HIFI-WAVEGAN: GENERATIVE ADVERSARIAL NETWORK WITH AUXILIARY SPECTROGRAM-PHASE LOSS FOR HIGH-FIDELITY SINGING VOICE GENERATION

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ABSTRACT

Entertainment-oriented singing voice synthesis (SVS) requires a vocoder to generate high-fidelity (e.g., 48kHz) audio. However, most text-to-speech (TTS) vocoders cannot reconstruct the waveform well in this scenario. In this paper, we propose HiFi-WaveGAN to synthesize the 48kHz high-quality singing voices in real-time. Specifically, it consists of an Extended WaveNet served as a generator, a multi-period discriminator proposed in HiFiGAN, and a multi-resolution spectrogram discriminator borrowed from UnivNet. To better reconstruct the high-frequency part from the full-band mel-spectrogram, we incorporate a pulse extractor to generate the constraint for the synthesized waveform. Additionally, an auxiliary spectrogram-phase loss is utilized to approximate the real distribution further. The experimental results show that our proposed HiFi-WaveGAN obtains 4.23 in the mean opinion score (MOS) metric for the 48kHz SVS task, significantly outperforming other neural vocoders.

Index Terms— generative adversarial network, vocoder, high-fidelity, singing voice generation

1. INTRODUCTION

Speech synthesis has been a prominent area of research in the speech community for an extended period. With the advent of deep learning, neural networks have replaced various components in the speech synthesis pipeline, including front-end text analysis \([1,2]\), acoustic model \([3,4,5,6,7]\), and vocoder \([8,9,10]\). Singing voice synthesis (SVS), given its similarity to speech synthesis in workflow, can benefit significantly from the advancements in Text-to-Speech (TTS) \([11,12,13,14]\).

For instance, \([13]\) proposed an acoustic model for SVS based on Fastspeech \([4,15]\), originally designed for speech synthesis. However, when it comes to the vocoder, most studies \([13,16]\) have simply borrowed existing models such as WORLD \([17]\) and WaveRNN \([18]\) from the speech synthesis domain without customizing them to account for the unique characteristics of singing voices. Consequently, these vocoders struggle to accurately reconstruct the high-frequency components of the mel-spectrogram, particularly when dealing with entertainment-oriented scenarios that require generating high-fidelity (e.g., 48kHz) singing voices.

The SingGAN vocoder \([19]\) designed for SVS highlighted several reasons why vanilla TTS vocoders are not well-suited for generating natural singing voices, including:

- Long continuous pronunciation,
- Strong expressiveness,
- Higher sampling rate than speech.

SingGAN addressed these characteristics by designing a generative adversarial network capable of generating singing voices at a 24kHz sampling rate. However, this sampling rate limitation may impact the quality of the singing voices, particularly in the high-frequency parts, as it cannot fully capture information beyond 12kHz, in accordance with Nyquist’s sampling law. Therefore, there is room to enhance the quality further by generating singing voices at a higher sampling rate.

To address this, we propose a novel HiFi-WaveGAN in this paper, capable of generating high-fidelity singing voices at a human-level quality with a 48kHz sampling rate. Our approach consists of an Extended WaveNet \([20]\) (ExWaveNet) serving as the generator, a multi-period discriminator (MPD) proposed in HiFiGAN \([9]\), and a multi-resolution spectrogram discriminator (MRSD) borrowed from UnivNet \([21]\).

For the ExWaveNet generator, we expand the kernel size of the convolutional layers to accommodate a larger receptive field, enabling it to handle the long continuous pronunciation in SVS. Recognizing that pitch carries greater expressiveness in SVS compared to TTS, we concatenate it with the mel-spectrogram and input it into an upsample network.

