WOLONet: Wave Outlooker for Efficient and High Fidelity Speech Synthesis

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Abstract

Recently, GAN-based neural vocoders such as Parallel WaveGAN[1], MelGAN[2], HiFiGAN[3], and UnivNet[4] have become popular due to their lightweight and parallel structure, resulting in a real-time synthesized waveform with high fidelity, even on a CPU. HiFiGAN[3] and UnivNet[4] are two SOTA vocoders. Despite their high quality, there is still room for improvement. In this paper, motivated by the structure of Vision Outlooker from computer vision, we adopt a similar idea and propose an effective and lightweight neural vocoder called WOLONet. In this network, we develop a novel lightweight block that uses a location-variable, channel-independent, and depthwise dynamic convolutional kernel with sinusoidally activated dynamic kernel weights. To demonstrate the effectiveness and generalizability of our method, we perform an ablation study to verify our novel design and make a subjective and objective comparison with typical GAN-based vocoders. The results show that our WOLONet achieves the best generation quality while requiring fewer parameters than the two neural SOTA vocoders, i.e., HiFiGAN and UnivNet.

Index Terms: generative adversarial networks, speech synthesis, neural vocoder, HiFiGAN, UnivNet, WOLONet

1. Introduction

In recent years, the development of vocoders based on deep neural networks has been rapid. Compared to conventional vocoders [5], [6], neural vocoders can significantly improve the speech synthesis quality of the current text-to-speech (TTS) system. Most early studies on neural vocoders are based on autoregressive (AR) models such as WaveNet[7], WaveRNN[8], SampleRNN[9], FeatherWave[10], etc. In these models, the samples are generated sequentially, while the RNNs are used to model the long-term relationship in the natural waveform. Although they generate very high-quality waves, the generation speed is unfavorable due to the sequential structure, which limits their practical use in real-time TTS systems.

To address the efficiency problem, many approaches have been proposed to accelerate the inference rate of AR models. Yu et al.[11] modify the original WaveRNN[8] and divide the full-band audio signal into four subbands and predict the four sub-band parameters simultaneously, resulting in reduced prediction time and model parameters. [12] proposes another lightweight vocoder based on the WaveRNN framework. It can synthesize high-quality waveforms using linear prediction coefficients (LPC).

Recently, non-AR models have attracted increasing attention from researchers. These models are capable of generating a waveform in a highly parallelizable manner to take full advantage of modern hardware with high inference speed. Among all these methods, the Knowledge Distill technique plays an important role [13], [14]. Specifically, the ‘knowledge’ of an AR teacher model is transferred to a small student model based on the inverse autoregressive fluxes combined with an additional perceptual loss. Although the resulting model can synthesize high-quality waveforms at a reasonable rate, it requires a well-trained teacher model as well as complex training strategies. The gigantic size of the model also limits its ability to compute in real-time. Another notable attempt in this area is flow-based models such as WaveFlow[15], FloWavenet[16], MelFlow[17], WaveFlow[18], and FBWAVE[19], etc. They use a single log-likelihood loss to train specially designed invertible models. The inference speed is faster than AR models and can even be used on mobile devices after additional development efforts on CPU [19]. However, the unstable training process and unsatisfactory synthesis quality prevent it from being used in industrial applications.

Instead of modeling the waveform directly, WaveGrad[20] uses the diffusion probability technique to model the multiscale distribution gradient field and uses Langevin dynamics to generate the waveform from random white Gaussian noise. Although the generated audio signals have high fidelity, the generation speed is greatly reduced by the multistage sampling processes.

