A Fully Time-domain Neural Model for Subband-based Speech Synthesizer

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Abstract

This paper introduces a deep neural network model for subband-based speech synthesizer. The model benefits from the short bandwidth of the subband signals to reduce the complexity of the time-domain speech generator. We employed the multi-level wavelet analysis/synthesis to decompose/reconstruct the signal to subbands in time domain. Inspired from the WaveNet, a convolutional neural network (CNN) model predicts subband speech signals fully in time domain. Due to the short bandwidth of the subbands, a simple network architecture is enough to train the simple patterns of the subbands accurately. In the ground truth experiments with teacher forcing, the subband synthesizer outperforms the fullband model significantly. In addition, by conditioning the model on the phoneme sequence using a pronunciation dictionary, we have achieved the first fully time-domain neural text-to-speech (TTS) system. The generated speech of the subband TTS shows comparable quality as the fullband one with a slighter network architecture for each subband.

1 Introduction

Text-to-speech (TTS) synthesizers have been vital assistants of disabled persons, new language learners, as well as a wide range of human-computer interactions for decades. Researchers have presented various techniques starting from concatenative synthesis [1], [2] to statistical parametric speech synthesis [3]–[5], either based on hidden Markov model (HMM) or deep neural network (DNN), and eventually end-to-end fully neural network based models [6], [7].

Recent speech synthesizers have employed giant neural networks and high configuration GPUs to achieve remarkable success in more natural and fast speech generation. Of such models, WaveNet [8] has achieved the most natural generated speech that significantly closes the gap with human. As a deep generative network, WaveNet directly models the raw audio waveform, which has changed the existing paradigms. The model is applicable for every audio such as speech and music. It made a paradigm to absorb a tremendous amount of attention for sequential modeling [9], speech enhancement [10], [11], and vocoder, which is the wave synthesizer from acoustic features [12]–[15]. Furthermore, the state-of-the-art TTS, Tacotron 2 [16] benefits from the WaveNet as the back-end vocoder for transforming the spectrogram as acoustic features to the waveform.

Thanks to its convolutional structure, WaveNet benefits from parallel computing in train. However, the generation is still a sequential sample-by-sample process. Thus, due to the very high temporal resolution of speech signals (at least 16000 samples per second), the vanilla WaveNet suffers from the long generation time. Therefore, fast [17] and parallel [18] models are introduced. The fast model is an efficient implementation that removes redundant convolutional operations by caching them. While the parallel model utilized a new method, named probability density distillation, which leads to the speech synthesis faster than real-time.

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Table 1: The list of symbols and notations used in this paper

Symbol	Description
$s(t)$	The fullband speech signal ($\hat{s}$ is the estimation)
$s_l(t)$	The l^{th} subband obtained from the l^{th} level of the wavelet transform
c	Conditional features
h	Latent variables
x	Previous clean (generated) subband samples in train (test)
k	The dilation layer index, $k = 1, \ldots, K$

Table 2: Applications of the model with different conditional features

Latent features	Application (if x is speech)
None	Speech-like wave generator
Speaker ID	Speech-like wave generator with the speaker's voice
Acoustic features (like f_0, MFCC)	Vocoder
Linguistic features	Text-to-Speech synthesizer

Unlike the huge network hired in the parallel model, some studies benefit from subband decomposition to reduce the complexity. Previously, a hybrid TTS [19] applied HMM-based and waveform-based synthesis for low and high frequencies, respectively. However, the TTS suffers from the drawbacks of the HMM-based models and the overall performance is not satisfying. In addition, a subband WaveNet vocoder [20] is presented using a frequency filterbank analysis. However, to have a TTS based on the subband vocoder, separate acoustic and linguistic models are required.

Similar to [20], the aim of this research is to break down the WaveNet architecture into smaller networks for each subband of the speech signal. The benefits of the subband model is the reduced computational complexity and the feasibility of training accurately for each subband due to their short bandwidth. In addition, The similar morphological structure of the dilated convolutions in WaveNet and the wavelet transform has inspired us to use the wavelet. Thus, the innovation is utilizing the wavelet analysis to decompose the time-domain speech signal $s(t)$ into subbands $s_l(t)(l = 1, \ldots, L)$. Then, an integrated model generates each subband signal in parallel. The subband signal generator is based on the fast WaveNet [17]. Our wavelet decomposition seems to be more accurate for the reconstruction in time domain compared to the frequency domain filterbank used in [19] and [20].

