PERIODNET: A NON-AUTOREGRESSIVE WAVEFORM GENERATION MODEL WITH A STRUCTURE SEPARATING PERIODIC AND APERIODIC COMPONENTS

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1. INTRODUCTION

In recent years, speech synthesis technology has rapidly improved with the introduction of deep neural networks. In particular, WaveNet [1], which has an autoregressive (AR) structure, directly models the distributions of waveform samples and has demonstrated remarkable performance. WaveNet can be used as a speech vocoder by conditioning auxiliary features such as Mel-spectrogram and acoustic features extracted by conventional signal processing-based vocoder [2]. This is also used in state-of-the-art speech synthesis systems, which greatly contributes to improving the quality of synthesized speech [3,4]. However, WaveNet suffers from slow inference speed because of the AR mechanism and huge network architectures. Although compact AR models [5,6] have been proposed to accelerate inference speed, it is limited because audio samples must be generated sequentially. Thus, such models are not suited for real-time TTS applications.

Recently, significant efforts have been devoted to building non-AR models to resolve this problem. Parallel WaveNet [7] and ClariNet [8] introduce the teacher-student knowledge distillation. This framework transfers the knowledge from an AR teacher WaveNet to an inverse autoregressive flow (IAF)-based non-AR student model [9]. The IAF student model is highly parallelizable and can synthesize high-quality waveforms. However, the training procedure is complicated because it requires a well-trained teacher model as well as a mix of distilling and other perceptual training criteria. WaveGlow [10] and FloWaveNet [11] with flow-based generative models have been proposed as well. Although these models can be directly learned by minimizing the negative log-likelihood of the training data, they need a huge number of parameters and require many GPU resources to obtain optimal results for a single speaker model.

Another approach for parallel waveform generation is to use generative adversarial networks (GANs) [12]. A GAN is a powerful generative model that has been successfully used in various research fields such as image generation [13], speech synthesis [14], and singing voice synthesis [15]. GAN-based models have also been proposed for waveform generation [16,17]. Since these training frameworks enable models to effectively capture the time-frequency distribution of the speech waveform and improve training stability, these GAN-based models are much easier to train than the conventional non-AR methods described above.

A neural vocoder can generate high-fidelity waveforms since it can restore missing information from the acoustic feature in a data-driven fashion and is less limited by the knowledge and assumptions of the conventional vocoder [15,19]. However, this also results in a lack of acoustic controllability and robustness. In fact, it is difficult for a neural vocoder to generate a speech waveform with accurate pitches outside the range of the training data. Some methods with explicit periodic signals [20,21] and methods with a pitch-dependent convolution mechanism [22] address this problem.

It is known that both periodic and aperiodic components are mixed in speech waveforms. Although neural vocoders often model speech waveforms as single signals without considering these mixed components, it is important to take them into account to model speech waveforms more effectively. In particular, when the neural vocoder is used in a singing voice synthesis system [23,24], the accuracy of pitch and breath sound reproduction has a significant effect on quality and naturalness. Several methods for decomposing the periodic and aperiodic components contained in the speech waveform have been proposed [25,26]. However, it is still difficult to decompose them, and it is not optimal to use decomposed waveforms, including decomposition errors, as the training data for the neural vocoders.

In this paper, we consider speech waveform modeling in terms of the model structures and propose PeriodNet, a non-autoregressive neural vocoder for better speech waveform modeling. We introduce two versions with different model structures, a parallel model and a series model, assuming that the periodic and aperiodic waveforms can be generated from the explicit periodic and aperiodic signals, such as a sine wave and a noise sequence, respectively. Our proposed methods also can generate a waveform that includes a pitch outside the range of the training data. Moreover, our models have the robustness of the input pitch since these generate the periodic and aperiodic waveforms with two separate neural networks.
2. WAVEFORM MODELING

2.1. Autoregressive neural vocoder

In neural vocoders with an AR structure [1][5][6], a speech waveform at each timestep is modeled as a probability distribution conditioned on past speech samples and auxiliary features such as Mel-spectrograms and acoustic features. An overview of the AR neural vocoder is shown in Fig. 1(a). In this paper, we use WaveNet [1] as a neural network to generate waveforms (referred to as a generator in this paper). WaveNet has a stack of dilated causal convolution with a gated activation function, and it is capable of modeling speech waveforms with complex periodicity. However, there is a problem that it cannot make a parallel inference and takes time to generate waveform because of the AR structure.