Some recent work has used generative adversarial networks (GAN) to train the vocoders. The generator attempts to synthesize the waveform to fool the discriminator, while the discriminator figures out the difference between the synthesized wave and the ground truth wave. When the generator reaches a Nash equalization point, it is expected to synthesize a high-quality waveform. GAN-based methods [1], [2], [21], [22], [23], [24], [3], [4], [25], etc.) are promising, as some models are even capable of synthesizing waves in real-time on a single GPU or even CPU while achieving a comparable MOS that is very suitable for actual industrial use. Most of the above GAN-based vocoders differ in their network architecture and discriminator loss function. Specifically, MelGAN[2] first proposes the multiscale wave discriminator and feature matching loss, while ParallelWaveGAN[1] uses the WaveNet[7] generator structure and introduces the multi-resolution STFT loss function to accelerate the coverage, which became an important auxiliary loss in the later vocoders. MB-MelGAN[21] adopts the same idea as multi-band WaveRNN and synthesizes the sub-band signals to speed up the inference speed. Recently, HiFiGAN[3] proposed a novel multi-period discriminator and achieved the state of the art in wave quality and real-time speed at CPU. UnivNet[4] and Universal MelGAN[25] also propose multi-resolution spectrogram discriminators using a 2D convolution-based discriminator in the frequency domain to eliminate high-frequency artifacts, such as mental noise and reverberation in the auditory domain. StyleMelGAN[26] synthesizes high-quality waves by using the Adaptive Batch Normalization block conditioned by the Mel spectrogram.

Despite the aforementioned advances, there is still room for improvement in wave quality. We note that different wave segments may have different semantic content and phase. Using the same and fixed kernel weights for each wave segment is a suboptimal choice and the generalization ability may be lim-
Most Prior works use fixed convolution kernel weights across each time step, as shown in left. Whereas our work use various kernel weights for different time steps, i.e. location variant convolution kernel, as shown in right.

Our main idea is to develop a lightweight and location-aware generator that can improve the quality of synthesis with fewer parameters and FLOPs. The works that are most similar to ours are LVCNet[24] and UnivNet[4]. They both use a dynamic kernel prediction module that can generate different weights and biases for different wave segments. However, due to the limited computational budget, the hidden channel dimension is very small, i.e., 8 for LVCNet and 32 for UnivNet. The reason is due to their dynamic convolution structure, the kernel weight parameters and FLOPs are in proportion to $O(k \cdot C_{in} \cdot C_{out})$, which means the kernel size and channel dimension cannot be large with the same computational budget. The shrunken channel and kernel size severely limits their modeling power. To solve this problem, we propose a novel structure WOLONet that uses location-variable, channel-agnostic, and depthwise dynamic convolution kernels. To stabilize the training process, inspired by the Fourier activation function proposed in [27] and [28], we use a sine-activated dynamic kernel and have found its superior performance over other alternative activation functions such as Softmax[29] or Tanh in our ablation experiments. In our experiments, we have shown that our proposed WOLONet performs better than existing models on both subjective and objective scores with fewer parameters and FLOPs.

2. Proposed Method

2.1. HiFiGAN

HiFiGAN[3] can generate high-fidelity waveforms in real-time on a CPU that forms the basis for our WOLONet. As a GAN-based model, HiFiGAN consists of a generator (G), a discriminator (D), and Mel spectrogram auxiliary losses and feature matching losses for faster coverage. The generator is very similar to the original MelGAN, but with several stacks of residual dilated convolutional blocks with normalized acoustic features (e.g., Mel spectrogram) as input. In HiFiGAN, a least-squares method GAN is used to minimize loss. The multiscale waveform and the proposed multi-period discriminators are used for training. The final loss is as follows:

$$L_G = \sum_{k=1}^{n} [L_{adv}(G; D_k) + \lambda_{fm}L_{FM}(G; D_k)] + \lambda_{mel}L_{Mel}(G)$$