To address the challenge of accurately reconstructing the high-frequency regions from the full-band mel-spectrogram, we introduce an additional Pulse Extractor (PE) to generate a pulse sequence, which is then incorporated as a conditional constraint input to the ExWaveNet. This operation plays a crucial role in rectifying unexpected distortions in the waveform. Furthermore, we leverage the auxiliary spectrogram-phase loss \([22]\), which is combined with the adversarial training loss and feature match loss, to supervise the training process of our HiFi-WaveGAN. The inclusion of the phase-related term in the auxiliary loss enhances our model’s ability to approximate the real distribution more effectively when compared to models that lack this component.

In the experiment, Xiaoicesing2 \([23]\) is combined with the proposed HiFi-WaveGAN and other neural vocoders, which are used as the baseline models. The experimental results show that the quality of the synthesized singing voice of our proposed HiFi-WaveGAN not only outperforms all baselines but also comes very close to the human level under the MOS metric.

The rest of this paper is organized as follows. HiFi-WaveGAN is illustrated in Section 2 in detail, including the ExWaveNet generator, discriminators, and training loss functions. The experimental settings and results are reported in Section 3. Finally, we conclude our paper in Section 4.

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\*Demo page: https://wavelandspeech.github.io/hifi-wavegan/
2. HIFI-WAVEGAN

Before introducing our proposed HiFi-WaveGAN, we conducted an analysis of the limitations of TTS neural vocoders when synthesizing 48kHz singing voices, using the PWG vocoder as an example. In Figure 1(a), we observed glitches in the low-frequency part that disrupt the continuity of the spectrogram. These glitches arise because the receptive field of PWG is insufficient to cover the long continuous pronunciation required for singing voices. Furthermore, the high-frequency harmonics in Figure 1(a) appear blurry, indicating that the PWG neural vocoder struggles to accurately reconstruct the high-frequency components necessary for SVS tasks. We further investigated the source of these problems in the PWG spectrogram, as well as in other neural TTS vocoders. Figure 1(b) reveals periodic distortions in the waveform generated by the PWG vocoder, leading to trembling and low-quality singing voices.

To address the aforementioned issues, we present a detailed illustration of our HiFi-WaveGAN in the subsequent part of this section. As depicted in Figure 2, our HiFi-WaveGAN consists of an ExWaveNet generator, responsible for generating high-quality singing voices. Additionally, we employ two independent discriminators: MPD (Multi-Period Discriminator) and MRSD (Multi-Resolution Spectrogram Discriminator). These discriminators are designed to distinguish real/fake waveforms from periodic patterns and consecutive long dependencies, respectively.

2.1. Extended WaveNet

Similar to the generator in PWG [8], we also adopt a WaveNet-based model as the generator. However, recognizing that singing voices exhibit longer continuous pronunciation compared to speech [19], we enhance the architecture of WaveNet by utilizing an 18-layer one-dimensional CNN with larger kernel sizes, resulting in an improved model called Extended WaveNet (ExWaveNet). Specifically, we evenly divide the 18 layers of the generator into three stacks, and the kernel sizes in each stack are set to {3, 3, 9, 9, 17, 17}, determined through neural architecture search [24]. This modification empowers the network to effectively capture longer continuous pronunciation in singing voices with high sampling rates, courtesy of the increased receptive field.

In addition to modeling long continuous pronunciation, restor- ing expressiveness in singing voices is also crucial. To achieve this, we concatenate the pitch with the mel-spectrogram as the input to the upsampling network, following the same approach as in PWG. The upsampled representation is then concatenated with a pulse sequence \( T \), which will be explained in detail in the next paragraph, serving as the conditional input for generating singing voices with strong expressiveness. Moreover, we observed that upsampling the random input noise using an identical network also improves the expressiveness of the synthesized audio.

