Quasi-Periodic Parallel WaveGAN: A Non-autoregressive Raw Waveform Generative Model with Pitch-dependent Dilated Convolution Neural Network

Yi-Chiao Wu, Tomoki Hayashi, Takuma Okamoto, Hisashi Kawai, and Tomoki Toda

Abstract—In this paper, we propose a quasi-periodic parallel WaveGAN (QPPWG) waveform generative model, which applies a quasi-periodic (QP) structure to a parallel WaveGAN (PWG) model using pitch-dependent dilated convolution networks (PD-CNNs). PWG is a small-footprint GAN-based raw waveform generative model, whose generation time is much faster than real time because of its compact model and non-autoregressive (non-AR) and non-causal mechanisms. Although PWG achieves high-fidelity speech generation, the generic and simple network architecture lacks pitch controllability for an unseen auxiliary feature such as a scaled $F_0$. To improve the pitch controllability and speech modeling capability, we apply a QP structure with PD-CNNs to PWG, which introduces pitch information to the network by dynamically changing the network architecture corresponding to the auxiliary $F_0$ feature. Both objective and subjective experimental results show that QPPWG outperforms PWG when the auxiliary $F_0$ feature is scaled. Moreover, analyses of the intermediate outputs of QPPWG also show better tractability and interpretability of QPPWG, which respectively models spectral and excitation-like signals using the cascaded fixed and adaptive blocks of the QP structure.

Index Terms—Neural vocoder, parallel WaveGAN, quasi-periodic WaveNet, pitch-dependent dilated convolution

I. INTRODUCTION

SPEECH synthesis (SS) is a technique to generate specific speech according to given inputs such as texts (text-to-speech, TTS), the speech of a source speaker (speaker voice conversion, VC), and noisy speech (speech enhancement, SE). The core of SS is the controllability of speech components, and the fundamental technique is called a vocoder [1], [2]. A vocoder encodes speech into acoustic representations such as spectral and prosodic features and then decodes specific speech on the basis of the manipulated acoustic features. Conventional vocoders such as STRAIGHT [3] and WORLD [4] are based on a source-filter model [5], which models speech with vocal fold movements (excitation) and vocal tract resonances (spectral envelope). However, many oversimplified assumptions of SS such as a fixed length of the analysis window, a time-invariant linear filter, and a stationary Gaussian process are imposed on the conventional vocoders. The losses of phase information and temporal details caused by these ad hoc designs result in speech quality degradation.

To tackle these problems, most neural network (NN)-based speech generation models [6]–[28] have been proposed. In contrast to the conventional source-filter-based vocoders, most of these models directly model the relationships among speech waveform samples. Specifically, autoregressive (AR) models such as WaveNet (WN) [6] and SampleRNN [7] achieve high-fidelity SS by modeling the probability distribution of each speech sample with the given auxiliary features and previous samples. Taking conventional-vocoder-extracted acoustic features as the auxiliary features for NN-based SS models [29]–[33], which replace the synthesizer of the conventional vocoders, also achieved early success. However, the AR mechanism and huge network architectures of WN and SampleRNN result in very slow generation, making these models impractical for realistic scenarios. To tackle these problems, many compact AR models with specific knowledge [8]–[10] and non-AR NN-based SS models such as flow-based [11]–[15] and generative adversarial network (GAN)-based [16]–[23] models have been proposed. Although these NN-based SS models achieve high-fidelity speech generation without the many ad hoc assumptions of SS, the data-driven nature, the generic network architecture, and the lack of prior acoustic knowledge of these models make most of them lose acoustic controllability and robustness to unseen auxiliary features [34]–[38]. For instance, without explicitly modeling the excitation signals as conventional source-filter models, it is difficult for WN to generate speech with accurate pitches outside the fundamental frequency ($F_0$) range of training data when conditioned on the scaled $F_0$ feature [27], [28]. However, using carefully designed mixed periodic and aperiodic inputs and source-filter-like architectures, the authors of [24]–[26] proposed different NN-based models attaining pitch controllability. In our previous works [27], [28], we also proposed a quasi-periodic WN (QPNet), which has a conventional-vocoding-like framework.

This work was supported in part by the Japan Science and Technology Agency (JST), Precurory Research for Embryonic Science and Technology (PRESTO) under Grant JPMJPR1657, in part by the JST, CREST under Grant JPMICR19A3, and in part by the Japan Society for the Promotion of Science (JSPS) Grants-in-Aid for Scientific Research (KAKENHI) under Grant 17H06101. The initial investigation in this study was performed while Y.-C. Wu was interning at NICT.

Y.-C. Wu is with Graduate School of Informatics, Nagoya University, Aichi, Japan (e-mail: yichiao.wu@gs.sp.ms.is.nagoya-u.ac.jp).

T. Hayashi is with Graduate School of Information Science, Nagoya University, Aichi, Japan (e-mail: hayashi.tomoki@gs.sp.ms.is.nagoya-u.ac.jp).

T. Okamoto and H. Kawai are with National Institute of Information and Communications Technology, kyoto, Japan (e-mail: okamoto@nict.go.jp, hisashi.kawai@nict.go.jp).

T. Toda is with Information Technology Center, Nagoya University, Aichi, Japan (e-mail: tomoki@icts.nagoya-u.ac.jp).
while using a unified network without the requirement of specific mixed inputs. QPNet advances the dilated convolution neural networks (DCNNs) \cite{39} of WN with a pitch-dependent mechanism to improve the pitch controllability of WN by dynamically changing the network architecture according to the auxiliary $F_0$ feature.