(1)

$$L_D = \sum_{k=1}^{n} L_{adv}(D_k; G)$$

(2)

where the adversarial loss $L_{adv}$ is the LSGAN framework:

$$L_{adv}(D_k; G) = \mathbb{E}_{(x,s)}[(D_k(x) - 1)^2 + (D_k(G(s)))^2]$$

(3)

$$L_{adv}(G; D_k) = \mathbb{E}_{s}[(1 - D_k(G(s)))^2]$$

(4)

the feature matching loss is used to match all the feature maps of each discriminator, formulated as:

$$L_{FM}(G, D_k) = \mathbb{E}_{(x,s)} \left[ \frac{1}{N} \sum_{i=1}^{N} \|D_k(x) - D_k(G(s))\|_1 \right]$$

(5)

the Mel loss is simply to match generated mel-spectrogram with the ground truth mel-spectrogram:

$$L_{Mel}(G) = \mathbb{E}_{(x,s)} \|\phi(x) - \phi(G(s))\|_1$$

(6)

2.2. Wave Outlooker Attention Block

Similar to [29], we also call our core block outlooker attention block, but this time we will use a 1D convolution due to our 1D wave signal input. The original vision outlooker attention [29] is used in the ImageNet classification task. As far as we know, this is the first time we use the local attention mechanism in the neural vocoder domain. In the following section, we will describe the Wave Outlooker Attention Block (WOLO block) in detail. The overall structure of the WOLO block is shown in figure 2.

The Wave-Outlooker-Attention block consists of a local dilated-attention layer as a locality-variant and depthwise dynamic convolution and a post-convolution layer for mixing the channel-wise information. Note that the local dilated-attention layer uses depthwise convolutions to maintain both the efficiency and complexity of the model. Given the input wave function $X \in \mathbb{R}^{G \times T}$, we can write our WOLO block as follows:

$$Z = X + \text{Conv}(\text{Act}(\text{WOLOAttn}(\text{Act}(X))))$$

(7)

Here $\text{Act}()$ is LeakyReLU used in HiFiGAN[3], $\text{Conv}$ is a normal 1D convolution.

WOLO Attention. The WOLO Attention is simple and efficient. The basic idea is that, first, the feature at each time step in the wave is highly representative and sufficient to generate the appropriate dynamic depth-wise weights and biases for local aggregation of neighboring wave features in the timeline, and second, local aggregation in the channel and time dimensions can efficiently encode very fine details and enlarge the resulting receptive field.

Figure 1: Most Prior works use fixed convolution kernel weights across each time step, as shown in left. Whereas our work use various kernel weights for different time steps, i.e. location variant convolution kernel, as shown in right.

Figure 2: Structure of the proposed WOLO Attention.
For each time step \( t \) with feature \( X_t \in \mathbb{R}^C \), the Wave Outlooker Attention computes its kernel weights and biases using pointwise convolution. After an activation function, the kernel weights and biases per time step are used to compute depth-wise convolution at each time step \( t \). and posterior pointwise convolution is used to mix the channel information similar to MobileNet ([30], [31]).

Mathematically, given the input \( X \in \mathbb{R}^{C \times T} \) and the current time step \( t \), we first calculate the kernel weight \( W_t \in \mathbb{R}^{K \times K} \) and the bias \( b_t \in \mathbb{R}^K \) for kernel size \( K \) using point-wise convolution. The kernel weights are processed by the periodic activation functions (the sinusoidal activation) as proposed by [27]:

\[
w_t, b_t = UX_t + V \tag{8}
\]

\[
W_t = \sin(w_t) \tag{9}
\]

\( U \) and \( V \) are pointwise convolution weight and bias, which are shared in all time steps. We then consider the \( K \) neighborhood of \( X_t \), denoted as \( Y_t \in \mathbb{R}^{K \times C} \) as:

\[
Y_t = \left\{ X_t + p - \left\lfloor \frac{K}{2} \right\rfloor \right\}_{0 \leq p < K} \tag{10}
\]

Note here the neighborhood definition will change according to the specified dilation factor, we ignore it in the equation for brevity.