2.2. Non-autoregressive neural vocoder

In non-AR neural vocoders [7][8][10][11][16][17], the neural network represents the mapping function from a pre-generated input signal, such as Gaussian noise, to the speech waveform. Hence, all waveform samples can be generated in parallel without incurring the expense of having to make predictions autoregressively. However, it is difficult to predict a speech waveform with autocorrelation from a noise sequence without autocorrelation properly. Prior studies [20][21] have proposed methods that use explicit periodic signals such as sine waves. These methods provide high pitch accuracy and can synthesize waveforms with a pitch not included in the training data. In this paper, following these attempts, we use the sine wave, noise, and voiced/unvoiced (V/UV) sequence as input signals, as shown in Fig. 1(b). Note that this V/UV sequence is smoothed in advance. Various architectures can be used for the generator in Fig. 1(b); we use a Parallel WaveGAN [16]-based architecture. Details of model architectures will be described in Sec. 3.2.

3. PROPOSED MODEL STRUCTURES SEPARATING PERIODIC AND APERIODIC COMPONENTS

3.1. Model structures

A speech waveform contains periodic and aperiodic waveforms. In the structure shown in Fig. 1(b), the generation process of the periodic and aperiodic waveforms is represented by a single model. However, this structure is not always optimal for waveform modeling, especially when the accuracy of pitch and breath sound reproduction has a significantly affects quality and naturalness, such as in singing voice synthesis. We assume that the speech waveform is the sum of periodic and aperiodic components. The periodic and aperiodic components are expected to be easily created from the periodic and aperiodic signal (such as the sine waves and noise sequences), respectively. Thus, in this paper, we propose a parallel mode structure and a series model structure based on these assumptions.

The parallel model structure is shown in Fig. 1(c). This structure assumes that the periodic and aperiodic waveforms are independent of each other. An explicit periodic signal consisting of a sine wave and V/UV sequence is used to predict the periodic waveform, and an explicit aperiodic signal consisting of noise and V/UV sequence is used to predict the aperiodic waveform.

The series model structure is shown in Fig. 1(d). In this structure, we assume that the aperiodic waveform depends on the periodic waveform, considering the possibility that there is an aperiodic waveform corresponding to the phase of the periodic waveform. Specifically, we introduce a residual connection between two generators so that the latter generator can predict the aperiodic component taking into account the dependence of the periodic component.

In the parallel model and the series model, different acoustic features can be selected for the auxiliary features of the periodic and aperiodic generators, making it possible to obtain more robust neural vocoders with proper conditioning.

3.2. Model details

In this paper, we incorporate Parallel WaveGAN [16]-based framework into our non-AR baseline and proposed models, as shown in Fig. 1(b). Each generator has the same architecture as the generator of [16], which is a modified WaveNet-based model with non-causal convolution. On the other hand, for the discriminators, we utilize a multi-scale architecture with three discriminators that have identical network structures but operate on different audio scales, following [17]. Each discriminator has the same architecture as the discriminator of [16]. These models are trained by optimizing the combination of multi-resolution short-time Fourier transform loss and adversarial loss in the same fashion as [16].

In the training vocoder with the parallel and series model structures, the final output sequence, which is the sum of two generators' output sequence, is only evaluated. This is the same as the baseline model with the single model structure. From the assumptions presented in Sec. 3.1 by inputting the sine wave and noise sequence separately, each generator should be trained to predict periodic and aperiodic waveforms, respectively.