Although QPNet markedly improves the pitch accuracy of the generated speech, the AR mechanism and the huge network requirement of WN result in slow generation. To address this problem, we apply the quasi-periodic (QP) structure to parallel WaveGAN (PWG) \cite{17}, which is a compact non-AR model with a WN-like network architecture consisting of stacked DCNN layers. The proposed QPPWG SS model \cite{40} attains pitch controllability using a simple pitch-dependent architecture without the requirement of specific mixed periodic and aperiodic inputs as in \cite{24}–\cite{26}. In this paper, we conduct more evaluations with several hyperparameter settings and network architectures to comprehensively explore the efficiency of model structures and the internal behaviors and mechanisms of QPPWG. Specifically, model details such as the order of the cascaded structure, the numbers of dilation cycles and residual blocks, and the balanced ratio of adaptive and fixed modules are investigated. Both objective and subjective evaluations are conducted, and the experimental results show the effectiveness of the proposed QP structure for PWG. In addition, more analyses of intermediate outputs of QPPWG are presented to show the tractability and interpretability of QPPWG. The analyses confirm our assumption that QPPWG respectively models harmonic components with long-term correlations and non-harmonic components with short-term correlations using the adaptive module with pitch-dependent DCNNs (PDCNNs) and the fixed module with DCNNs of QPPWG.

This paper is organized as follows. In Section \ref{sec:related_work}, we review the recent GAN-based neural vocoders. In Section \ref{sec:problem_formulation}, a brief introduction to PWG is presented. In Section \ref{sec:proposed_model}, we describe the concepts and details of the proposed QPPWG. In Section \ref{sec:evaluation} objective and subjective tests are presented to show the effectiveness of QPPWG for generating speech with scaled $F_0$. Further discussion of QPPWG is presented in Section \ref{sec:discussion}. Finally, the conclusion is given in Section \ref{sec:conclusion}.

II. RELATED WORK

A. Source-filter and Data-driven Vocoder

Because of the high temporal resolution of speech signals, directly modeling raw speech waveforms is challenging. One of the standard speech modeling methods is source-filter modeling \cite{5}. Specifically, the speech generative process is formulated as a convolution of an excitation (voice source) signal and a spectral filter. The excitation signal models the glottal waveform generated by vocal fold movements, and the spectral filter models vocal tract resonances. As shown in Fig. 1, the conventional parametric vocoders generate speech samples in an AR manner such as LPC vocoders \cite{41}, \cite{42} and mel-generalized cepstrum (MGC) vocoders \cite{43}, \cite{44} or in a non-AR manner such as STRAIGHT \cite{3} and WORLD \cite{4}. Motivated by the development of deep NNs, NN-based excitation generation models with the AR mechanism such as LPCNet \cite{10} and the non-AR mechanism such as GlotGAN \cite{20}, \cite{21} and GELP \cite{22} have been proposed to improve the generated speech quality. Moreover, the authors of \cite{25} and \cite{26} also proposed a neural source-filter (NSF) network to model the source-filter generative framework with an advanced neural filter.

In addition to the source-filter-based vocoders, many unified NN-based waveform generative models have been proposed to directly generate high-fidelity speech waveforms from acoustic features in a purely data-driven manner as shown in Fig. 1. For example, the WN \cite{6} and WaveRNN \cite{9} models autoregressively generate speech samples conditioned on acoustic/linguistic features and the previous samples, and the non-AR Parallel WN \cite{11} and Clarinet \cite{12} models simultaneously generate all speech samples with acoustic/linguistic features and white noise inputs. Although these models achieve high-fidelity speech generation without many ad hoc assumptions imposed on them, pitch controllability is degraded because of the data-driven nature of not explicitly modeling excitation signals as the source-filter-based models. To improve the pitch controllability while keeping the unified and generic network architectures, we proposed a QP structure \cite{27}, \cite{28} for WN. The proposed QPNet implemented a source-filter-like mechanism into WN to simultaneously model the periodicity and aperiodicity of speech signals using a pitch-adaptive network
architecture. In this paper, we further extend the QP structure to the non-AR PWG model [17] to markedly improve the generation speed and show the generality of the proposed PDCNN, which can be easily integrated into any CNN-based network.

B. GAN-based Vocoders

Recently, because of the successes of GAN [45] in image and video generation, GAN-based neural vocoders [16]–[24] have also been proposed. The two main categories of recent GAN-based neural vocoders are models with prior speech knowledge and models directly trained in a data-driven manner as mentioned in the previous section.

Among the models with speech knowledge, GlotGAN [20], [21] achieved early success in generating glottal excitation signals, but it suffered severe speech quality degradation when directly applied to raw speech waveform generation. GELP [22] has been proposed to improve the glottal generator by using short-time Fourier transform (STFT)-based regression loss and the adversarial loss of the final generated waveforms. The authors of [24] also proposed a GAN-based vocoder with tailored periodic and aperiodic inputs, and the model was trained with the GAN loss of the generated waveform and the Gaussian loss of its aperiodic components.

Among the purely data-driven models, teacher–student-based parallel WN [11] conditioned on the mel-spectrogram has been combined with a GAN structure of the waveform domain for joint optimization [16] and speaker adaptation [23]. Furthermore, MelGAN [18] and GAN-TTS [19] have been proposed to directly transform acoustic features to speech waveforms using GAN structures with tailored generators and discriminators. Specifically, both MelGAN and GAN-TTS have an upsampling generator that gradually expands the temporal resolution of the input acoustic features to match the speech waveforms. MelGAN adopts a multi-scale discriminator with several different downsampling rates to enable its generator to capture the information of different levels. GAN-TTS also adopts an ensemble of 10 similar discriminators with different input window sizes with or without the conditional acoustic features to guide its generator to learn different aspects of speech information.

Another purely data-driven model called PWG [17], which transforms white noise into speech with conditional mel-spectrograms, has also been proposed. Instead of complex discriminators, PWG adopts a simple one with stacked DCNN layers. To achieve stable PWG training, STFT-based losses are also utilized. In conclusion, most recent GAN-based neural vocoders have adopted a convolutional feedforward network, and the hierarchical information of speech waveforms such as multi-resolution STFT-based losses is essential for training a high-quality raw waveform generator.

In this paper, we focus on introducing prior pitch knowledge to the data-driven PWG model, which is fast, compact, simple, and easy to train, to improve its pitch controllability and speech modeling capability and make it more consistent with the definition of a vocoder.