As mentioned in the previous paragraph, there are some periodic distortions in the waveform generated by TTS neural vocoders, leading to low-quality synthesized singing voices. To address this, we propose an additional Pulse Extractor (PE) to generate a pulse sequence as a constraint condition during waveform synthesis. As shown in Figure 2, the extractor takes the mel-spectrogram and pitch as input. The pulse is extracted at each extreme point of the waveform envelope, determined by the V/UV decision and mel-spectrogram, and can be formulated as:

\[
T[i] = \begin{cases} 
||M[i]||_F, & UV = 1, i = \frac{s}{f_0} \\
0, & UV = 1, i \neq \frac{s}{f_0} \\
\text{noise}, & UV = 0 
\end{cases}
\]

where \( M \) represents the mel-spectrogram, \( i \) is the time index, \( || \cdot ||_F \) denotes the Frobenius norm, \( T[i] \) indicates the pulse value at index \( i \), and \( s \) and \( f_0 \) denote the sampling rate and pitch, respectively. The noise in the formula is generated from a Gaussian distribution.

2.2. Discriminators

Identifying both consecutive long-term dependencies and periodic patterns plays a crucial role in modeling realistic audio [9]. In the proposed HiFi-WaveGAN, we employ two independent discriminators to evaluate singing voices from these two aspects.

The first discriminator is MRSD, adapted from UnivNet [21], which identifies consecutive long-term dependencies in singing voices from the spectrogram. We transform both real and fake singing voices into spectrograms using different combinations of FFT size, window length, and shift size. Then, two-dimensional convolutional layers are applied to the spectrograms. As depicted in Figure 3, the model employs \( K \) sub-discriminators, each utilizing a specific combination of spectrogram inputs. In our implementation, \( K \) is set to four.

The second discriminator is MPD, identical to the one used in HiFiGAN [9]. It transforms the one-dimensional waveform with length \( T \) into 2-d data with height \( T/p \) and width \( p \) by setting the periods \( p \) to \( M \) different values, resulting in \( M \) independent sub-discriminators within MPD. In this paper, we set \( M \) to five and \( p \) to \( 2, 3, 5, 7, 11 \). As described in [9], this design allows the discriminator to capture distinct implicit structures by examining different parts of the input audio.

2.3. Loss function

Similar to other models [9][19], we adopt a weighted combination of multiple loss terms as the final loss function formulated by Eq. (2) and Eq. (3) to supervise the training process of our HiFi-WaveGAN.

\[
L_D = L_{adv}(D; G),
\]

\[
L_G = \lambda_1 * L_{adv}(G; D) + \lambda_2 * L_{aux} + \lambda_3 * L_{fm},
\]

where \( L_{adv}, L_{aux}, \) and \( L_{fm} \) denote adversarial loss, auxiliary spectrogram-phase loss, and feature match loss, respectively. In this paper, \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) are set to 1, 120, and 10, respectively.

2.3.1. Adversarial loss

For the adversarial loss, we adopt the format in LS-GAN [25] to avoid the gradient vanishing. The formula is shown as

\[
L_{adv}(G; D) = \mathbb{E}_{z \sim \mathcal{N}(0,1)}[1 - D(G(z))^2],
\]

\[
L_{adv}(D; G) = \mathbb{E}_{y \sim p_{data}}[1 - D(y)^2] + \mathbb{E}_{z \sim \mathcal{N}(0,1)}[D(G(z))^2],
\]
where $G$ and $D$ denote the generator and discriminators, respectively, $z$ is the random noise and $y$ represents the real singing voice.

2.3.2. Auxiliary spectrogram-phase loss

The auxiliary spectrogram-phase loss is utilized to constrain the behavior of the generator by measuring the metrics between real and fake features including STFT spectrogram, STFT phase, and mel-spectrogram. First, we define two functions for calculating the convergence loss term and magnitude loss term [26] as

$$L_{sp} = \frac{1}{H_1} \sum_{h=1}^{H_1} (L_{sp}^h(x, y) + L_{sp}^h(x, y)),$$

$$L_{mel} = \frac{1}{H_2} \sum_{h=1}^{H_2} (L_{mel}^h(x, y) + L_{mel}^h(x, y)),$$

where $H_1$ and $H_2$ are the numbers of different combinations of transformation parameters for STFT and mel-spectrogram, and they are set as 3 and 2 in this paper, respectively. Compared with the auxiliary spectrogram loss $L_{sp}$ described in SingGAN [19], we use an additional phase convergence term $L_{sp}$ for faster convergence. Finally, the auxiliary loss is defined as a summary of the mel-spectrogram term and STFT term as