Even though many recent studies utilized the WaveNet as a vocoder, we believe that converting the spectrogram information to waveform is an inverse spectrogram process and may not necessarily need such a huge architecture. Instead, our hypothesis is that the WaveNet is able to perform some parts of the TTS front stage, as well. In addition, a single integrated model is likely to be more stable than a multi-stage model [6], [21]. Hence, another contribution of this paper is that by simply conditioning the proposed model on the phoneme sequence and benefitting from an encoder, we have achieved the first fully time-domain neural TTS.

Table 1 reports the list of symbols and notations used in this paper. Section 2 describes the proposed subband speech synthesizer. Section 3 explains our experiments and results. Finally, conclusion comes in Section 4.

2 Proposed subband speech synthesizer

The aim of this paper is to reduce the complexity of the time-domain TTS by decomposing the fullband speech signal s into the subbands s_l ($l = 1, ..., L$) using the wavelet analysis. Benefiting from the parallel processing, our designed model estimates the subband signals based on conditional features. Due to the short bandwidth of the subbands, the structure of the subband generator can be much slighter than the fullband one. Our hypothesis is that estimations can be more accurate because subband generators are trained for the localized frequency patterns. When the subband signals are generated according to the corresponding conditional features using the localized TTS, then the wavelet synthesis reconstructs the fullband signal. Details of the wavelet transform is described in Subsection 2.1.

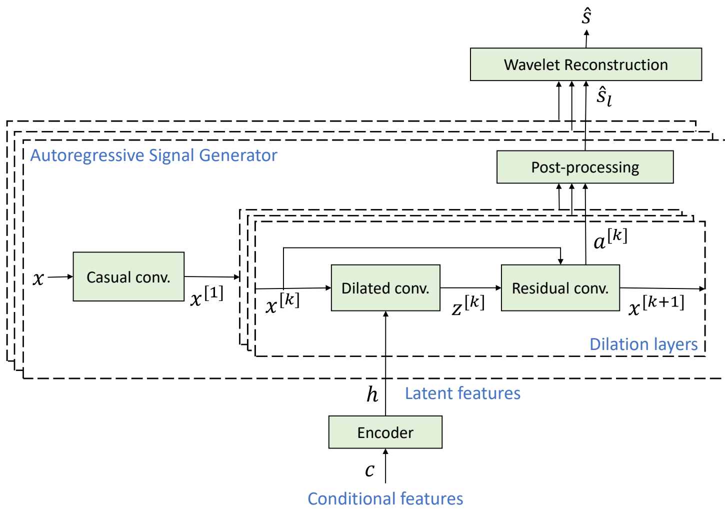

Figure 1: Schematic diagram of the proposed time-domain subband-based speech synthesizer. The model is trained to estimate subband signals s_l conditioning on the latent variable h extracted from c and the previous time samples of the subband signal x. Linguistic and acoustic features can feed to the model as the conditional features for TTS.

Figure 1 depicts the architecture of the proposed subband-based time-domain speech synthesizer. In the designed model, given the conditional features c, an encoder extracts the latent variables h for generating samples conditioning on them (detailed in Subsection 2.2). Table 2 explains applications of the model with different latent features. According to the table, if the conditional features are linguistic features such as character or phoneme sequence, then the latent features would be linguistic features to make the model as a TTS.

The main part of the model is the autoregressive signal generators, shown by the outer dashed blocks in Figure 1. Each generator is in charge of modeling the probability distribution of each subband. The subband generator has similar structure as the WaveNet. Subsection 2.3 explains details of the autoregressive signal generator.

In the training phase, the loss is defined by summation of the subband losses, which is the cross-entropy of the estimated and target subband signal, as

$$loss = -\sum_{l=1}^{L} \mathbb{E}_{p_l}[\log q_l], \tag{1}$$

in which p_l and q_l are the probability distribution of $s_l(t)$ and $\hat{s}_l(t)$, respectively. Since it is a probabilistic model, the generation model estimates the t^{th} sample of each subband by sampling the learned probability distribution.