III. PARALLEL WAVEGAN

A. GAN-based Waveform Generation

A WN-like architecture is adopted for the generator of PWG. The main differences between the PWG generator and WN are a Gaussian noise input instead of previous samples, a raw waveform output instead of a probability distribution, and a non-AR manner. Specifically, the inputs of the generator are a Gaussian noise sequence and auxiliary acoustic features, and $z$ is drawn from a Gaussian distribution with zero mean and standard deviation, denoted as $N(0, I)$. The output of the generator is the waveform samples. The generator, which tries to generate realistic speech samples, is trained in a manner adversarial to the discriminator, which attempts to distinguish natural (real) and generated (fake) speech waveforms. The adversarial loss of the generator ($L_{\text{adv}}$) is formulated as

$$L_{\text{adv}}(G, D) = \mathbb{E}_{x \in p_{\text{data}}}[(1 - D(G(x)))^2]$$.

Note that all auxiliary features of the generator are omitted in this section for simplicity. Unlike some flow-based models [13], [14], which adopt an invertible network to map the real data into the Gaussian noise sequence, the generator of PWG learns to transfer the input noise sequence to the output waveforms via the feedback from the discriminator.

Furthermore, a simple architecture consisting of stacked DCNN layers with LeakyReLU [46] activation functions is adopted for the discriminator of PWG, and the dilation size of each DCNN layer increase exponentially with a base of 2 and the exponent of its layer index. The discriminator is trained to minimize the adversarial loss ($L_D$) formulated as

$$L_D(G, D) = \mathbb{E}_{x \in p_{\text{data}}}[(1 - D(x))^2] + \mathbb{E}_{z \in N(0, I)}[D(G(z))^2]$$,

where $x$ denotes the natural samples and $p_{\text{data}}$ denotes the data distribution of the natural samples.
B. Multi-resolution STFT Loss

Since training PWG with only adversarial losses is difficult and tends to be unstable, an additional STFT-based loss ($L_{sp}$) is adopted to improve the stability and efficiency of the GAN training. Specifically, a spectral convergence loss ($L_{sc}$) is formulated as

$$L_{sc}(x, \hat{x}) = \frac{\|\text{STFT}(x) - \text{STFT}(\hat{x})\|_F}{\|\text{STFT}(x)\|_F}, \quad (3)$$

and a log STFT magnitude loss ($L_{mag}$) is formulated as

$$L_{mag}(x, \hat{x}) = \frac{1}{N} \log \|\text{STFT}(x)\| - \log \|\text{STFT}(\hat{x})\|_{L1}, \quad (4)$$

where $\hat{x}$ denotes the samples generated from the generator, $\|\cdot\|_F$ is the Frobenius norm, $\|\cdot\|_{L1}$ is the L1 norm, $|\text{STFT}(\cdot)|$ denotes the STFT magnitudes, and $N$ is the number of magnitude elements. $L_{sp}$ is the summation of several $L_{sc}$ and $L_{mag}$ losses of the STFT features extracted with different FFT sizes, frame lengths, and frame shifts. The multiple STFT losses prevent the generator from a suboptimal problem and enhance the modeling capability of the generator by making it capture speech structures with different resolutions. In conclusion, the overall training loss of the PWG generator ($L_{G}$) is formulated as

$$L_{G}(G, D) = L_{sp}(G) + \lambda_{adv} L_{adv}(G, D), \quad (5)$$

which is a weighted sum of $L_{adv}$ and $L_{sp}$ with weight $\lambda_{adv}$. The hyperparameter $\lambda_{adv}$ is empirically set to 4.0 in this paper.

C. Problems in Using PWG as a Vocoder

Although PWG achieves high-fidelity speech generation with acoustic features, it is still vulnerable to unseen acoustic features such as scaled $F_0$. That is, the speech quality and pitch accuracy of the PWG-generated speech will markedly degrade when the $F_0$ of the auxiliary acoustic features is scaled or is outside the training data range [27], [28]. The possible reasons for the degradation are the generic architecture, data-driven nature, and lack of prior speech knowledge. Moreover, since speech is a quasi-periodic signal, which includes both periodic components with long-term correlations and aperiodic components with short-term correlations, modeling both components with the fixed network architecture of PWG is inefficient. For instance, the fixed receptive field size of the network for both periodic and aperiodic components is not reasonable, and the receptive field may include many redundant samples when modeling the periodic structures of speech.

IV. QUASI-PERIODIC PARALLEL WAVEGAN

Since pitch controllability is an essential feature of a vocoder, we propose QPPWG [49] to improve the pitch controllability and speech modeling efficiency of PWG. Specifically, since the effectiveness of the GAN structure and the multi-resolution STFT losses have been shown for PWG, the proposed QPPWG inherits the discriminator and $L_{sp}$ of PWG and focuses on improving the generator. The QP structure of the proposed generator introduces pitch information to the network via a PDCNN module and a cascaded architecture. The details are as follows.

A. Pitch-dependent Dilated Convolution

Inspired by pitch filtering in code-excited linear prediction (CELP) [47], [48], we proposed a PDCNN for causal AR models [27], [28]. In this paper, we further extend the PDCNN in a non-causal manner for the non-AR PWG model. As shown in Fig. 3 a DCNN is a convolution layer with gaps between input samples, and the length of each gap is a predefined hyperparameter called the dilation size (rate). The non-causal dilated convolution can be formulated as

$$y_t^{(c)} = W^{(c)} * y_t^{(i)} + W^{(p)} * y_{t-d}^{(i)} + W^{(f)} * y_{t+d}^{(i)}, \quad (6)$$