$$L_{aux} = L_{sp} + L_{mel}.$$

2.3.3. Feature match loss

Feature match loss was proposed in MelGAN [10] to measure the $L_1$ norm between the feature maps of real and fake audios, which are extracted from the hidden layers of the discriminator. In HiFi-WaveGAN, we apply the constraint to both MRSD and MPD as Fig. 2 shows. Therefore, it can be defined as

$$L_{fm} = \mathbb{E}_{x, y} [\sum_{i=1}^{L_{MRSD}} ||D_i(y) - D_i(G(z))||_1 + \sum_{j=1}^{L_{MPD}} ||D_j(y) - D_j(G(z))||_1],$$

where $L_{MRSD}$ and $L_{MPD}$ are the number of layers of MRSD and MPD, respectively, $D_i(\cdot)$ and $N_i$ represent the feature map and the number of feature map of the $i$-th layer in MRSD, and $D_j(\cdot)$ and $N_j$ the feature map and the number of feature map of the $j$-th layer of MPD.

3. EXPERIMENT

3.1. Dataset

All experiments related to 48kHz SVS were conducted on our internal singing dataset, which comprises 6917 pieces sung by a female singer, with durations ranging from 4 seconds to 10 seconds. For the experiments, we randomly selected 300 pieces as validation data and another 300 pieces as testing data, while the remaining data were utilized for training. When preparing the acoustic features, we used a window length and shift length of 20ms and 5ms, respectively, for the Short-Time Fourier Transform (STFT). Furthermore, we applied 120 mel filters to transform the spectrogram into mel-scale and subsequently normalized it. Additionally, pitch and V/UV (voiced/unvoiced) decisions were also extracted from the data.

3.2. Experimental setup

To evaluate the performance of our proposed HiFi-WaveGAN and make a comparative analysis with other vocoders in the context of 48kHz SVS, we integrated them with an acoustic model named XiaoiceSing2 [23]. The acoustic model, based on Fastspeech, comprises an encoder, a duration predictor, and a decoder, collectively forming a comprehensive SVS system. The input to this SVS system consists of the musical score, encompassing lyrics, note pitch, and
To train the HiFi-WaveGAN, we randomly choose 4k iterations, employing a batch size of 32, and employing the Adam optimizer with hyperparameters $\beta_1 = 0.9$, $\beta_2 = 0.98$, and $\epsilon = 10^{-9}$. This configuration facilitates an effective and comprehensive evaluation and comparison of the performance of HiFi-WaveGAN and other vocoders within the 48kHz SVS task.

In our experiment, we selected three neural vocoders, namely Parallel WaveGAN [8], HiFiGAN [9], and RefineGAN [28], as the baseline models for high-fidelity singing voice generation. These vocoders were combined with the acoustic model to form complete SVS systems. During training, we utilized the ground truth mel-spectrogram, V/UV decision, and logF0 as inputs to train these vocoders. When synthesizing the high-fidelity waveform, the acoustic model generated the mel-spectrogram, V/UV decision, and logF0, which were then used as input features for the vocoders.

It is worth noting that PWG and HiFiGAN vocoders were originally designed for speech synthesis with a sampling rate of 16kHz or 22kHz. To enable a fair comparison, we also improve the architecture of the generator of them to generate singing voices at a higher sampling rate of 48kHz. As a result, we referred to these adapted versions as PWG-48kHz and HiFiGAN-48kHz in our experiments. This adaptation allows these vocoders to generate high-fidelity singing voices with the desired sampling rate for evaluation and comparison.

3.3. Training methodology

To train the HiFi-WaveGAN, we randomly choose 4s as a training sample and train the model for 200k iterations with 8 batch size by using an AdamW [29] optimizer with 0.0002 learning rate and 0.01 weight decay. Other hyper-parameters of AdamW are set as $\beta_1 = 0.8$ and $\beta_2 = 0.99$. An exponential learning rate scheduler with 0.999 learning rate decay is used to better optimize the model. The training process costs about 70 hours on 4 NVIDIA V100 GPUs.