Then we can compute the transformed convolution values \( \hat{Y}_t \in \mathbb{R}^{K \times C} \) using the matrix multiply:

\[
\hat{Y}_t = \text{MatMul}(W_t, Y_t) + b_t \tag{11}
\]

The dense aggregation operation is used to obtain the attention feature \( Y_t \in \mathbb{R}^C \):

\[
\hat{Y}_t = \sum_{0 \leq p < K} \hat{Y}_{t+p-\left\lfloor \frac{K}{2} \right\rfloor} \tag{12}
\]

Actually, the dense aggregation is implemented by the fold function in the PyTorch.

**Discussion.** From the block construction approach, we can calculate the multiplicity addicts (M-Adds) for the WOLO Attention Block, approximately \( 2(K^2 + K)C + C^2 + C \), for a typical structure such as the residual block in HiFiGAN, M-Adds is approximately \( KC^2 + C \). Thus, when \( C = 512, K = 5 \), the M-Adds reduction ratio is about \( \frac{510720}{202576} = 4.468 \), i.e., about a fourfold reduction, which theoretically shows that our proposed WOLO block is lightweight and efficient. Another advantage of the WOLO block over alternative structures such as LVCNet [24] or UnivNet [2] is that the dimensions of the location variant weights and biases are channel-independent, so we can easily maintain the channel size with a large number and preserve model complexity.

### 2.3. Wave Outlooker Network

Based on the Wave Outlooker Attention Block described in the previous section, we now describe our proposed WOLONet. As shown in Figure 3, our WOLONet is similar to the HiFiGAN structure, except that the remaining dilated convolutional blocks are replaced by our WOLO block. The discriminator structure and training loss are the same as HiFiGAN. We have found that this is sufficient for the high quality of WOLONet.

![Figure 3: Structure of the proposed WOLONet.](image)

### 3. Experiments

#### 3.1. Experiments Setup

For experiments, we use an open-source studio-quality LJSpeech dataset [1] which contains 13100 audio samples from an English female speaker. The total length of the audio samples are 24 hours. All the recordings have been resampled to 22050 Hz sampling rate with the PCM-16-bit format. Follow the recipe of Parallel WaveGAN [2] We randomly selected 250 utterances from the corpus as a validation set and another 250 utterances as our test set. All remaining samples are used for training. We extracted 80 dim log-Mel-spectrograms by 1024-point Fourier transform with 256 hop lengths. With the minimum and maximum frequency as 80 and 7600. We conducted our experiment on a server with a single NVIDIA Tesla V100 GPU for training and evaluation.

#### 3.2. Implementation details

For the HiFiGAN structure, we strictly follow the original implementation, and use HiFiGAN v1 as our baseline structure. Concretely, The generator consists of four transposed convolutional blocks where each block has stride 8, 8, 2, 2 respectively. Each transposed block contains 3 residual blocks with dilated convolutions, and their dilation factors are 1, 3, 5. For the discriminator, we use the exact implementation from Parallel WaveGAN Code [3].

Adam [22] is chosen as the optimizer for HiFiGAN. As for [1] available at https://github.com/kan-bayashi/ParallelWaveGAN

[2] https://github.com/kan-bayashi/ParallelWaveGAN

[3] available at http://data.keithito.com/data/speech/LJSpeech-1.1.tar.bz2
Comparison Against Alternative Methods. We conducted experiments to evaluate the effect of our proposed methods on the LJSpeech dataset. Our experiment is called Mel2Wav, i.e., synthesizing the wave using the ground truth Mel-spectrogram. For this experiment, we use the 250 test utterances as the input to the alternative vocoders as well as our model and measure the average MCD, PESQ, and the MOS score for each method and the recording audios. Table 2 demonstrates the results. As proved in [4], UnivNet-32 achieves a better score than HiFiGAN vocoders, but the improvement is small in our limited bandwidth dataset (80HZ-7600HZ). However, the WOLONet achieves the optimal PESQ score in both narrow and wide bands with a margin of 0.09 over the current UnivNet-32, and the parameter number is still less than HiFiGAN and UnivNet-32, which demonstrates that WOLONet is a lightweight, efficient, and high fidelity neural vocoder. Other vocoders such as MelGAN and Parallel WaveGAN, despite their low computational demand and fewer parameters, have inferior wave quality compared with HiFiGAN, UnivNet, and our WOLONet. Note that the RTF (realtime factor) value for the WOLONet is larger than UnivNet and HiFiGAN, the main reason lies in the slow implementation of fold operation in PyTorch. However, when written in an optimized CUDA kernel, the inference speed will be faster than HiFiGAN and UnivNet, since we have theoretically analyzed the computational complexity of WOLONet and HiFiGAN in the previous section. Above all, when compared with alternative GAN-based vocoders, WOLONet can generate higher quality waves while keeping the parameter number small for the actual deployment.

