A POST AUTO-REGRESSIVE GAN VOCODER FOCUSED ON SPECTRUM FRACTURE

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Abstract

Generative adversarial networks (GANs) have been indicated their superiority in usage of the real-time speech synthesis. Nevertheless, most of them make use of deep convolutional layers as their backbone, which may cause the absence of previous signal information. However, the generation of speech signals invariably require preceding waveform samples in its reconstruction, as the lack of this can lead to artifacts in generated speech. To address this conflict, in this paper, we propose an improved model: a post auto-regressive (AR) GAN vocoder with a self-attention layer, which merging self-attention in an AR loop. It will not participate in inference, but can assist the generator to learn temporal dependencies within frames in training. Furthermore, an ablation study was done to confirm the contribution of each part. Systematic experiments show that our model leads to a consistent improvement on both objective and subjective evaluation performance.

Index Terms: speech synthesis, neural vocoder, generative adversarial networks, autoregressive model, self-attention

1. Introduction

With the development of artificial intelligence, text to speech (TTS) has made a remarkable progress. Conditional waveform generation has migrated from traditional digital signal processing (DSP) techniques, such as the Griffin-Lim [1] and the World [2], to neural networks. There are mainly two types of the state-of-the-art neural vocoders: AR and Non-AR vocoders. Since WaveNet [3], the AR vocoder has made a significant breakthrough, as the AR structure improves the continuity reconstruction in the generated waveform. On this account, the main weakness of AR model is the inference speed. WaveRNN [4] is similar to WaveNet, but a smaller model size and weighting sparsification method are applied to improve inference speed. LPCNet [5] realizes the efficient and fast neural speech synthesis by linear prediction method.

Non-AR models such as GAN have been demonstrated to be computationally efficient for conditional waveform generation. It could learn the probabilistic distribution in the parallel way, which means less training and inference time cost, such as MelGAN [6] and HiFi-GAN [7]. A well trained Non-AR vocoder outperforms the AR vocoder in terms of both speech quality and inference speed [8, 9]. DiffWave [10] is also a Non-AR model, which converts the noise signal into waveform through a Markov chain. It matches WaveRNN in terms of speech quality, but the inference speed of a diffusion model is still not fast enough for real-time synthesis tasks.

Despite advances made in neural vocoders, we find that there is a quality gap between the neural networks generated speech and the real human voice. In real TTS tasks, especially when applying GAN vocoders, we can hear some vocal tremors at specific places, as demonstrated in Fig. 1(b), we could observe a fracture in HiFi-GAN generated spectrogram, which results in the tremor of generated voice. It has been exhibited [11], that some artifacts of generated speech, such as pitch error effects and periodicity artifacts, are mainly due to the pitch and period mismatch caused by the mechanism of non-AR models.

In order to solve this problem, some hybrid models are brought to the forefront, which combine the advantages of AR and non-AR model. One productive model is WaveFlow [8], which uses an AR module to learn short range dependencies and a non-regressive 2-D convolutional architecture to capture long range dependencies. CARGAN [11] reduces the pitch and periodicity errors with an AR loop. However, it still takes 18 times longer on GPU and 3 times longer on CPU by inference compared with HiFi-GAN.

Inspired by prior works, in this paper, we aim to find a feasible solution on the lack of sequential modeling in GAN vocoders without any reduction of inference speed. We will systematically present a series of experiments, then discuss how GAN can be equipped with self-attention and AR to capture long-range decencies within frames. Finally, we verify that the proposed model leads to a better generation performance compared with the baseline and no extra time cost on inference.

We summarize our contributions as follows:

- We propose a self-attention and AR loop based post-net, which could capture long-term dependencies within waveform frames in training and will not be used in inference.
- We use a new objective loss function called Teager Energy Operator loss to enhance the interaction of frames.
- We indicate that our proposed post-net is robust and can
be integrated into other GAN vocoders for a performance gain.

2. Related Works

2.1. HiFi-GAN

In HiFi-GAN, several transposed convolutional layers with diverse upsampling rate, and the residual stack, which is made up of dilation convolutional layers and normal convolutional layers, are used to transform Mel-spectrogram into waveform. The multi-receptive field fusion in residual stacks could observe patterns of various length in parallel and improve the quality of speech. Besides, HiFi-GAN upgrades the discriminators from MelGAN to multi-period (MPD) and multi-scale (MSD) perspective, handling the portion of periodic signals and evaluating audio signal at different levels.

2.2. Chunked autoregressive GAN (CARGAN)

In CARGAN, an extra AR conditioning stack is proposed to constraint the generation of waveform. The previous samples and the generated speech are summarized into fixed-length, injected to an encoder and finally spliced with the raw Mel-spectrogram feature to generate a new chunk of speech.