2.1 Subband decomposition/reconstruction

A set of analysis filters can decompose speech signal $s(t)$ into subbands $s_l(t)$, and their paired synthesis filters are able to reconstruct back the fullband signal. The proposed synthesizer utilizes multi-level orthogonal time-domain wavelet as follows,

$$\begin{cases} u_l(t) = u_{l-1}(t) * \varphi_l(t) \\ s_l(t) = u_{l-1}(t) * \psi_l(t) \end{cases} \tag{2}$$

where $\varphi_l(t)$ and $\psi_l(t)$ are Daubechies scaling (low-pass) and mother wavelet (high-pass) functions [22], respectively. Moreover, $l = 1, \ldots, L$ refers to the wavelet level and $u_0(t) = s(t)$. The downsampling is omitted in every level of the wavelet transform because the downsampling widens the bandwidth, which needs more complex model for training. In addition, it decreases the size of the dataset. Since there is no data like more data for the training, we ignored the downsampling after each layer.

Reasons for selecting the wavelet transform rather than the short time Fourier transform (STFT) filterbank are as follows. First, the wavelet transform is very robust for reconstruction [23]. Corruption of the wavelet coefficients will only affect the reconstructed signal locally near the perturbed position, while the STFT will spread out the error everywhere in time. Second, output of the Fourier analysis filters are complex. Most of the spectrogram-based speech synthesizers ignore modeling the phase spectrogram [6], while the Fourier synthesis filters are sensitive to phase errors. Therefore, compared to the wavelet, the STFT models are unable to reconstruct the phase correctly. Third, the logarithmic spectral resolution of the wavelet are more compatible with the nature of speech compared to the uniform tiling of the spectrogram. Due to the nonlinear bandwidth divisions of the wavelet, high frequencies (e.g. above 4 kHz for 16 kHz sampling rate) fall in one subband. Whereas, there are fine divisions for the low frequencies.

Later in the experiments, we will see the signal-to-noise ratio (SNR) of the consecutive decomposition and reconstruction is about 41 dB, in which the noise is hardly sensible by the human ear.

2.2 Conditional/latent features

A variety of conditional features can be fed to the model. Table 2 gives some examples. Of such features, we use phoneme sequence produced by a text normalization and lexicon to have a TTS model. The phoneme sequence speeds up the training [24]. As shown in Figure 1 by the encoder block, a number of convolutional layers along time axis can extract the linguistic features implicitly. The activation of the last layer, denoted by latent features h, is used for the generators. In fact, the encoder plays the role of the linguistic model for TTS.

2.3 Subband autoregressive signal generator

The subband generator has a similar architecture as the WaveNet. Unlike the WaveNet, our autoregressive signal generator is in charge of generating subband signals. The model estimates the posterior probability of each subband time-sample x_t conditioned on the previous samples, $x_{<t}$ and some latent features h_t as $p(x_t|x_{<t}, h_t)$.

As shown in Figure 1, each generator contains:

- a causal convolution layer as the preprocessing,
- dilation area, which is illustrated by the inner dashed blocks in the figure, and
- post-processing.

As an input of the generator, x refers to the previous clean samples of each subband s_l for training. Similarly, in generation or test phase, x is previously generated samples $\hat{s}_l$. The causal convolution layer is used to make sure that the model does not violate the order and therefore the generation is based on the previous time samples. Later, stacks of K dilation layers in the dilations area perform dilated convolutions, residual connections, and skip connections. Note that the superscripts in Figure 1 show the layer index $(k = 1, \ldots, K)$. Convolutions with holes, as the dilated convolution layers, process the input in a fine to coarse scale with fewer weight parameters in the sufficient receptive field size. However, the residual and skip connection layers help avoiding the gradient vanishing problem. In addition, the output of the skip connection layers $a^{[k]}$ contains various latent feature of the input in different scales.

The morphological structure of the dilated convolutions resemble the wavelet transform. In fact, with a specific set of weights, the first dilation layer can resemble the first level of the wavelet transform. Hence, the first layer mostly models the high frequency features, likewise, the higher dilations for the low frequencies. Thus, a stack of r repeats of $1, 2, 4, \ldots, 2^n$ dilations for modeling the fullband signal could be equivalent to r repeats of one dilation layer for each wavelet subband. Therefore, in our experiments with subband signals, the number of dilation layers K is much smaller than the original fullband WaveNet.