### 3.3. Evaluation

**Ablation Study.** To validate our choice of periodic activation function, we compared the performance of three alternative activation functions, `softmax`, `Tanh`, and the sinusoidal function used in WOLONet. The results from the table clearly show the superior performance of the sinusoidal function. It is known that the softmax activation function is commonly used for the self-attention mechanism, while in speech synthesis, the wave signals seem to prefer the periodic activation function, which matches the periodic property of the signal itself. Softmax activation largely limits the expressive power of WOLONet and Tanh is a sub-optimal choice for our WOLONet. Therefore, we propose that the periodic activation function could be very useful in other speech synthesis tasks, such as text-to-speech, which is our future work.

| Table 1: Ablation study on the choice of activation function in WOLO block. |
| Activation | MCD(\(\downarrow\)) | PESQ(wb) | PESQ(nb) | MOS |
|------------|-----------------|---------|---------|-----|
| Softmax    | 2.45            | 3.34    | 3.67    | 3.78±0.17 |
| Tanh       | 2.35            | 3.55    | 3.82    | 3.96±0.12 |
| Sine       | **2.32**        | **3.62**| **3.87**| **4.02±0.11** |

The learning rate configuration, the learning rate of a generator was initialized to 2e-4, reducing by half every 200K iterations. The discriminator was also set to 2e-4 and halved at every 200K iterations. The total training iteration is set to 800K, and batch size is set to 16. For MelGAN and ParallelWaveGAN, we use the exactly same recipe from [1]. For UnivNet [4], we strictly follow the training recipe in [7] i.e., AdamW as the optimizer and the upsampling factor is 8, 4, 4. Other training configurations are the same as HiFiGAN for a fair comparison.

We have used two objective metrics and one subjective metric to evaluate our methods. To measure the accuracy of the synthesized waveform, we measured the Mel Cepstral Distortion (MCD) proposed in [33]. For the evaluation of synthesized waveform quality, we measured narrow and wide band PESQ [29] scores (Note the audios are downsampled to 16kHz before evaluating PESQ score), and use 5-point (1 point is the worst and 5 point is the best) Mean Opinion Score (MOS) to evaluate subjective synthesis quality. To obtain the subjective MOS, we ask 20 subjects to evaluate the synthesized and recording audio samples, the assessed scores were collected to compute the mean and 95% confidence intervals for each assessment.

| Table 2: Comparison against alternative methods. The results of subjective and objective scores are listed. |
| Method          | MCD(db) | PESQ(wb) | PESQ(nb) | Param(M) | RTF  | MOS         |
|-----------------|---------|----------|---------|----------|------|-------------|
| HiFiGAN V1 [1]  | 2.286   | 3.46     | 3.74    | 13.29    | 0.014| 3.87±0.15  |
| FB-MelGAN [21]  | 2.522   | 3.03     | 3.47    | 4.07     | 0.009| 3.51±0.16  |
| Parallel-WaveGAN [11] | 2.94 | 2.97     | 3.39    | 1.28     | 0.048| 3.41±0.15  |
| UnivNet32c [4]  | 2.55    | 3.47     | 3.78    | 14.16    | 0.024| 3.91±0.12  |
| WOLONet         | 2.32    | **3.62** | **3.87**| 9.09     | 0.027| **4.02±0.11** |
| Recordings      | 0.0     | 4.5      | 4.5     | N/A      | N/A  | 4.22±0.07  |