2.3. Multi-resolution STFT Loss

The multi-resolution short-time Fourier transform (STFT) loss proposed in Parallel WaveGAN. It is the sum of Mel-spectrogram losses with various STFT analysis parameters. It consists of spectral convergence loss ($L_{SC}$) and magnitude loss ($L_{Mag}$):

\[
L_{SC}(x, \tilde{x}) = \frac{\|\text{STFT}(x) - \text{STFT}(\tilde{x})\|_F}{\|\text{STFT}(\tilde{x})\|_F}, \tag{1}
\]

\[
L_{Mag}(x, \tilde{x}) = \frac{1}{N} \log |\text{STFT}(x)| - \log |\text{STFT}(\tilde{x})|_1, \tag{2}
\]

where $x$ and $\tilde{x}$ mean target speech and generated speech, $\| \cdot \|_F$ and $\| \cdot \|_1$ mean Frobenius and L1 norm, respectively. $\text{STFT}(\cdot)$ and $N$ denote the STFT magnitudes and the number of elements in the magnitude, respectively. So the multi-resolution STFT loss can be converted into:

\[
L_{mr, stft}(G) = E_{x, \tilde{x}} \left[ \frac{1}{M} \sum_{m=1}^{M} \left( L_{sc}^m(x, \tilde{x}) + L_{mag}^m(x, \tilde{x}) \right) \right], \tag{3}
\]

where $M$ is the number of STFT parameter groups.

3. Our Model

3.1. GAN Architecture

Conforming to GAN’s principle, on the one hand, the generator is designed for learning the reverse mapping from acoustic features such as Mel-spectrogram to audio waveform. On the other hand, the discriminator plays the role of a binary classifier which distinguished the real audio samples from the dataset as true, and the fake samples produced by generator as false. Simultaneously, discriminator guides the parameters updating of generator.

3.2. Auto-regressive Loop

As mentioned in the introduction, most GAN vocoders possess the fracture spectrum problem due to the Non-AR mechanism. The continuity between speech signal frames is ignored, which leads to the phase and periodicity mismatch of the audio samples. Although there exist AR GAN vocoders such as CARGAN addressing this problem, the inference speed becomes their shortcoming. Therefore, we consider using a posterior AR loop to assist the training of generator, but it will not participate in inference.

The joint probability of a waveform $x = \{x_1, ..., x_T\}$, where $x_i$ is a single sample, $i$ is the time index and $T$ is the length of the waveform. $x$ could be factorized as a product of conditional distribution as follows:

\[
p(x) = \prod_{t=1}^{T} p(x_t | x_1, ..., x_{t-1}), \tag{4}
\]

we regard each audio sample as the conditioned distribution of all previous samples. Differing from CARGAN, we utilize the AR structure only in the time domain (as shown in Fig. 2). One frame of previous AR-loop’s output $\tilde{x}$, previous real speech $x$ and current generated speech $\tilde{x}$ are concatenated, then directly
fed into the post-net, to generate a new frame of waveform, the Eq. (4) could be reformed as:

\[
p(\tilde{x}) = \prod_{i=1}^{N} p(\tilde{x}_i; \tau \mid \tilde{x}_{i-1}; \tau, x_{i-1}; \tau, \tilde{x}_i; \tau),
\]

(5)

where \( N \) is the number of frames of the whole audio, \( i \) is the current waveform frame, and \( \tau \) is the length of one frame. Here we handle the waveform into frames, there are two reasons: firstly, we believe handling with every sample is inefficient. Secondly, the speech signal is stationary in a short time frame. The size of input frames is one of the hyper-parameters and we will discuss it in the ablation study shortly. This AR loop is used only in training, and the output will be sent to discriminator to be classified as real or fake, then to affect the iteration of generator parameters through back propagation.

3.3. Post Self-attention Augmented Network

Considering that the self-attention layer can better capture the context information in time sequence, we develop it according to the self-attention GAN [13] and the non-local net [15]. As shown in Fig. 3(b), given the feature map of \( F \in \mathbb{R}^{N \times C} \) as input of the self-attention layer, where \( L \) is the time dimension and \( C \) is the number of channels, the query matrix \( Q \), the key matrix \( K \), and the value matrix \( V \) are obtained via matrix transformation:

\[
Q = FW^Q, K = FW^K, V = FW^V,
\]