where $y_t^{(i)}$ and $y_t^{(o)}$ are the input and output of the DCNN layer, respectively, $W^{(c)}$, $W^{(p)}$, and $W^{(f)}$ are the trainable 1 × 1 convolution filters of the current, previous, and following samples, respectively, $*$ is the convolution operator and $d$ is the dilation size. For the DCNN, $d$ is a predefined time-invariant constant. As an extension of a DCNN, the dilation size $d'$ of a PDCNN is pitch-dependent and time-variant. Specifically, the pitch-dependent dilated factor $E_t$ is multiplied by the dilation size $d$ in each time step $t$ to dynamically set the dilation size $d'$ as

$$d' = E_t \times d. \quad (7)$$

The dilated factor $E_t$ is derived from

$$E_t = F_s / (F_0 \times a), \quad (8)$$

where $F_s$ is the sampling rate, $F_0$ is the fundamental frequency of the input sample, and $a$ is the dense factor. The dense factor $a$ is a hyperparameter that indicates the number of samples in one cycle taken as the inputs of a PDCNN. The higher the dense factor, the lower the sparsity of the PDCNN. Using the pitch-dependent dilation size, the architecture of QPPWG with PDCNNs is dynamically changed according to the input $F_0$ feature. In conclusion, the adaptive architecture of QPPWG introduces pitch knowledge to the network to improve the pitch controllability and allows each sample to have a specific receptive field size, extending the receptive field more efficiently.

B. QPPWG Generator with PDCNNs

As shown in Fig. 4, the QPPWG generator is composed of several residual blocks, and each block consists of a
The auxiliary features of these speech generation models were composed of one-dimensional continuous $F_0$, one-dimensional unvoiced/voiced binary code ($U/V$), 35-dimensional mel-cepstrum (mcep), and two-dimensional coded aperiodicity (codeap) features. Specifically, the WORLD (WD) vocoder was adopted to extract one-dimensional $F_0$ and 513-dimensional spectral (sp) and aperiodicity (ap) features with a frameshift of 5 ms. $F_0$ was interpolated to the continuous $F_0$ and converted to $U/V$, ap was coded into codeap, and sp was parameterized into mcep. To simulate unseen data, the continuous $F_0$ was scaled by ratios of 0.5, 1.5, and 2 while keeping the other features the same. Moreover, the dilated factor $E_t$ of QPPWG was empirically calculated on the basis of the continuous $F_0$ because of the better speech quality.

All PWG-like models were trained with the RAdam optimizer $\left(\epsilon = 10^{-4}\right)$ with 400K iterations. Specifically, the generators were trained with only multi-resolution STFT losses for the first 100K iterations and then jointly trained with the discriminators for the following 300K iterations. The multi-resolution STFT losses were calculated on the basis of three different FFT sizes (1024/2048/512), frame shifts (120/240/50), and frame lengths (600/1200/240). The balanced weight $\lambda_{adv}$ of $L_{adv}$ was set to 4.0. The generators learning rate was $10^{-4}$ and the discriminators learning rate was $5 \times 10^{-5}$. Both learning rates decayed by 50% every 200K iterations. The minibatch size was six and the batch length was 25,520. Furthermore, the baseline QPNet [27], [28] model was trained with the Adam optimizer $\left(\epsilon = 10^{-4}\right)$ without decay, and the minibatch size was one with a batch length of 22,050.

### B. Model Descriptions

In this paper, several variants of PWG and QPPWG models and a baseline QPNet model were involved in the evaluations. To describe the different architecture of each model, several basic modules are introduced. Specifically, a macroblock module consisting of stacked residual blocks was adopted, and each macroblock was only composed of one type of residual block namely, adaptive blocks (B_A) or fixed blocks (B_F). The PWG models only consisted of one macroblock (Macro 0) with fixed residual blocks. The models with a QP structure, namely, the QPPWG and QPNet models, were composed of two cascaded macroblocks (Macro 0 and 1) with different types of residual block. Taking vanilla PWG as an example, the architecture composed of 30 fixed blocks with three cycles (repeats) of exponentially increasing dilation size was denoted as B_F-30C3. Moreover, all PWG and QPPWG models had the same discriminator architecture, which consisted of 10 non-causal DCNN layers with 64 convolution channels, three kernels, and LeakyReLU ($\alpha = 0.2$) activation functions. For each adaptive/fixed block of the QPPWG/PWG generator, a gated activation with tanh and sigmoid functions was adopted, and the number of CNN channels of residual and skip connections and auxiliary features was also 64. The QPNet structure followed that in our previous works [28], and the number of CNN channels of residual connections and auxiliary features was 512 and that of skip connections was 256.
C. Objective Evaluations

As reported in this section, the quality of the vocoders was evaluated by the mel-cepstral distortion (MCD), root mean square error (RMSE) of $F_0$, and $U/V$ decision error. These measurements were calculated using the auxiliary features and the acoustic features extracted from the generated speech. The following objective evaluations were conducted to explore the different hyperparameter settings, and the WD vocoder was used as a reference.

1) Number of CNN Channels: To explore the relationship between model capacities and the number of CNN channels, vanilla PWG generators with 8–64 CNN channels were evaluated. Note that because this work focused on improving the generator, all PWG/QPPWG models in this section adopted the same discriminator, whose number of CNN channels was 64 and whose model size was 0.1 M. The results in Table I show that the original setting (64 CNN channels) predictably achieves the best performance characteristics of all objective measurements. However, even if the number of CNN channels is reduced to 16, which greatly reduces the training time because of the compact model size, the speech quality and pitch accuracy are still acceptable. To efficiently explore the efficiency of the network architectures, the objective evaluations in the following sections were conducted on the basis of models with 16 CNN channels.

2) Numbers of Blocks and Cycles: The importance of the numbers of residual blocks and dilation cycles was evaluated. The results in Table II show that the model capacity is highly dependent on the number of residual blocks, which is directly related to the receptive field length. However, the results of $B_8$20C2, $B_8$20C1, and $B_8$16C4 also imply that not only the number of residual blocks but also the number of dilation cycles is important. Although fewer dilation cycles result in a longer receptive field, the network may not model the speech well. By contrast, the larger the number of dilation cycles, the shorter the receptive field. Since a longer effective receptive field can be achieved by replacing fixed blocks with adaptive blocks, we focus on improving the $B_8$20C2 and $B_8$16C4 PWG generators using the QP structure in this paper.