4. Conclusions

In this work, we proposed WOLONet, a lightweight and efficient neural vocoder whose core is a location-variant, channel-independent, and depthwise dynamic convolutional kernel with a sinusoidally activated dynamic kernel weight. Our experimental results have shown that WOLONet can achieve higher subjective and objective scores when compared against alternative baseline methods with fewer parameters and FLOPs. In the future, we will train our WOLONet with more different training configurations.
datasets and develop a universal neural vocoder that can be used for various speakers and heterogeneous environments.

5. References

[1] R. Yamamoto, E. Song, and J.-M. Kim, “Parallel wavenet: 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.

[2] K. Kumar, R. Kumar, T. de Boissiere, L. Gestin, W. Z. Teoh, J. Sotelo, A. de Brébisson, Y. Bengio, and A. C. Courville, “Melgan: Generative adversarial networks for conditional waveform synthesis,” in Advances in Neural Information Processing Systems, 2019, pp. 14910–14921.

[3] J. Kong, J. Kim, and J. 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.

[4] W. Jang, D. Lim, J. Yoon, B. Kim, and J. Kim, “Univnet: A neural vocoder with multi-resolution spectrogram discriminators for high-fidelity waveform generation,” arXiv preprint arXiv:2101.07789, 2021.

[5] M. Morise, F. Yokomori, and K. 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.

[6] H. Kawahara, “Straight, exploitation of the other aspect of vocoder: Perceptually isomorphic decomposition of speech sounds,” Acoustical science and technology, vol. 27, no. 6, pp. 349–353, 2006.

[7] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, “Wavenet: A generative model for raw audio,” arXiv preprint arXiv:1609.03499, 2016.

[8] N. Kalchbrenner, E. Elsen, K. Simonyan, S. Noury, N. Casagrande, E. Lockhart, F. Stimberg, A. v. d. Oord, S. Dieleman, and K. Kavukcuoglu, “Efficient neural audio synthesis,” arXiv preprint arXiv:1802.08435, 2018.

[9] S. Mehr, K. Kumar, I. Gulrajani, R. Kumar, S. Jain, J. Sotelo, A. Courville, and Y. Bengio, “Samplernn: An unconditional end-to-end neural audio generation model,” 2017.

[10] Q. Tian, Z. Zhang, H. Lu, L.-H. Chen, and S. Liu, “Featherwave: An efficient high-fidelity neural vocoder with multi-band linear prediction,” arXiv preprint arXiv:2005.05551, 2020.

[11] C. Yu, H. Lu, N. Hu, M. Yu, C. Weng, K. Xu, P. Liu, D. Tuo, S. Kang, G. Lei et al., “Durian: Duration informed attention network for multimodal speech,” arXiv preprint arXiv:1909.01700, 2019.

[12] J.-M. Valin and J. Skoglund, “Lpcnet: Improving neural speech synthesis through linear prediction,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 5891–5895.

[13] A. Oord, Y. Li, I. Babuschkin, K. Simonyan, O. Vinyals, K. Kavukcuoglu, G. Dieessche, E. Lockhart, L. Cobo, F. Stimberg et al., “Parallel wavenet: Fast high-fidelity speech synthesis,” in International conference on machine learning. PMLR, 2018, pp. 3918–3926.

[14] W. Ping, K. Peng, and J. Chen, “Clarinet: Parallel wave generation in end-to-end text-to-speech,” arXiv preprint arXiv:1807.07281, 2018.

[15] R. Prenger, R. Valle, and B. Catanzaro, “Waveglow: A flow-based generative network for speech synthesis,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 3617–3621.

[16] S. Kim, S. gil Lee, J. Song, J. Kim, and S. Yoon, “Flowwavelet: A generative flow for raw audio,” 2019.