(6)

where \( W^Q, W^K, W^V \in \mathbb{R}^{C \times \frac{L}{C}} \) denote the learnable weight matrices of the \( 1 \times 1 \) convolutional layer. Therefore, the dimension of the metrics \( Q, K, V \) are \( \mathbb{R}^{L \times \frac{L}{C}} \) and the attention map \( A \) is then computed as:

\[
A = \text{softmax}(QK^T), A \in \mathbb{R}^{L \times L},
\]

(7)

\[
a_{j,i} = \frac{\exp(s_{ij})}{\sum_{i=1}^{L} \exp(s_{ij})}, \quad s_{ij} = Q(x_i)K(x_j)^T,
\]

(8)

\( a_{j,i} \) denotes the extent to which the model attends to the \( i \)-th location when synthesizing the \( j \)-th column \( v_j \) of \( V \). The output of the attention layer \( \mathcal{O} \) is computed as:

\[
\mathcal{O} = (AV)W^O, \quad W^O \in \mathbb{R}^{C \times \frac{L}{C}},
\]

(9)

with the weight matrix \( W^O \) realized by a \( 1 \times 1 \) convolution layer of \( C \) filters, the shape of \( O \) is restored to the origin shape \( L \times C \). Eventually, there is a learnable scalar weight \( \gamma \) in the output of the attention layer, so the final output is:

\[
F = \gamma \mathcal{O} + F,
\]

(10)

We integrate the self-attention layer into the autoencoder network [10], as illustrated in Fig. 3(a), we also tried to realize the regressive loop directly with a LSTM layer of 256 hidden units, but the performance was not satisfied. Here we adopt the traditional autoencoder with the shortcut connection. The encoder consists of 2 one-dimensional strided convolutional layers with the same kernel size of 31 and a stride of 2, and the increased filter number of 8, 16. Self-attention layer is applied in higher-dimensional latent space to enhance the continuity in adjacent frames. The decoder, on the other hand, reverses the encoding process by deconvolution and restores information into waveform.

3.4. Training Objectives

We replace the Mel-spectrogram loss from original HiFi-GAN to the multi-resolution STFT loss, the benefit of which is that the generator is able to learn the features of speech in the time-frequency domain [17], and could prevent over-fitting in a fixed STFT representation. Moreover, we propose a new time-domain loss to enhance the temporal dependencies within frames.

**Teager Energy Operator (TEO) Loss** The TEO was proposed by H. M. Teager [18] while working on non-linear audio signals, which is widely used to detect voice event:

\[
\Psi(x(t)) = \dot{x}(t)^2 - x(t) \ast \ddot{x}(t),
\]

(11)

discrete speech signal, it could be rewritten as:

\[
\Psi(x[n]) = x[n]^2 - x[n-1] \ast x[n+1],
\]

(12)

where \( x[n], x[n-1] \) and \( x[n+1] \) represent the current, past and next audio sample, \( n \) is the discrete time index. Normally, the audio signal can not change suddenly in a short time, the non-continuity could be captured by this difference \( \Psi \). Therefore, the TEO loss could constraint signal generation in the time domain. The TEO loss is defined as:

\[
L_{\text{TEO}}(\mathcal{G}) = \mathbb{E}_{x, \tilde{x}} \left[ \frac{1}{N} \sum_{i=1}^{N} \| \Psi(x_i) - \Psi(\tilde{x}_i) \|_2 \right],
\]

(13)

where \( N \) is the length of the original speech samples. Here, we calculate the TEO of original speech \( x \) and generated speech \( \tilde{x} \) respectively, then compute them in \( L1 \) norm.

**Final Loss** Combined with all objective loss functions, we could summarize a jointly loss function:

\[
\begin{align*}
\min_{\mathcal{G}} \mathbb{E}_{x, \tilde{x}} & \left[ \sum_{k=1}^{K} (D_k(\mathcal{G}) - 1)^2 \right] \\
& + \mathbb{E}_{x, \tilde{x}} \left[ \mathcal{L}_{\text{stft}}(\mathcal{G}) + \lambda L_{\text{TEO}}(\mathcal{G}) \right],
\end{align*}
\]

(14)

where \( D_k \) denotes the \( k \)-th sub-discriminator in MPD and MSD, and \( \mathcal{L}_{\text{stft}} \) stands for multi-resolution STFT loss.
Table 1: Comparison of HiFi-GAN V2 (base), MB MelGAN, CARGAN, Our model, MB MelGAN with post-net

| Model                        | Params(M) | MOS↑ | RTF↓ | BCR↓ | MOS−TTS↑ |
|------------------------------|-----------|------|------|------|----------|
| Ground Truth                 | —         | 4.43±0.03 | —    | —    | 4.48±0.03 |
| Our model                    | 0.92      | 4.17±0.02 | 0.385 | 0.13 | 3.87±0.03 |
| CARGAN                       | 25.5      | 4.20±0.03 | 1.035 | 0.03 | 3.90±0.03 |
| HiFi−GAN(v2)                 | 0.92      | 4.12±0.05 | 0.385 | 0.3  | 3.84±0.04 |
| MB MelGAN                    | 1.62      | 4.00±0.04 | 0.069 | 0.27 | 3.73±0.06 |
| MB MelGAN with post−net      | 1.62      | 4.07±0.05 | 0.069 | 0.37 | 3.73±0.03 |