3.4. Experimental result

As our focus is on 48kHz singing voice generation, the number of parameters for PWG and HiFiGAN in Table 1 appears slightly larger compared to the numbers reported in [8] and [9]. This is due to our adaptation of these models to handle the higher sampling rate. Specifically, our HiFi-WaveGAN has more parameters than PWG, as we utilize larger kernel sizes to model long continuous pronunciation. Despite this, the inference speed of HiFi-WaveGAN remains comparable to PWG, as demonstrated in the table. HiFiGAN, on the other hand, boasts the fastest inference speed in this comparison, but it comes with the highest number of parameters. Meanwhile, RefineGAN [28] has fewer parameters than our HiFi-WaveGAN but has the slowest inference speed among the models in the table.

For evaluating the quality of the synthesized audio, we conducted both subjective and objective assessments comparing our HiFi-WaveGAN with other vocoders, as well as the ground truth. The subjective evaluation involved preparing 20 segments of singing voices for each vocoder and ground truth, with durations ranging from 6s to 10s. Twenty listeners participated in our listening test, and the results in Table 1 reveal that our HiFi-WaveGAN obtained the highest scores among all vocoders. Notably, despite both PWG and HiFi-WaveGAN utilizing WaveNet as the generator, our HiFi-WaveGAN significantly outperformed PWG by 1.68 and PWG-48kHz by 1.45 in terms of MOS. This improvement can be attributed to the adoption of larger kernel sizes and the addition of the extra Pulse Extractor in our HiFi-WaveGAN.

Moreover, in comparison to HiFiGAN, HiFi-WaveGAN achieved a MOS score that was 0.46 higher, primarily due to better reconstruction of high-frequency parts. Although HiFiGAN-48kHz achieved a slightly higher MOS score than HiFiGAN, it still did not surpass the performance of HiFi-WaveGAN. Interestingly, the subjective result of our HiFi-WaveGAN even outperformed RefineGAN, which was specifically designed for generating high-quality singing voices (at 44.1kHz in [28]). It is worth noting that the MOS score of HiFi-WaveGAN was competitive with the ground truth, demonstrating its high quality close to the human level.

For objective evaluation, we calculated STOI and PESQ scores for all vocoders, and the results, shown in Table 1 indicate that our HiFi-WaveGAN achieved the best performance in these metrics as well. This further demonstrates the superior quality of HiFi-WaveGAN compared to the other vocoders in the context of 48kHz SVS.

3.5. Spectrogram analysis

In this section, we conducted a detailed comparison of the waveforms and spectrograms generated by our HiFi-WaveGAN and Parallel WaveGAN to gain deeper insights. Starting with the waveforms shown in Fig. 3(a) and Fig. 3(b), it is evident that the distortions present in the orange solid box of the waveform generated by Parallel WaveGAN have been effectively rectified in our HiFi-WaveGAN. This outcome confirms that the pulse sequence generated by the Pulse Extractor plays a crucial role in addressing the defects found.
in the waveform generated by PWG. Furthermore, upon observing the low-frequency part of the spectrogram in Fig. 1(a) and Fig. 3(a), it becomes apparent that the glitches, which correspond to the distortions in the waveform, have also been successfully eliminated from the spectrogram in HiFi-WaveGAN. This achievement is primarily attributed to the pulse sequence and the larger receptive field of our generator.

Moreover, a comparison of the high-frequency part of the spectrogram in Fig. 1(a) and Fig. 3(a) reveals that the harmonics in Fig. 3(a) are notably clearer than those in Fig. 1(a). This improvement indicates that our HiFi-WaveGAN excels at reconstructing the rich details of the high-frequency components. This success can be attributed to our approach of incorporating informative pitch information into the mel-spectrogram and combining it with the pulse sequence to serve as the conditional input to the generator.

