $a$ and all guidance alignment scores (alignment score of forward attention $a_f$ and alignment score of GMM-based attention $a_g$). $\lambda$ is used to control the intensity of guidance learning.

\[
L = \ell_1(o,r) + \ell_1(o_f, r) + \ell_1(o_g, r) + \ell_1(p, r) + ga\_loss \tag{5}
\]

\[
ga\_loss = \lambda(\ell_1(a, a_f) + \ell_1(a, a_g)) \tag{6}
\]

All guidance-related modules are trained together with the basic text-to-feature module. After the guidance attention mechanisms became reliable, the basic attention mechanism begins to learn from them. Only the basic text-to-feature module is retained in inference.

2.2. Multi-band multi-time LPCNet

2.2.1. LPCNet

As a relatively lightweight neural vocoder, the key idea of LPCNet [11] is to model the vocal tract response through a low-cost linear prediction filter and use a smaller network to obtain the excitation. However, for large-scale applications, the computational overhead of the LPCNet still has room for improvement. The original LPCNet is composed of the frame rare network (FRN) and the sample rate network (SRN). The former extracts high-level representations from conditional acoustic features. The latter including two GRU layers (GRU-A and GRU-B) and a dual FC layer needs to loop N times per frame to

Figure 1: System architecture of our proposed Triple M.
obtain N sampling points corresponding to this frame. Therefore, the SRN occupies a major part of the overall calculation.

2.2.2. Multi-band multi-time processing

As analyzed above, the computational complexity of the original LPCNet is mainly concentrated on SRN. Reducing the number of SRN inference steps can effectively reduce the computational overhead of LPCNet. In this work, a multi-band multi-time processing framework is proposed to further reduce the computational complexity of LPCNet (The pipeline is shown in Figure 2). Multi-band processing is initially used for parallel acceleration of vocoder [14, 15]. By deploying multiple models to calculate different subband signals in parallel, the speed can be effectively increased, but the computational overhead cannot be truly reduced. The Durian proposed in [16] introduces multi-band processing into a single WaveRNN model, reducing the total computational complexity from 9.8 to 3.6 GFLOPS. We apply the multi-band strategy to the classic LPCNet to further exploit the potential of SRN and further reduce its overall computational complexity (Combined with the multi-time strategy, the overall computational complexity is about 1.0 GFLOPS). As in [16], a type of Cosine-Modulated Filter Bank (CMFB), named Pseudo Quadrature Mirror Filter Bank (Pseudo-QMF) [17], is applied to multi-band processing. After processing, the original signal is divided into N subbands, and down-sampling each subband N times will not cause the loss of original information. Intuitively, using SRN to predict N down-sampled subband signals at the same time, the number of inferences required will be reduced by N times. Since Pseudo-QMF is a low-cost filter bank, the cost of reconstructing the original signal from the subband signals is much less than the cost saved by reducing the number of SRN forwards. Multi-band strategy improves the efficiency of LPCNet from the frequency domain. The multi-time strategy takes two adjacent sampling points in the subband signal into consideration. SRN predicts adjacent points in N subbands at the same time, which can reduce the number of SRN inference steps by 2N times. Bunched LPCNet [18] predicts a bunch of original samples in an autoregressive way. Within a bunch, the first excitation is only conditioned on the output from GRU-B. While for the rest excitation, it depends on all the previous excitations in the same bunch. Different from the Bunched LPCNet, our multi-band multi-time LPCNet predicts the adjacent samples of each subband signal at the same time. Due to the small time span, we remove the autoregressive module for simplicity.

2.2.3. Audio generation framework

As shown in Figure 3, in each forward, except for the dual FC layer, the rest of the SRN layers are shared. The excitations ($e^{t-1}_{4b}$ and $e^{t-2}_{4b}$), audio samples ($s^{t-1}_{4b}$ and $s^{t-2}_{4b}$) from the last adjacent time and obtained predictions (at the last time $p^{t-1}_{4b}$ and the current time $p^{t}_{4b}$) are used as the input of the first GRU layer (GRU-A). The output of the second GRU layer (GRU-B) is sent to 8 independent dual FC layers to predict the excitation of sub-bands at adjacent time ($e^{t-1}_{4b}$ and $e^{t-1}_{4b}$). After that, the audio samples at the current adjacent time can be acquired recursively (Eq.7,8). Finally, the LPC queues of all subbands are updated to prepare for next round. Although 7 more dual FC layers are introduced and the input matrix of GRU-A layer will become larger (the table lookup operation makes this overhead negligible), the multi-band multi-time strategy reduces the number of cycles required for SRN by 8 times. Therefore, the speed of the vocoder is increased by 2.75x without other calculation optimization.

\[
\begin{aligned}
    s_t^{1:b} &= e_t^{1:b-4} + p_t^{1:b-4} \\
    p^{t}_{i+1} &= LPCPrediction(s_{t-6:t-1}^{1:b-4}: s_{t-1:t}^{1:b-4}) \\
    s_{t+1}^{1:b} &= e_{t+1}^{b} + p_{t+1}^{b}
\end{aligned}
\]

3. Experiments

3.1. Experimental setup

The experiments used a Mandarin corpus recorded by a Chinese male speaker. All recordings were sampled at 16kHz with 16-bit quantization. About 16 hours of recordings (with an average length of 90 characters) were used for training. 100 regular
sentences and 50 passages selected from the WeChat official account (with an average length of 1000 characters, which was 10 times longer than the training sentences) were tested. Consistent with the original LPCNet, 18 Bark cepstral coefficients and 2 pitch parameters were extracted as conditions of the vocoder. At the same time, they were also used as the prediction targets of the text-to-feature module.