3) Ratio of Fixed and Adaptive Blocks: To find the efficient ratio of fixed and adaptive blocks, four QPPWG models with 16 residual blocks, four cycles, and dense factor 8 were evaluated. These settings followed those of QPNet. As shown in Table III, although the $B_8$12C3+$B_8$4C1 model, which is also adopted in QPNet, achieves the lowest MCD, its $F_0$ and $U/V$ accuracies are also lowest. On the other hand, when the ratio of adaptive blocks increases, the $F_0$ and $U/V$ accuracies become higher, but the MCD also becomes higher. The same tendency can also be observed in the spectral domain. The more adaptive blocks the model has, the more harmonic components the generated speech has. However, overenhanced harmonic structures generate significantly robotic and unnatural sounds. Therefore, the balanced $B_8$8C2+$B_8$8C2 model achieves the best overall performance. To summarize, the balance between adaptive and fixed blocks is crucial to prevent the network from over/undermodeling the harmonic structures, and this observation is consistent with our previous work.

4) Order of Macroblocks and Cycles of Adaptive Blocks: Because the performance of the QPPWG model with 16 residual blocks was still markedly worse than that of the vanilla PWG, we increased the number of residual blocks to 20. Since one dilation cycle including 10 fixed blocks is important. Although fewer dilation cycles result in a number of residual blocks but also the number of dilation cycles was evaluated. The results in Table II show that the model capacity is highly dependent on the number of residual blocks, which is directly related to the receptive field length. However, the results of $B_8$20C2, $B_8$20C1, and $B_8$16C4 also imply that not only the number of residual blocks but also the number of dilation cycles is important. Although fewer dilation cycles result in a longer receptive field, the network may not model the speech well. By contrast, the larger the number of dilation cycles, the shorter the receptive field. Since a longer effective receptive field can be achieved by replacing fixed blocks with adaptive blocks, we focus on improving the $B_8$20C2 and $B_8$16C4 PWG generators using the QP structure in this paper.

### Table I

| Channels |
|----------|
| WD       |
| PWG      |
| 64       |
| 32       |
| 16       |
| 8        |
| MCD (dB) |
| 2.58     |
| 3.69     |
| 4.15     |
| 4.23     |
| 4.89     |
| $F_0$/RMSE |
| 0.10     |
| 0.12     |
| 0.14     |
| 0.15     |
| 0.20     |
| $U/V$ (%) |
| 10       |
| 14       |
| 16       |
| 16       |
| Size ($\times 10^6$) |
| -        |
| 1.16     |
| 0.34     |
| 0.11     |
| 0.04     |
| 0.06     |

### Table II

| Block (B_f) | Cycle (C) |
|------------|-----------|
|            |           |
| 30         | 20        |
| 20         | 20        |
| 20         | 10        |
| 16         | 16        |
| 16         | 8         |
| MCD (dB)   | 4.23      |
| 4.61      | 5.98      |
| 5.95      | 5.07      |
| $F_0$/RMSE | 0.15      |
| 0.17      | 0.30      |
| 0.31      | 0.41      |
| $U/V$ (%)  | 16        |
| 17        | 27        |
| 33        | 57        |
| Size ($\times 10^6$) | 0.11 |
| 0.08      | 0.08      |
| 0.04      | 0.06      |

### Table III

| Macro 0 | Macro 1 |
|---------|---------|
| $B_8$12C3 | $B_8$12C3 |
| $B_8$8C2 | $B_8$8C2 |
| $B_8$4C1 | $B_8$4C1 |
| -        | $B_8$16C4 |
| MCD (dB) |
| 1 $F_0$ | 5.27       |
| 5.69 | 6.37 |
| 5.71 | 6.98 |
| 3 $F_0$ | 5.46       |
| 5.81 | 6.54 |
| 5.77 | 6.80 |
| 2 $F_0$ | 5.77       |
| 6.02 | 8.15 |
| 5.92 | 6.67 |
| Average | 5.55       |
| 5.92 | 6.67 |
| 5.81 | 6.54 |
| 5.77 | 6.80 |
| 5.92 | 6.67 |
| U/V decision error (%) |
| 1 $F_0$ | 0.20       |
| 0.14 | 0.15 |
| 0.15 | 0.17 |
| 1 $F_0$ | 0.27       |
| 0.19 | 0.24 |
| 0.13 | 0.14 |
| 3 $F_0$ | 0.16       |
| 0.13 | 0.14 |
| 0.12 | 0.14 |
| 2 $F_0$ | 0.19       |
| 0.13 | 0.14 |
| 0.12 | 0.14 |
| Average | 0.21       |
| 0.15 | 0.16 |
| 0.16 | 0.15 |
| 1 $F_0$ | 25         |
| 14 | 16 |
| 17 | 22 |
| 1 $F_0$ | 29         |
| 20 | 22 |
| 22 | 22 |
| 3 $F_0$ | 31         |
| 14 | 14 |
| 15 | 14 |
| 2 $F_0$ | 44         |
| 18 | 13 |
| 14 | 14 |
| Average | 32         |
| 16 | 16 |
| 17 | 17 |
dilation cycles (BA10C2) also outperforms that with the af order and BA10C1. In conclusion, the QPPWG model with the BA10C2+BF10C1 (QPPWGaf_20) architecture achieves the best performance among the systems in Table [IV]. Further discussion and more details about the macroblock order will be presented in Section [VI].

5) Dense Factor: The dense factor is inversely proportional to the receptive field size, and the QPPWGaf_20 models with 1–16 dense factors were evaluated. The results in Table [V] show that while the models with dense factors of 4–16 achieve similar generative performance, the models with dense factors of 1 and 2 achieve slightly worse performance. A similar tendency was also observed by listening to the generated speech. The generated utterances from the models with dense factors of 1 and 2 were more unstable. Furthermore, PDCNN degenerates to DCNN when Ef is one, and a larger dense factor makes Ef closer to one for more F0 values. Therefore, since a lower dense factor attains a longer receptive field expansion and a higher lower bound of F0, which makes PDCNN degenerate to DCNN, the dense factors of the following QPPWG models were set to 4.

