Singing voice synthesis based on convolutional neural networks

Kazuhiro Nakamura\textsuperscript{1}, Kei Hashimoto\textsuperscript{1,2}, Keiichiro Oura\textsuperscript{1,2}, Yoshihiko Nankaku\textsuperscript{2}, and Keiichi Tokuda\textsuperscript{1,2}

\textsuperscript{1}Department of Research and Development, Techno-Speech, Inc., Nagoya, Japan
\textsuperscript{2}Department of Computer Science, Nagoya Institute of Technology, Nagoya, Japan

nkazu@techno-speech.com, bonanza, uratec, nankaku, tokuda@sp.nitech.ac.jp

Abstract

The present paper describes a singing voice synthesis based on convolutional neural networks (CNNs). Singing voice synthesis systems based on deep neural networks (DNNs) are currently being proposed and are improving the naturalness of synthesized singing voices. In these systems, the relationship between musical score feature sequences and acoustic feature sequences extracted from singing voices is modeled by DNNs. Then, an acoustic feature sequence of an arbitrary musical score is output in units of frames by the trained DNNs, and a natural trajectory of a singing voice is obtained by using a parameter generation algorithm. As singing voices contain rich expression, a powerful technique to model them accurately is required. In the proposed technique, long-term dependencies of singing voices are modeled by CNNs. An acoustic feature sequence is generated in units of segments that consist of long-term frames, and a natural trajectory is obtained without the parameter generation algorithm. Experimental results in a subjective listening test show that the proposed architecture can synthesize natural sounding singing voices.

Index Terms: Singing voice synthesis, statistical model, acoustic modeling, convolutional neural network

1. Introduction

Deep neural networks (DNNs), which are artificial neural networks with many hidden layers, are attaining significant improvement in various speech processing areas, e.g., speech recognition [1], speech synthesis [2, 3] and singing voice synthesis [4]. In DNN-based singing voice synthesis, a DNN works as an acoustic model that represents a mapping function from musical score feature sequences (e.g., phonetic, note key, and note length feature) to acoustic feature sequences (e.g., spectrum, excitation, and vibrato). DNN-based acoustic models can represent complex dependencies between musical score feature sequences and acoustic feature sequences more efficiently than hidden Markov model (HMM)-based acoustic models [5]. Neural networks that can model audio waveforms directly, e.g., WaveNet [6], SampleRNN [7], WaveRNN [8], FFTNet [9], and WaveGlow [10], are currently being proposed. Such neural networks are used as vocoders in the speech field and improve the quality of synthesized speech compared to conventional vocoders [11]. The neural vocoders use acoustic features as inputs. Therefore, accurately predicting acoustic feature sequences from musical score feature sequences by acoustic models is still an important issue for generating high-quality speech or singing voices.

One limitation of the feed-forward DNN-based acoustic modeling [2] is that the sequential nature of speech is not considered. Although there are certainly correlations between consecutive frames in speech data, the feed-forward DNN-based approach assumes that each frame is generated independently. As a solution, recurrent neural networks (RNNs) [12], especially long short-term memory (LSTM)-RNNs [13], provide an elegant way to model speech-like sequential data that embodies short and long-term correlations. Furthermore, this problem can be relaxed by smoothing predicted acoustic features using the speech parameter generation algorithm [14], which utilizes dynamic features as constraints to generate smooth speech parameter trajectories. On the other hand, some techniques to incorporate the sequential nature of speech data into an acoustic model itself have been proposed [15, 16].

This paper proposes an architecture that converts musical score feature sequences to acoustic feature sequences in units of segments by using convolutional neural networks (CNNs). The proposed approach can capture long-term dependencies of singing voices and can generate natural trajectories without the speech parameter generation algorithm [14]. Furthermore, parallel computation can be applied easily, i.e., the training of CNNs and the generation of acoustic features are fast, because there is no recurrent structure in this architecture.

The rest of this paper is organized as follows. Section 2 gives an overview of the CNN-based singing voice synthesis system. Related work is described in Section 3. Details of the proposed CNN-based singing voice synthesis architecture are described in Section 4. Experimental results in subjective evaluation are given in Section 5. The key points are summarized, and future work is mentioned in Section 6.