The text-to-feature module was a sequence-to-sequence structure, with a CBHG (convolutional bank, highway network and bidirectional gated recurrent unit) module at the beginning and the end as encoder and post-net respectively. The main component of decoder was a two-layer 512-dimensional unidirectional LSTM. All attention modules were composed of a unidirectional GRU layer and a corresponding attention mechanism. \( \lambda \) was used to control the intensity of guidance learning, which was set to 10 in our experiment. All modules were trained together at the beginning. After the guidance attention mechanisms became reliable, the basic attention mechanism began to learn from them.

In the original LPCNet, SRN consisted of a 90% sparse 384-dimensional GRU layer(GRU-A), a normal 16-dimensional GRU layer(GRU-B) and a 256-dimensional dual FC layer. As to the multi-band multi-time LPCNet, dimensions of all GRU layers kept unchanged. Different from [11], in addition to being input to GRU-A, condition feature was also used as input to GRU-B. The hyper-parameters of sub-band and time span included in the inference were set to 4 and 2 respectively in order to reach a reasonable compromise between the quality and the computational cost.

3.2. Evaluations

The experiment found that learning from forward attention and GMM-based attention, the basic attention formed a clear alignment at the second epoch. It took much less epochs than 10 epochs required without guidance mechanisms. This prevented the model falling into bad alignment in early stage of training and provided a stable basis for the subsequent training. From another view, the well-learned basic attention provided an approximate diagonal mask, which gave a constraint to the forward attention. So that it was not easy to collapse during the training as mentioned in [12].

In the long sentence synthesis experiment, 50 passages were selected from the WeChat official account, covering the fields of politics, sports, entertainment, literature, cooking and so on. The failure rates were more than 80% when GMM-based attention and forward attention were severally used as guidance mechanisms. Compared with the baseline model (no guidance), there was no obvious improvement in the long sentences synthesis. The failure was mainly identified by whether the synthesized audio ended early, repeated the same clip, or contained meaningless clip (examples of failed synthesis can be found on our demo page). Applying two attention mechanisms simultaneously to guide the learning of the basic attention reduced the failure rate to 2%. These results showed that only using forward attention as a supervisory signal cannot provide long sentence synthesis capabilities. But without the constraint of forward attention, basic attention cannot learn long sentence synthesis ability from GMM-based attention well. Only using GMM-based attention (no guidance) can achieve a similar failure rate. However, in terms of the naturalness of long sentences, almost all listeners thought that the audio synthesized by multi-guidance attention was better (examples for comparison are available on our demo page). In addition, the word error rate (measured by WeChat-ASR system) using only GMM-based attention was 8.1% (6.2% when using multi-guidance attention). This might be related to the ability of forward attention to generate features stably.

In order to verify the influence of the multi-guidance attention mechanism on perceptual quality, a mean opinion score (MOS) listening test was implemented. For all MOS listening test in this work, three groups of Native Chinese speakers (5 in each group) were invited to listen and score 125 audio. 100 synthesized results were mixed with 25 original recordings, and the listener did not know which category each audio belonged to. Scores range from 1 to 5, with 5 representing “completely natural speech”. The final MOS was obtained by averaging the scores of the three groups. Table 1 summarized the results of the MOS test. Experiments showed that the basic attention can learn the advantages of the guiding attention (faster convergence, stable long sentence synthesis) while maintaining the in-domain naturalness (MOS slightly improved). In this way, new characteristics can be assigned to the text-to-speech system without modifying the online service (just reload the new model parameters). In addition, multi-guidance attention also provides a new way to improve the performance of attention mechanism through transfer learning.

| Model | MOS | RTF |
|-------|-----|-----|
| Baseline | 4.52 ± 0.08 | 0.303 |
| Multi-guidance | 4.57 ± 0.05 | 0.110 |
| Ground truth | 4.65 ± 0.04 | |

According to the calculation method (14) mentioned in [4], the total complexity of the SRN was around 2.8 GFLOPS. The introduction of the multi-band multi-time strategy reduced the complexity of the SRN to around 1.0 GFLOPS.

\[
C = \frac{(3dG_A^2 + 3G_B(G_A + G_B) + 2G_BQN_BN_TR)2F_S}{N_BN_T}.
\]

To demonstrate that the multi-band multi-time strategy can accelerate synthesis without significantly degrading the perceptual quality, the comparison experiment of MOS and real-time factor was implemented. The experimental results were presented in Table 2. The results showed that the multi-band and multi-time strategy brought a 2.75x improvement in speed while the MOS has only dropped by 3%.

| Model                | MOS     | RTF  |
|----------------------|---------|------|
| LPCNet               | 4.57 ± 0.05 | 0.303 |
| Multi-band & Multi-time | 4.45 ± 0.07 | 0.110 |

4. Conclusions

In this paper, we have proposed triple M, a robust and efficient text-to-speech system. This system integrated the advantages of various attention mechanisms (such as stable learning and robust long sentence synthesis) by a novel multi-guidance strategy, which makes the system more robust. Exploiting the acceleration potential of the LPCNet through our multi-band multi-time strategy makes the system more efficient (2.75x speedup without significantly reducing synthesis quality).
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