4. EXPERIMENTS

4.1. Experimental conditions

Seventy Japanese children’s songs (total: 70 min) performed by one female singer were used for the experiments. Sixty songs were used for training, and the rest were used for testing. Singing voice signals were sampled at 48 kHz, and each sample was quantized by 16 bits. The auxiliary features consisted of 50-dimensional WORLD mel-cepstral coefficients [19], 25-dimensional mel-cepstral analysis aperiodicity measures, one-dimensional continuous log fundamental frequency ($F_0$) value, and one-dimensional voiced/unvoiced binary code. Feature vectors were extracted with a 5-ms shift, and the features were normalized to have zero mean and unit variance before training.

In the training stage, the sine waves for the input of the non-AR neural vocoder were generated based on the glottal closure point extracted from a natural speech using REAPER [27]. The purpose of
this is to input a sine wave that is close in phase to the target’s natural speech during training. Meanwhile, the sine waves were generated based on the $F_0$ values in the synthesis stage.

The following seven systems were compared.

- **WN**: The AR WaveNet [1].
- **BM1**: The non-AR baseline model, as shown in Fig. 1(b), that used noise and a V/UV signal as the generator input and is conditioned on all auxiliary features.
- **BM2**: The non-AR baseline model, as shown in Fig. 1(b), that used a sine wave and a V/UV signal as the generator input and is conditioned on all auxiliary features.
- **BM3**: The non-AR baseline model, as shown in Fig. 1(b), that used noise, a sine wave, and a V/UV signal as the generator input and is conditioned on all auxiliary features.
- **PM1**: The non-AR parallel model, as shown in Fig. 1(c). The periodic generator takes a sine wave and a V/UV signal as input, and the aperiodic generator takes noise and a V/UV signal as input. Both generators are conditioned on all auxiliary features.
- **PM2**: The non-AR parallel model, as shown in Fig. 1(c). Unlike PM1, the aperiodic generator is conditioned by auxiliary features other than $F_0$.
- **SM**: The non-AR series model, as shown in Fig. 1(d). The periodic generator takes a sine wave and a V/UV signal as input, and the aperiodic generator takes noise, a V/UV signal, and the output signal of the periodic generator as input. Both generators are conditioned on all auxiliary features.

WN consisted of 30 layers of dilated residual convolution blocks with causal convolution. The dilations of WN were set to 1, 2, 4, ..., 512, and the 10 dilation layers were stacked three times. The channel size for dilation, residual block, and skip-connection in WN was set to 256, and the filter size in WN was set to two. The singing voice waveforms to train WN were quantized from 16 bits to 8 bits by using the $\mu$-law algorithm [28].

The generators of BM1, BM2, and BM3, and periodic generators of PM1, PM2, and SM consisted of 30 layers of dilated residual convolution blocks with three dilation cycles, the same as WN. The aperiodic generators of PM1, PM2, and SM consisted of 10 layers of dilated residual convolution blocks without dilation cycles. The channel size for dilation, residual block, and skip-connection was set to 64, and the filter size was set to three. The discriminators of BM1, BM2, BM3, PM1, PM2, and SM had the multi-scale architecture with three discriminators. The discriminators took 48 kHz full-resolution waveforms, and 24 kHz and 16 kHz downsampled waveforms. The downsampling was performed using average pooling. Each discriminator consisted of 10 non-causal dilated convolutions with leaky ReLU activation function. We applied weight normalization [29] to all convolutional layers.

All models were trained using the RAdam optimizer [30] with 100K iterations. Specifically, in BM1, BM2, BM3, PM1, PM2, and SM, the discriminators were fixed for the first 100K iterations, and then both the generator and discriminator were jointly trained afterward.