As the last block in each autoregressive subband generator, the post-processing performs two consequent convolutional layers on summation of $a^{[k]}$s, which are activations of the skip connection layers.

Because the signal is represented as one-hot vector, the post-processing ends with a softmax layer to increase the probability of the maximum value compared to others and to have a summation of probabilities equal to one.

3 Experiments

We used the TTS benchmark dataset LJ Speech[1] consisting of 13,100 short audio clips uttered by a female speaker, varying in length from 1 to 10 seconds, recorded in 16kHz sampling rate. We kept around 11 minutes of the speech signals (100 utterances) for test, which was not included in the train. The training set lengths more than 23 hours after the silence removal using voice activity detector (VAD).

3.1 Parameter settings

The subband decomposition is performed by Daubechies wavelet `db10` for eight levels (L=8). Subband amplitude normalization is unavoidable because of the quantization in generator.

We found the Carnegie Mellon university pronouncing dictionary (CMUdict)[2] as a good choice for the lexicon including three levels of stress. The input phoneme sequence has 70 dimensions. The encoder contains three convolutional layers with filter width equals 5 and 256 channels. The HTK[3] aligns the phoneme sequence with the speech samples using forced-alignment. We have replaced the monophone with the triphone sequence but not that much change in results. In addition, we have tried summation of the activations of each layer in encoder as the latent feature but the results were worse.

The dilations of each generator are $1, 2, 4, 8$, and 16. The channel size for dilation, residual, and skip-connection were set to 256. Adam optimizer [25] is used for training with the learning rate initiating from 10^{-3} and decaying every $50k$ iteration by a factor of 0.5.

3.2 Evaluation metrics

The evaluation metrics are signal-to-noise ratio in time domain and logarithmic spectral distortion (SD) which are defined as follows:

$$SNR_{[dB]} = 10log_{10}\frac{\sum_{t=1}^{T} s(t)^2}{\left|\sum_{t=1}^{T} s(t)^2 - \sum_{t=1}^{T} \hat{s}(t)^2\right|} \tag{3}$$

$$SD_{[dB]} = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{1}{F}\sum_{f=1}^{F}\left[20log_{10}\frac{|S(f,t)|}{\left|\hat{S}(f,t)\right|}\right]^2}\,, \tag{4}$$

where $S(f,t)$ and $\hat{S}(f,t)$ are spectrograms of the target signal and the generated signal, respectively. The spectrograms are calculated by 16 ms frame length, 1 ms shift and Hanning window. In addition, because the human auditory perception is based on the Mel spectrogram representation, we considered Mel spectral distortion (MSD) as the third quantitative metric for the objective evaluation. The MSD is calculated similar to the SD, replacing the linear spectrogram with the 40-filters Mel spectrogram, which is obtained by 25 ms window length, and 5 ms shift. In addition, we calculated the SNR in the linear spectrogram domain. We did not mention the spectrogram SNR results because with two digits precision they are the same as the time domain ones.

The generation is time consuming in the proposed model because the speech is synthesized sample-by-sample and sequentially. Therefore, in addition to the above-mentioned metrics, we have measured the training and the synthesis time. The next subsection will explain results and discussions.

[1]https://keithito.com/LJ-Speech-Dataset/

[2]http://www.speech.cs.cmu.edu/cgi-bin/cmudict

[3]http://htk.eng.cam.ac.uk/

Table 3: Evaluation results (mean $\pm$ 95% CI) for 100 test set utterances

		SNR [dB]	SD [dB]	MSD [dB]
Decomposition-Reconstruction		41.5 ± 1.14	0.61 ± 0.01	$0.08 \pm .002$
Ground truth	Subband ($K = 5$)	**23.5 ± 0.31**	**4.3 ± 0.02**	**2.5 ± 0.01**
	Fullband ($K = 24$)	18.8 ± 0.47	8.1 ± 0.03	5.5 ± 0.04
Synthesis	Subband ($K = 5$)	4.0 ± 0.88	**13.3 ± 0.01**	**10.0 ± 0.10**
	Fullband ($K = 24$)	**5.2 ± 0.93**	15.2 ± 0.10	11.8 ± 0.11