6) Overall Objective Evaluation: An overall objective evaluation was conducted including the WD, QPNet, PWG, and QPPWG models. The number of CNN channels of the PWG and QPPWG models was set to 64 following the original setting. The model sizes are shown in Table [VI]. Since the model size is proportional to the square of the number of CNN channels, the model size of vanilla PWG is only 5% of that of QPNet because of the greatly reduced number of CNN channels. The sizes of the QPPWG models were reduced further by 30–50% because of the reduced number of residual blocks compared with that of vanilla PWG.

According to the MCD results shown in Table [VII] the QPPWG models with the af order still achieve a higher spectral accuracy than those with the fa order. The QPPWG models with 20 residual blocks also predictably outperform those with only 16 residual blocks. Moreover, the QPPWGaf_20 model achieves a comparable spectral accuracy with the PWG_30 and PWG_20 models. On the other hand, although the average MCD of PWG_16-generated utterances is not very high, the QP structure further improves the pitch accuracy of the non-AR PWG models. The QPPWGaf_16 model even attains a

### Table IV

**Comparison of Cycles and Macroblock Orders of QPPWG Generators with 16 CNN Channels**

| Macro 0 | BF10C1 | BF10C1 | BA10C1 | BA10C1 |
|---------|--------|--------|--------|--------|
| 1 × F0  | 5.65   | 5.92   | 5.41   | 5.26   |
| 1.2 × F0| 6.03   | 6.72   | 5.64   | 5.57   |
| 3 × F0  | 5.86   | 6.17   | 5.69   | 5.55   |
| 2 × F0  | 6.24   | 6.79   | 6.04   | 6.06   |
| Average | 5.95   | 6.40   | 5.70   | 5.61   |

### Table V

**Comparison of Dense Factor of QPPWGaf_20 Generator with 16 CNN Channels**

| Dense α | 16 | 8  | 4  | 2  | 1   |
|---------|----|----|----|----|-----|
| MCD (dB) |    |    |    |    |     |
| 1 × F0  | 5.26 | 5.26 | 5.10 | 5.35 | 5.36 |
| 1/2 × F0| 5.64 | 5.57 | 5.49 | 5.61 | 5.61 |
| 3/2 × F0| 5.48 | 5.55 | 5.47 | 5.61 | 5.61 |
| 2 × F0  | 5.92 | 6.06 | 6.32 | 5.99  | 6.03 |
| Average | 5.57 | 5.61 | 5.59 | 5.64 | 5.66 |

### Table VI

**Comparison of Model Size (G: Generator; D: Discriminator)**

| QPNet | - | 30 | 20 | 16 |
|-------|---|----|----|----|
| Macro 0 | BF12C3 | BF10C1 | BA4C1 | BA4C1 |
| Macro 1 | BF30C3 | BF20C2 | BF16C4 | BF16C4 |
| G (×10^6) | 24 | 1.16 | 0.78 | 0.63 |
| D (×10^6) | - | 0.10 | 0.10 | 0.10 |

| PWG | QPPWG |
|-----|-------|
| Macro 0 | BAYC2 | BA8C2 | BF10C1 | BF8C2 |
| Macro 1 | BF10C1 | BF8C2 | BA10C2 | BA8C2 |
| G (×10^6) | 0.79 | 0.63 | 0.79 | 0.63 |
| D (×10^6) | 0.10 | 0.10 | 0.10 | 0.10 |
similar pitch accuracy to the reference WD vocoder. Moreover, although the pitch and U/V accuracies of PWG_16 markedly degrade because of the short receptive field, the QPPWG model significantly improves them to an acceptable level. In conclusion, the QP structure efficiently increases the effective receptive field size and introduces the pitch information to the network, resulting in a comparable spectral accuracy, a much higher pitch accuracy, and a smaller model size. The objective results show the effectiveness of the proposed QP structure for the PWG models.

D. Subjective Evaluations

The set of samples used for subjective evaluation was composed of 1680 synthesized and 80 natural utterances. The synthesized utterances were generated by seven vocoders conditioned on three \( F_0 \) scaled ratios (unchanged, halved, and doubled) and four speakers (the VCC2018 SPOKE set). For each vocoder, speaker, and \( F_0 \) scaled ratio, we randomly selected 20 utterances from the 35 testing utterances for both mean opinion score (MOS) and ABX evaluations. Specifically, the speech quality of each utterance was evaluated by listeners assigning MOSs of 1–5. The higher the MOS, the better the speech quality. For each ABX, two testing utterances were compared with one reference, and the listeners chose the one whose pitch was more consistent with that of the reference. Eight listeners evaluated part of the subjective evaluation set in both MOS and ABX tests, and each utterance/pair was evaluated by at least two listeners. Although the listeners were not native English speakers, they worked on audio-related research. The demo utterances can be found on the demo page [23].

1) MOS Evaluation of Speech Quality: The MOS evaluation included the vocoders of WD, QPNet, PWG of three different sizes, and QPPWG of two different sizes. The MOS results shown in Figs. 5 and 6 are presented for three different \( F_0 \) scaled ratios for male and female speakers, respectively. The overall results show that the proposed QP structure improves the speech modeling capacity of the PWG vocoders, especially when the PWG_16 vocoder has a very small receptive field. Because the QPPWG vocoders markedly outperform the PWG vocoders of the same size for all scenarios in the MOS evaluation, the following discussion focuses on comparisons among QPPWG\(_{f_{20}}\), PWG_30, and QPNet.