2. CNN-based singing voice synthesis

A DNN-based singing voice synthesis system is quite similar to a DNN-based text-to-speech synthesis system [2]. However, there are distinct differences. Figure 1 gives an overview of the DNN-based singing voice synthesis system [4, 17]. It consists of training and synthesis parts. In the training part, spectrum (e.g., mel-cepstral coefficients), excitation, and vibrato parameters are extracted from a singing voice database as acoustic features. Then, musical score feature sequences and acoustic feature sequences are time-aligned by well-trained HMMs, and the mapping between them is modeled by DNNs. In the synthesis part, an arbitrarily given musical score including lyrics to be synthesized is first converted into a musical score feature sequence, and it is mapped to an acoustic feature sequence by the trained DNNs. Next, the speech parameters (spectrum, excitation, and vibrato) are generated by a maximum likelihood parameter generation (MLPG) algorithm [14]. It is shown that the quality of the generated speech was improved by considering the explicit relationship between static and dynamic features [18]. Finally, a singing voice is synthesized from the generated parameters by using a vocoder based on a mel log spectrum approximation (MLSA) filter [19].
Rhythm and tempo of music are important factors in singing voice synthesis. In a human singing voice, there are differences between the start timing of the notes and the singing voices. The start timing of the synthetic singing voice is often earlier than that of a corresponding note. In order to predict such differences, time-lag models are introduced [17]. The naturalness of the synthesized singing voice is improved by accurately predicting the time-lag, i.e., the start timing and durations of the singing voices.

Vibrato is one of the important singing techniques that should be modeled, even though it is not included in the musical score. Vibrato has been assumed as periodic fluctuations of only $F_0$ for the sake of simplicity, and it is modeled by sinusoid [20]. The vibrato $v(t)$ of the $t$ frame in the $i$-th vibrato section $[i^{(s)}, i^{(s+1)}]$ can be defined as

$$v(m_a(t), m_f(t), f_s) = m_a(t) \sin \left(2\pi m_f(t) f_s (t - t^{(s)})\right), \quad (1)$$

where $m_a(t)$, $m_f(t)$, and $f_s$ correspond to the $F_0$ amplitude of vibrato in cents, the $F_0$ frequency of vibrato in Hz, and the frame shift, respectively. Two dimensional parameters, $m_a(t)$ and $m_f(t)$, are added to the acoustic feature vector.

The performance of statistical parametric approaches for singing voice synthesis heavily depends on the training data because these approaches are “corpus-based.” It is difficult to express contextual factors that barely ever appear in the training data. Databases including various contextual factors should be used in DNN-based singing voice synthesis systems, whereas it is almost impossible to cover all possible contextual factors because singing voices involve a huge number of them, e.g., keys, lyrics, dynamics, note positions, durations, and pitch. Among them, pitch should be correctly covered because generated $F_0$ trajectories greatly affect the quality of the synthesized singing voices. To address this problem, a musical-note-level pitch normalization technique has been proposed for DNN-based singing voice synthesis systems [4]. In this technique, the differences between the log $F_0$ sequences extracted from waveforms and the pitch of musical notes are modeled. This technique makes it possible for DNN-based singing voice synthesis systems to generate various singing voices including arbitrary pitch. Another problem for modeling differences in log $F_0$ is how to model log $F_0$ of singing voices including unvoiced frames and musical scores including rests. In [4], all unvoiced frames and musical rests in musical scores are linearly interpolated and modeled as voiced frames.

3. Related work

3.1. Modeling long-term dependencies of speech

The simplest way to apply neural networks to statistical parametric speech synthesis (SPSS) [21] is to use a feed-forward neural network (FFNN) [2] as a deep regression model to map linguistic features directly to acoustic features. One limitation of this architecture is that the mapping between linguistic and acoustic features is one-to-one. RNNs [12] provide an elegant way to model speech-like sequential data that embody correlations between neighboring frames. That is, previous input features can be used to predict output features at each frame. LSTM-RNNs [13], which can capture long-term dependencies, have been applied to acoustic modeling for SPSS. Fan et al. and Fernandez et al. applied deep bidirectional LSTM-RNNs, which can access input features at both past and future frames, to acoustic modeling for SPSS and reported improved naturalness [22, 23]. Trajectory training is another approach for capturing long-term dependencies of speech. In DNN-based systems, although the frame-level objective function is usually used for DNN training, the sequence-level objective function is used for parameter generation. To address this inconsistency between training and synthesis, a trajectory training method was introduced into the training process of DNNs [24]. It was also applied to a singing voice synthesis framework [17].

The RNN-based systems have the problem of taking time since parallelizing model training and parameter generation is difficult. And the trajectory training method has the problem that the computational cost increases significantly as the sequence length increases.

3.2. Acoustic model considering sequential nature of speech

One limitation of the DNN-based acoustic modeling is that the sequential nature of speech is not expressed enough. Although this problem can be relaxed by smoothing predicted acoustic features using the speech parameter generation algorithm [14], which utilizes dynamic features as constraints to generate smooth trajectories. However, it is desirable to incorporate the sequential nature of speech data into the acoustic model itself. Fan et al. claimed that deep bidirectional LSTM-RNNs can generate smooth speech parameter trajectories; thus, no smoothing step was required, whereas Zen et al. reported that having the smoothing step was still helpful with unidirectional LSTM-RNNs [2].