Table 4: Average required time (minutes) for Generating 1 second of speech

		Subband	
CPU configuration	Fullband	sequential	parallel
Intel(R) Core(TM) i7, 2.93 GHz, 8 cores	1.67	6.8	2.08
Intel(R) Xeon(R),2.4 GHz, 32 cores	2.09	5.36	1.87

3.3 Results and discussions

First experiment investigated the effect of the wavelet analysis/synthesis on the quality of speech without engaging any neural network model. The average results on 100 test set utterances with 95% confidence interval are reported in the first row of Table 3 as the extreme case for evaluations. For SNR, higher value shows more accurate model; whereas for both SD and MSD lower value means better performance. As shown in Table 3, the subband decomposition/reconstruction results provides near perfect performance.

Moreover, we compared the subband with the fullband speech synthesizer. The fullband term means that the model prediction $\hat{s}$ is the speech signal in its full frequency range. Hence, there is no subband decomposition. Therefore, one complex signal generator models the probability distribution. Basically, the two models are exactly the same, except in the fullband TTS, $K = 24$ dilation layers are defined with 4 stacks of $1, 2, 4, \ldots, 32$ dilations in our experiments; while in the subband TTS, the number of dilation layers is much lower than the fullband ($K = 5$). Fast WaveNet algorithm [17] is utilized for the synthesis of both models. We have examined the fullband model without the encoder, which is in fact the original WaveNet conditioning on phoneme sequence; but the results were worse since the features were not enough for the training.

We compare the two models by conditioning on the phoneme sequence as the conditional features in two cases: *ground truth* and *synthesis*. The ground truth means feeding the previous clean samples to the model and evaluating the accuracy of the prediction of the next sample. As depicted in Table 3, the subband model performs significantly better than the fullband one in ground truth. For synthesis, the results are somehow comparable. In fact, the results of synthesis are not satisfying for both subband and fullband models, which is probably due to the lack of acoustical conditioning features.

Table 4 reports the average required time for synthesizing one second of speech in terms of minutes on two different machines with 8 and 32 cores. The required time of the subband TTS is reported in two cases: *sequential* and *parallel*. For the earlier experiment, the speech signal is decomposed into subband signals; and they are kept in the original sampling rate, which is 16 kHz. Thus, the samples are *redundant*. Obviously, without parallelization, the synthesis time of the redundant samples should be 8 times more than the fullband because there are 8 subband signals in the experiments. Nevertheless, since the complexity of the signal generators in the subband model is less than the fullband one, it is 4 and 2.5 times slower for the first and the second machine, respectively. For the last experiment, the subband signals are downsampled by a factor of 2. Hence, the subband signals are not redundant any more. Even though the parallelization and the downsampling speed up the synthesis, but it is still not that much far from the fullband model.

Both models need less than a day (around 18 hours) for training up to an admissible output quality on a Titan X GPU. Such a fast training is because of their fully CNN architecture, which is much better than the RNN-based TTS, e.g. Tacotron [6]. It is reported that an implementation of the Tacotron takes 12 days (877K iterations) on a GTX 1080 Ti[4] . Note that the number of iterations is still much less than the original Tacotron reported by Google (2M iterations) [6].

4 Conclusion

We proposed a subband time-domain TTS system inspiring from the WaveNet. The main differences of our TTS with the WaveNet are twofold: first, rather than a complex deep neural network for modeling the probability distribution of the speech signal, we designed separate (but integrated) networks for each subband signal, which has much simple architecture and could estimate the probability distributions of the subband signals accurately. Second, the original WaveNet TTS benefits from pre-trained linguistic and acoustic feature extraction models; while an encoder in our system extracts the latent features from the phoneme sequence input in a nearly end-to-end way, which is more preferred.

The force alignment should be replaced by an attention mechanism for automatic aligning to have a fully end-to-end model. Still enriching the conditional features by acoustic features beside the current linguistic features is unavoidable. As another future work, we are trying to utilize the current dilated architecture to extract acoustic features in a top-down way to improve the quality of both fullband and subband models.

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