For the halved \( F_0 \) scenario, the QPPWG\(_{f_{20}}\) vocoder markedly outperforms the PWG_30 and WD vocoders and attains a similar speech quality to the QPNet vocoder for the male set. For the female set, the QPPWG\(_{f_{20}}\) vocoder is comparable to the PWG_30 and QPNet vocoders while still outperforming the WD vocoder. The results indicate that the models with the QP structure are more robust for an unseen \( F_0 \) range of the training data, such as most of the \( F_0 \) values in the male set. On the other hand, although the combination of the half \( F_0 \) and other acoustic features in the female set is still unseen, the scaled \( F_0 \) values are almost in the \( F_0 \) range of the training data. Therefore, the PWG_30 vocoder can still achieve a similar speech quality to the QPPWG\(_{f_{20}}\) vocoder.

For the doubled \( F_0 \) scenario, because most of the scaled \( F_0 \) values of the male set are in the \( F_0 \) range of the training data, the performance of the QPPWG\(_{f_{20}}\) vocoder is similar to that of the PWG_30 vocoder for the male set. The QPPWG\(_{f_{20}}\) vocoder outperforms the WD and QPNet vocoders in the male set, while the QPNet vocoder achieves an inferior speech modeling capacity for the doubled \( F_0 \) scenario [27], [28]. On the other hand, although the QPPWG\(_{f_{20}}\) vocoder predictably outperforms the PWG_30 and QPNet vocoders in the doubled female \( F_0 \) scenario, the WD vocoder achieves a higher speech quality than the

| Vocoder Blocks | WD | QPNet | PWG | QPPWG |
|---------------|----|-------|------|-------|
|               | af\(_{f_{20}}\) | af\(_{f_{16}}\) | f\(_{20}\) | f\(_{16}\) |
| 1 × \( F_0 \) | 2.58 | 4.20 | 3.69 | 4.25 | 3.80 | 4.18 | 4.54 | 4.99 |
| 1/2 × \( F_0 \) | 3.89 | 4.92 | 4.47 | 4.39 | 4.65 | 4.52 | 4.89 | 5.18 | 5.60 |
| 3/2 × \( F_0 \) | 3.09 | 4.32 | 4.23 | 4.12 | 4.36 | 4.21 | 4.73 | 5.00 | 5.44 |
| 2 × \( F_0 \) | 3.79 | 4.61 | 5.24 | 5.06 | 4.56 | 4.92 | 5.42 | 5.61 | 5.97 |
| Average | 3.34 | 4.51 | 4.41 | 4.33 | 4.45 | 4.36 | 4.80 | 5.08 | 5.50 |

| Vocoder Blocks | WD | QPNet | PWG | QPPWG |
|---------------|----|-------|------|-------|
|               | RMSE of log \( F_0 \) | U/V decision error (%) |
| 1 × \( F_0 \) | 0.10 | 0.11 | 1.01 | 0.11 |
| 1/2 × \( F_0 \) | 0.14 | 0.11 | 0.11 | 0.13 |
| 3/2 × \( F_0 \) | 0.10 | 0.11 | 0.11 | 0.11 |
| 2 × \( F_0 \) | 0.10 | 0.11 | 0.11 | 0.11 |
| Average | 0.11 | 0.11 | 0.11 | 0.11 |

| Vocoder Blocks | WD | QPNet | PWG | QPPWG |
|---------------|----|-------|------|-------|
|               | U/V decision error (%) |
| 1 × \( F_0 \) | 0.11 | 0.11 | 0.11 |
| 1/2 × \( F_0 \) | 0.15 | 0.20 | 0.19 |
| 3/2 × \( F_0 \) | 0.10 | 0.10 | 0.11 |
| 2 × \( F_0 \) | 0.10 | 0.10 | 0.11 |
| Average | 0.11 | 0.11 | 0.11 | 0.11 |

| Vocoder Blocks | WD | QPNet | PWG | QPPWG |
|---------------|----|-------|------|-------|
|               | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Average | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |

TABLE VII
Comparison of WORLD, QPNet, PWG, and QPPWG Vocoder

8
QPPWG_{af\_20} vocoder. A possible reason for this is that many PDCNNs of the QPPWG_{af\_20} model might degenerate to DCNNs because of the values of $E_t$ close to one due to the very high $F_0$ values.

In conclusion, the proposed QPPWG vocoder with 20 residual blocks attains speech quality competitive with the PWG vocoder with 30 residual blocks for natural auxiliary features even though the model size is only 70% of that of the PWG model. When conditioned on the auxiliary features with the unseen $F_0$ values, which are outside the $F_0$ range of the training data, the proposed QPPWG vocoders achieve a higher speech quality than the PWG vocoders. The results confirm the effectiveness of the proposed QP structure for the PWG model in efficiently modeling speech signals and dealing with unseen $F_0$ features.

2) **ABX Evaluation of Pitch Accuracy**: To evaluate the perceptual pitch accuracy, we conducted ABX tests of the QPPWG_{af\_20}, PWG_{30}, and QPNet vocoders with the WD-generated utterances taken as references. Note that since there were no natural utterances with scaled $F_0$ and the conventional signal-processing-based vocoder usually attains accurate pitch controllability, the WD-generated utterances were an alternative reference. Because the results of the female and male sets have the same tendency, only the overall results are shown in Fig. 7. We find that the perceptual pitch accuracy of the proposed QPPWG_{af\_20} vocoder is much better than that of the PWG and QPNet vocoders for both halved and doubled $F_0$ scenarios. To summarize, the ABX results show perceptible pitch differences between QPPWG- and PWG/QPNet-generated utterances, and the ABX experimental results are consistent with the objective results of the RMSE of log $F_0$.