4. Experiments

4.1. Dataset

In our experiments, we choose Chinese Mandarin Speech Corpus (CSMSC) dataset for training and testing, which consists of 10,000 audios of 12 hours’ recording, and all audios were downsampled by 16kHz with 16-bit PCM data format. We preprocess all raw audios into the 80-dimensional Mel-spectrogram with hop size as 256.

4.2. Experimental Setup

During training, the Adam optimizer was adopted with a learning rate varying with number of iterations for both generator and discriminator. For multi-resolution STFT loss, we applied three STFT groups \( (M = 3) \) with frame size as 512, 1,024, 2,048, the window size as 240, 600, and 1,200 and the frameshift as 50, 120, and 240. We set the \( \lambda \) of TEO loss as 50.

The synthesis quality was measured on the mean opinion score (MOS) which were obtained using the crowd sourcing methodology described in P.808 [19] with 95% confidence intervals. We chose 20 native Chinese speakers and randomly selected 200 sentences to score. Here, in order to clarify that the proposed model can have better performance on spectral fracture problem, we propose a new subjective evaluation named bad-case rate BCR, which stands for the rate of speech which has the spectral fracture problem. It could be computed as \( G_{audio}/Total_{audio} \), where \( G_{audio} \) represents the number of the generated audios in which the audio artifacts could be heard, and the \( Total_{audio} \) is the total number of original audios. In our experiment, we use 200 audio examples in total for the BCR calculation.

The synthesis speed is measured on GPU and CPU based on the research regarding efficiency of neural networks [6]. We choose 50 sentences to test RTF and averaged over three times. The devices are single NVIDIA TESLA (R) P40 GPU and an Intel Xeon (R) CPU E5-2630 v4 @ 2.20 GHz.

4.3. Experimental Results

We benchmark the HiFi-GAN V2, our model, CARGAN, Multi-band (MB) MelGAN, and MB MelGAN integrated with proposed post-net, in terms of MOS, number of parameters, RTF, and BCR. As shown in Tab.1, we find that our model gained an MOS improvement when compared to the baseline. Meanwhile, our model has a smaller model size when compared to CARGAN, but has the same RTF as baseline. By utilizing the post-net, the BCR dropped more than twice as baseline.

As for the TTS task, we also test vocoders with a acoustic model of Fastspeech2 [20]. FastSpeech2 predicts mel-spectrograms, which are fed into the vocoder to generate waveform. The results indicate that our model outperforms base models in TTS tasks.

4.4. Ablation Study

We design the a series of ablation studies to confirm the effect of each component and the corresponding results are showing in Tab.2, each model was trained for 600k steps in order to get stable results. Note that the absence of a regression loop means that we use a forward structure to replace AR loop but preserve the same post-net. As shown, every component has a positive contribution to the inference quality. When we remove the AR structure, the MOS and BCR fall noticeably. Simultaneously, the self-attention layer also benefits the connection detail within frames.

It is worth mentioning that the size of input for the AR post-net is a vital factor. To evaluate this, we conducted a series of tests, where the \( n \)-frame is the number of input frames of the post-net, here we choose 1, 2, 4, and as demonstrated in Tab.2. We find that the 2-frame input (our model) has the lowest BCR.

| Model                        | MOS    | BCR    |
|------------------------------|--------|--------|
| Our model                    | 4.17±0.02 | 0.13  |
| 1-frame                      | 4.17±0.02 | 0.16  |
| 4-frame                      | 4.12±0.02 | 0.15  |
| w/o AR loop                  | 4.10±0.02 | 0.25  |
| w/o self-attention layer     | 4.18±0.02 | 0.16  |
| w/o TEO loss                 | 4.16±0.02 | 0.15  |

5. Conclusions

In this paper, we designed a neural vocoder based on AR loop and self-attention. By using the proposed post-net integrated in the AR loop, the temporal dependency of generated audios is improved. Our experiment shows that the model outperforms base models in both subjective and objective evaluation. Furthermore, our model is generic and can easily be applied in existing non-AR vocoders to obtain potential improvements.
6. References

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