Overall, this thorough analysis highlights the superior performance of our HiFi-WaveGAN, which effectively addresses waveform distortions and achieves high-quality reconstruction of both low and high-frequency components in the generated singing voices. The incorporation of the pulse sequence and the use of pitch information prove to be instrumental in enhancing the fidelity and expressiveness of the synthesized audio.

### 3.6. Ablation study

Since we proposed three key components to synthesize high-quality 48kHz singing voices, we conducted an ablation study to determine the individual contribution of each component, as shown in Table 2.

First, we compared the results of HiFi-WaveGAN with the third row, where ExWaveNet was replaced with the original WaveNet. In this configuration, both subjective and objective metrics experienced a degradation, showcasing that the original WaveNet was inadequate in modeling the long pronunciation present in singing voices at this sampling rate.

Next, we examined the fourth row, where we removed the Pulse Extractor from our HiFi-WaveGAN. The significant decrease in the MOS score compared to the HiFi-WaveGAN result demonstrates that the Pulse Extractor is a pivotal component for synthesizing high-quality singing voices in our model.

Finally, in the fifth row, we omitted the phase loss term. Although MOS and other objective metrics only exhibited a slight decline compared to the HiFi-WaveGAN result, it can prove that the phase loss term leads to our model generating singing voices that were even closer to the human level in terms of quality.

Overall, the ablation study confirms the importance of each proposed component in our HiFi-WaveGAN. The ExWaveNet’s ability to model long pronunciation, the Pulse Extractor’s role in correcting waveform distortions, and the impact of the phase loss term on achieving high-quality singing voices all contribute significantly to the success of our model.

### 4. CONCLUSION

In this paper, we present HiFi-WaveGAN, a novel approach designed to generate high-quality 48kHz singing voices. Our method involves customizing the architecture of WaveNet to enhance its ability to model long continuous pronunciation, a crucial aspect of singing. Additionally, we introduce a novel Pulse Extractor, which is integrated with the customized WaveNet to effectively address waveform distortions, reduce glitches, and improve the clarity of high-frequency harmonics.

Furthermore, we incorporate pitch information into the mel-spectrogram as a condition, coupled with the upsampled intermediate representation from random input noise. This integration enhances the expressiveness of high-frequency parts in the synthesized singing voices. The results of our MOS test demonstrate that the quality of singing voices generated by HiFi-WaveGAN is remarkably close to human-level perception.

In the future, our work will concentrate on enhancing the acoustic model for 48kHz SVS and combining it with HiFi-WaveGAN. This collaboration will further contribute to the advancement of high-fidelity singing voice synthesis and enable even more realistic and expressive singing voices to be created.

### 5. REFERENCES

[1] Chunhui Lu, Pengyuan Zhang, and Yonghong Yan, “Self-attention based prosodic boundary prediction for Chinese speech synthesis,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 7035–7039.

[2] Bing Yang, Jiaqi Zhong, and Shan Liu, “Pre-Trained Text Representations for Improving Front-End Text Processing in Mandarin Text-to-Speech Synthesis.” in INTERSPEECH, 2019, pp. 4480–4484.

[3] Jonathan Shen, Ruoming Pang, Ron J Weiss, Mike Schuster, Navdeep Jaitly, Zongheng Yang, Zhifeng Chen, Yu Zhang, Yuxuan Wang, Rj Skerrv-Ryan, et al., “Natural tts synthesis by conditioning wavenet on mel spectrogram predictions,” in 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2018, pp. 4779–4783.

[4] Yi Ren, Yangjun Ruan, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu, “Fastspeech: Fast, robust and controllable text to speech,” Advances in Neural Information Processing Systems, vol. 32, 2019.

[5] Takuhiro Kaneko, Hirokazu Kameoka, Nobukatsu Hojo, Yusuke Ijima, Kaoru Hiratsugu, and Kunio Kashino, “Generative adversarial network-based postfilter for statistical parametric speech synthesis,” in 2017 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2017, pp. 4910–4914.