[17] Z. Zeng, J. Wang, N. Cheng, and J. Xiao, “Melonglow: Efficient waveform generative network based on location-variable convolution,” arXiv preprint arXiv:2012.01684, 2020.

[18] W. Ping, K. Peng, K. Zhao, and Z. Song, “Waveflow: A compact flow-based model for raw audio,” in International Conference on Machine Learning. PMLR, 2020, pp. 7706–7716.

[19] B. Wu, Q. He, P. Zhang, T. Koehler, K. Keutzer, and P. Vajda, “Fb-wave: Efficient and scalable neural vocoders for streaming text-to-speech on the edge;’” arXiv preprint arXiv:2011.12985, 2020.

[20] N. Chen, Y. Zhang, H. Ren, R. J. Weiss, M. Norouzi, and W. Chan, “Wavegrad: Estimating gradients for waveform generation,” arXiv preprint arXiv:2009.00713, 2020.

[21] G. Yang, S. Yang, K. Liu, P. Fang, W. Chen, and L. Xie, “Multiband melgan: Faster waveform generation for high-quality text-to-speech,” arXiv preprint arXiv:2005.01016, 2020.

[22] J. Yang, J. Lee, Y. Kim, H. Cho, and I. Kim, “Vocean: A high-fidelity real-time vocoder with a hierarchically-nested adversarial network,” arXiv preprint arXiv:2007.15256, 2020.

[23] R. Yamamoto, E. Song, M.-J. Hwang, and J.-M. Kim, “Parallel waveform synthesis based on generative adversarial networks with voicing-aware conditional discriminators,” arXiv e-prints, pp. arXiv–2105, 2019.

[24] Z. Zeng, J. Wang, N. Cheng, and J. Xiao, “Lvcnet: Efficient condition-dependent modeling network for waveform generation,” arXiv preprint arXiv:2102.10815, 2021.

[25] A. Mustafa, N. Pia, and G. Fuchs, “Stylemelgan: An efficient high-fidelity adversarial vocoder with temporal adaptive normalization,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 6034–6038.

[26] W. Jang, D. Lim, and J. Yoon, “Universal melgan: A robust neural vocoder for high-fidelity waveform generation in multiple domains,” arXiv preprint arXiv:2011.09631, 2020.

[27] V. Sitzmann, J. Martel, A. Bergman, D. Lindell, and G. Wetzstein, “Implicit neural representations with periodic activation functions,” Advances in Neural Information Processing Systems, vol. 33, pp. 7462–7473, 2020.

[28] N. Benbarka, T. Höfer, A. Zell et al., “Seeing implicit neural representations as fourier series,” in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2022, pp. 2041–2050.

[29] L. Yuan, Q. Hou, Z. Jiang, J. Feng, and S. Yan, “Volo: Vision outlier-search for visual recognition,” arXiv preprint arXiv:2106.13112, 2021.

[30] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, “Mobilenets: Efficient convolutional neural networks for mobile vision applications,” arXiv preprint arXiv:1704.04861, 2017.

[31] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, “Mobilenetv2: Inverted residuals and linear bottlenecks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 4510–4520.

[32] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[33] R. Skerry-Ryan, E. Battenberg, Y. Xiao, Y. Wang, D. Stanton, J. Shor, R. Weiss, R. Clark, and R. A. Saurous, “Towards end-to-end prosody transfer for expressive speech synthesis with tacotron,” in international conference on machine learning. PMLR, 2018, pp. 4693–4702.

[34] A. W. Rix, J. G. Bearends, M. P. Hollier, and A. P. Hekstra, “Perceptual evaluation of speech quality (pesq)–a new method for speech quality assessment of telephone networks and codecs,” in 2001 IEEE International Conference on Acoustics, Speech, and Signal Processing-Proceedings (Cat. No. 01CH37221), vol. 2. IEEE, 2001, pp. 749–752.