### 4.2. Comparison of spectrograms

Fig. 2 and Fig. 3 show the spectrograms in PM1 and SM, respectively. Each figure has three spectrograms of the waveform of the periodic generator’s output, the aperiodic generator’s output, and the sum of two predicted signals. Fig. 2(a) and Fig. 2(b) show that the waveform of the periodic generator contains many harmonic components, and that of the aperiodic generator contains the other frequency components. As seen in the highlighted boxes on the left and in the center, which represent parts of the breath and unvoiced plosives “/t/”, respectively, it can be seen that the spectra of these unvoiced sounds only appear in the output of the aperiodic generator. These tendencies can also be seen in Fig. 3(a) and Fig. 3(b). These results indicate that two generators in the parallel model and the series model work on modeling the transformation from the sine waves and the noise sequence to the periodic and the aperiodic waveforms. Comparing the highlighted box in the lower right of Fig. 2(b)
4.3. Subjective evaluations

4.3.1. Comparison of AR/non-AR neural vocoders and the input signals

We conducted a listening test using WN, BM1, BM2, BM3, and NAT to compare neural vocoders with and without the AR structure and the input signals for the non-AR neural vocoder. Note that NAT indicates a recorded natural waveform. The naturalness of the synthesized singing voice was assumed using the mean opinion score (MOS) test method. The participants were sixteen native Japanese speakers, and each participant evaluated ten phrases randomly selected from the test data. After listening to each test sample in the MOS test, the participants were asked to score the naturalness of the sample out of five (1 = Bad; 2 = Poor; 3 = Fair; 4 = Good; and 5 = Excellent).

The results of the subjective evaluation are shown in Fig. 4. BM1 yielded a lower MOS value than WN, indicating that it is difficult to generate high-quality singing voices from noise. On the other hand, BM2 showed the same score as WN. By inputting a periodic signal, the neural vocoder can appropriately synthesize waveforms with periodicity the lack of the AR structure. However, the waveform of WN contains quantization noise, so the quality of BM2 was insufficient. BM3, which inputs both explicit periodic and aperiodic signals, has reached the MOS value close to NAT. This indicates the effectiveness of using both explicit periodic and aperiodic signals as inputs for non-AR neural vocoders.

4.3.2. Comparison of model structures of non-AR neural vocoders

To compare the model structures of non-AR neural vocoders, we conducted two subjective evaluation experiments using BM3, PM1, PM2, and SM. In these experiments, the samples were generated by four vocoders conditioned on two different F0 scales: original and double scale. In the experiment with the original F0 scale, we also used the natural waveform NAT for comparison.

The results are presented in Fig. 5 and Fig. 6. These figures show that PM1, PM2, and SM attained higher naturalness than BM3. This indicates that it is effective for the non-AR neural vocoders using the explicit periodic signal to introduce a parallel or series structure. Although the difference between PM1, PM2, and SM was negligible when conditioning on the original F0 as shown in Fig. 5, PM2 was the best performance when conditioning on the doubled F0 as shown in Fig. 6. The waveform samples generated by BM3, PM1, and SM tended to contain more aperiodic waveforms than those generated by PM2. In BM3, the period and aperiodic components were not modeled separately, and speech waveforms were generated from a single generator conditioned by auxiliary features including F0. In PM1 and SM, although the networks for modeling these components were separate, both aperiodic generators were conditioned on auxiliary features including F0. In particular, the aperiodic generator in SM also depended on periodic waveforms predicted by the periodic generator. Therefore, it was assumed that BM3, PM1, and SM could not generate aperiodic waveforms when these vocoders took out-of-range F0 as the acoustic features in the synthesis stage. PM2 is more robust for an unseen F0 outside the F0 range of the training data because the aperiodic generator in PM2 does not depend on the periodic signal or F0.

5. CONCLUSIONS

We introduced PeriodNet, a non-AR neural vocoder with new model structures, to appropriately modeling the periodic and aperiodic components in the speech waveform. Each generator in the parallel or series model structure can model the periodic and aperiodic waveforms without the use of decomposition techniques. The experimental results showed that the proposed methods were able to generate high-fidelity speech waveforms and improve the ability to generate waveforms with a pitch outside the range of the training data. Future work includes investigating the effect of proposed methods on different datasets, such as a multi-speaker and multi-singer dataset.

6. ACKNOWLEDGEMENTS

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