[6] Yi Zhao, Shinji Takaki, Hieu-Thi Luong, Kunichi Yamagishi, Daisuke Saitoh, and Nobuaki Minematsu, “Wasserstein GAN and waveform loss-based acoustic model training for multi-speaker text-to-speech synthesis systems using a WaveNet vocoder,” IEEE access, vol. 6, pp. 60478–60488, 2018.
[7] Jonathan Shen, Ruoming Pang, Ron J Weiss, Mike Schuster, Navdeep Jaitly, Zongheng Yang, Zhifeng Chen, Yu Zhang, Yuxuan Wang, Rj Skerrv-Ryan, et al., “Natural tts synthesis by conditioning wavenet on mel spectrogram predictions,” in 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2018, pp. 4779–4783.

[8] Ryuichi Yamamoto, Eunwoo Song, and Jae-Min Kim, “Parallel WaveGAN: A fast waveform generation model based on generative adversarial networks with multi-resolution spectrogram,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 6199–6203.

[9] Jungil Kong, Jaehyeon Kim, and Jaekyoung Bae, “Hifi-gan: Generative adversarial networks for efficient and high fidelity speech synthesis,” Advances in Neural Information Processing Systems, vol. 33, pp. 17022–17033, 2020.

[10] Kundan Kumar, Rithesh Kumar, Thibault de Boissiere, Lucas Gestein, Wei Zhen Teoh, Jose Sotelo, Alexandre de Brébisson, Yoshua Bengio, and Aaron C Courville, “Melgan: Generative adversarial networks for conditional waveform synthesis,” Advances in neural information processing systems, vol. 32, 2019.

[11] Masanari Nishimura, Kei Hashimoto, Keiichiro Oura, Yoshikiko Nankaku, and Keiichi Tokuda, “Singing Voice Synthesis Based on Deep Neural Networks,” in Interspeech, 2016, pp. 2478–2482.

[12] Merlijn Blaauw and Jordi Bonada, “Sequence-to-sequence singing synthesis using the feed-forward transformer,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7229–7233.

[13] Peiling Lu, Jie Wu, Jian Luan, Xu Tan, and Li Zhou, “Xiaoic-eSing: A High-Quality and Integrated Singing Voice Synthesis System,” Proc. Interspeech 2020, pp. 1306–1310, 2020.

[14] British Chandra, Merlijn Blaauw, Jordi Bonada, and Emilia Gómez, “Wgansing: A multi-voice singing voice synthesizer based on the wasserstein-gan,” in 2019 27th European signal processing conference (EUSIPCO). IEEE, 2019, pp. 1–5.

[15] Yi Ren, Chengu Hu, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu, “FastSpeech 2: Fast and High-Quality End-to-End Text to Speech,” in 9th International Conference on Learning Representations, ICLR 2021, 2021.

[16] Yu Gu, Xiang Yin, Yonghui Rao, Yuan Wan, Benlai Tang, Yang Zhang, Jitong Chen, Yuxuan Wang, and Zejun Ma, “Bytessing: A chinese singing voice synthesis system using duration allocated encoder-decoder acoustic models and wavernn vocoders,” in 2021 12th International Symposium on Chinese Spoken Language Processing (ISCSLP). IEEE, 2021, pp. 1–5.

[17] Masanori Morise, Fumiya Yokomori, and Kenji Ozawa, “WORLD: a vocoder-based high-quality speech synthesis system for real-time applications,” IEICE TRANSACTIONS on Information and Systems, vol. 99, no. 7, pp. 1877–1884, 2016.

[18] Nal Kalchbrenner, Erich Elsen, Karen Simonyan, Seb Noury, Norman Casagrande, Edward Lockhart, Florian Stimberg, Aaron Oord, Sander Dieleman, and Koray Kavukcuoglu, “Efficient neural audio synthesis,” in International Conference on Machine Learning. PMLR, 2018, pp. 2410–2419.