VI. DISCUSSION

A. Understanding of QP Structure

Because of the direct waveform outputs of PWG/QPPWG, we can easily dissect the models to explore the internal speech modeling mechanisms. Specifically, the raw waveform outputs of the PWG/QPPWG models are the cumulative results of the skip connection outputs from the residual blocks. Therefore, the speech modeling behavior of the residual blocks can be explored via the visualized intermediate outputs of partial residual blocks. Spectrograms of the intermediate outputs of the cumulative residual blocks are presented in Fig. 8. For the PWG vocoder results (Figs. 8(a)–(d)), the spectrogram
contains more details and textures as the number of cumulative residual blocks increases. In contrast to the PWG vocoder, which gradually adds both harmonic and non-harmonic components to the spectrogram, the first 10 adaptive blocks of the QPPWGoF vocoder mostly focus on modeling the harmonic components as shown in Fig. 8 (f). By contrast, the first ten fixed blocks of the QPPWGoF vocoder mostly generate the non-harmonic part of the speech as shown in Fig. 8 (j). The results confirm our assumption that the adaptive blocks with the PDCNNs primarily model the pitch-related speech components with long-term correlations, while the fixed blocks with the DCNNs mainly focus on the spectrum-related components with short-term correlations.

In addition, to explore the behaviors of the adaptive and fixed blocks for different scaled $F_0$ features, comparisons among the visualized cumulative outputs of the first 10 residual blocks from the QPPWGoF and QPPWGoF vocoders are presented. The spectrograms of QPPWGoF shown in Figs. 9 (a)–(c) have similar structures along the time axis but increasingly stretched harmonic structures along the frequency axis as $F_0$ increases. By contrast, despite the different $F_0$ scaled ratios, both the frequency and temporal structures of the spectrograms of QPPWGoF shown in Figs. 9 (d)–(f) are similar. The results imply that the adaptive blocks primarily model the pitch-dependent harmonic components and the fixed blocks mainly focus on the pitch-independent non-harmonic components. Furthermore, although the QPPWGoF vocoder is a unified NN-based waveform generative model, the generative mechanism of its QP structure is similar to that of a source-filter model. The cascaded adaptive (pitch-dependent) and fixed macroblocks of the QP structure are analogous to the excitation generation and spectral filtering of the source-filter model. In conclusion, because of the QP structure, the QPPWGoF vocoder is more consistent with the definition of a vocoder while having a more tractable and interpretable architecture. More details of the visualized intermediate outputs can be found on our demo page [55].

### B. Effective Receptive Field

Our previous works [27], [28] showed that the capacity of an AR vocoder is strongly related to the length of its receptive field, and we argue that a non-AR vocoder has a similar tendency. Specifically, the receptive field length of PWG_30 is 6139 ($2^0 + \cdots + 2^5 = 1023$ with three cycles and two sides plus one) and that of PWG_20 is 4093. For the QPPWGoF, the effective receptive field length is the summation of 2047 for $B_F 10C1$ and $124 \times E_0$ ($2^0 + \cdots + 2^4 = 31$ with two cycles and two sides) for $B_A 10C2$. The male $F_0$ range is around 40–240 Hz and the female $F_0$ range is around 100–400 Hz, so the $E_0$ of the male set is around 20–140 and that of the female set is around 10–60 when the dense factor is set to four. As shown in Fig. 10, most of the effective receptive filed lengths of QPPWGoF for the male set are longer than the receptive filed length of PWG_30, which may result in the better pitch accuracy and comparable speech quality of QPPWGoF. The slightly lower speech quality of QPPWGoF than of PWG_30 for the female set may result from the shorter effective receptive fields of QPPWGoF_20. In conclusion, the
quality of the non-AR-vocoder-generated speech still strongly depends on the length of the receptive field, and QPPWG has longer effective receptive fields by skipping some redundant samples of the periodic components. Although the network may also lose some details of the aperiodic components owing to the skipping mechanism, the experimental results still show the effectiveness of the QP structure.

C. Deformable Dilated Convolution

The idea of a dynamically updated attention mechanism, which makes a sequential network know “where to look” at each time step, is not new. Generative models [54]–[56] that utilize differentiable attention mechanisms to constrain the read and write operations of the network to specific parts of the scene have been proposed. To handle the limitation of the fixed geometric structure of the CNNs, the authors of [57] proposed a learnable spatial transformation of the input feature maps of the CNNs to regularize the input of each CNN layer. Moreover, the authors of [58] proposed a deformable convolution to enable the freeform deformation of the CNN sampling grid. The deformable convolution gives the network an adaptive receptive field that focuses on different locations of the input feature map corresponding to the current conditions.

Since the offsets of the grid sampling locations in PDCNN are derived from the $F_0$ values, the proposed PDCNN is a special case of a deformable CNN. As a deformable CNN with few additional parameters and computations, the PDCNN is implemented with a simple indexing technique without a large extra computational cost. As shown in Table VIII, the average real-time factor (RTF) of the QPPWG_20 inferences is similar to that of PWG_20 and less than that of PWG_30 when running on an Intel Xeon Gold 6142 CPU (2.60 GHz and 32 threads). However, because of the different indexing processes of each CNN kernel, the parallelization of the CNN computation on a GPU is degraded. As shown in Table VIII, although the model size of QPPWG_20 is only 70% of that of PWG_30, the QPPWG_20 model has 170% of the training time and 130% of the inference time of the PWG_30 model when using an Nvidia TITAN V GPU. However, since the RTF of the PWG generation is much less than one, the additional inference time of QPPWG is insignificant.

VII. Conclusion

To improve the pitch controllability of the PWG vocoder, we propose a QPPWG vocoder to introduce the prior pitch information to the network using the QP structure. Using the proposed non-AR PDCNN, the network architecture is dynamically adapted to the input $F_0$ feature of each input sample. Both objective and subjective experimental results show the effectiveness of the QP structure for the PWG vocoder. The QPPWG vocoder outperforms the PWG vocoder in pitch accuracy and speech quality for unseen scaled $F_0$ features while attaining a comparable speech quality to the PWG vocoder for natural $F_0$ features. Because of the more efficient receptive field expansion by PDCNNs, the model size of the QPPWG vocoder is only 70% of that of the PWG vocoder for natural $F_0$ features.
WaveGlow: A flow-based model with higher pitch controllability, smaller model size, and better interpretability and tractability than vanilla PWG.

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