As many text-to-speech (TTS) applications require fast and low-latency speech synthesis, an existing problem is the high-latency that the MLPG algorithm brings during generation. An efficient way to remove this problem is not to use the dynamic features during modeling. Zen et al. proposed a recurrent output layer [15], and Wang et al. proposed a convolutional output layer [16] to achieve smooth transitions between consecutive frames, and accordingly, the MLPG is replaced. They were used with unidirectional LSTM to achieve both natural sounding speech and low-latency speech synthesis.
4. CNN-based singing voice synthesis

4.1. CNN-based architecture for capturing long-term dependencies of singing voice

In the proposed method, the relatively long musical score feature sequence, equivalent to several seconds to tens of seconds, is regarded as a segment and converted to the acoustic feature sequence by CNNs at the same time. The overview of the proposed method is shown in Figure 2. The first part consists of $1 \times 1$ convolutional layers that convert the musical score feature sequence frame-by-frame. The dropout technique is used to keep the robustness against the unknown musical scores. The second part consists of $1 \times n$ convolutional layers, and the intermediate output feature sequence of the first part is converted to the acoustic feature sequence in units of segments. The dimension of the acoustic features is represented as the number of channels of the output features. The size of the segment is $1 \times T$, and $T$ means the number of frames of each segment. Since a fully convolutional network (FCN) [25] is used as the CNN structure, the segment size $T$ is adjustable. These parts are integrated and trained simultaneously.

The relationship between a musical score feature vector sequence $s = [s_1, s_2, \ldots, s_T]^\top$, and an acoustic feature vector sequence $c = [c_1, c_2, \ldots, c_T]^\top$ is represented as follows

$$c = G([F(s_1)^\top, F(s_2)^\top, \ldots, F(s_T)^\top]^\top),$$

where $F(\cdot)$ is a frame-by-frame mapping function in the first part, and $G(\cdot)$ is a segment-by-segment mapping function in the second part.

As the pitch of musical notes greatly affects the synthesized singing voices, we concatenate them with the output features from the first part of the proposed CNNs and use them as the input of the second part. In particular, the alignment of notes is adjusted to the recorded singing voices, and log $F_0$ parameters from musical notes are concatenated. The musical rests in musical scores are interpolated linearly. The effectiveness of the use of log $F_0$ parameters extracted from the interpolated musical scores was confirmed in the preliminary subjective experiment.

4.2. Loss function for obtaining smooth parameter sequence without parameter generation algorithm

In the proposed method, a loss function based on the likelihood of $o_t$ is used to obtain smooth parameter sequences. A parameter vector $o_t$ of a singing voice consists of a $D$-dimensional static feature vector $c_t = [c_t(1), c_t(2), \ldots, c_t(D)]^\top$ and their dynamic feature vectors $\Delta^{(1)}c_t, \Delta^{(2)}c_t$.

$$o_t = [c_t^\top, \Delta^{(1)}c_t^\top, \Delta^{(2)}c_t^\top]^\top$$

The sequences of the singing voice parameter vectors and the static feature vectors can be written in vector forms as follows

$$o = [o_1^\top, \ldots, o_t^\top, \ldots, o_T^\top]^\top,$$

$$c = [c_1^\top, c_2^\top, \ldots, c_T^\top]^\top,$$

where $T$ is the number of frames. The relation between $o$ and $c$ can be represented by $o = Wc$, where $W$ is a window matrix extending the static feature vector sequence $c$ to the singing voice parameter vector sequence $o$ (Fig. 3).

In the training part, an objective function is defined as

$$L = \mathcal{N}(\hat{o} | o, \Sigma),$$

where $\hat{o}$ is represented by $\hat{o} = Wc$, where $c$ is the static feature vector sequence of the recorded singing voice. $\Sigma$ is a globally tied covariance matrix given by

$$\Sigma = \text{diag}(|\Sigma_1|, \ldots, |\Sigma_t|, \ldots, |\Sigma_T|)$$

and is updated during the training.

The proposed method can generate a natural trajectory without the parameter generation algorithm by considering not only static features but also dynamic features in the training part of the CNNs.

5. Experiments

5.1. Experimental conditions

To evaluate the effectiveness of the proposed method, a subjective comparison test of mean opinion scores (MOS) was conducted. For training, 55 Japanese children’s songs and 55 J-POP
songs by a female singer were used, and 5 other J-POP songs were used for the test. Singing voice signals were sampled at 48 kHz and windowed with a 5-ms shift. The number of quantization bits was 16. The feature vectors consisted of 0-th through 49-th STRAIGHT [26] mel-cepstral coefficients, log $F_0$ values, 22-dimensions aperiodicity measures, and 2-dimensions vibrato parameters. The vibrato parameter vectors consisted of amplitude (cent) and frequency (Hz). The areas that do not have a value were interpolated linearly for log $F_0$ and vibrato parameters, and with/without value flags were added to feature vectors. The input features including 724 binary features for categorical contexts (e.g., the current phoneme identity and the key of the current measure) and 122 numerical features for numerical contexts (e.g., the number of phonemes in the current syllable and the absolute pitch of the current musical note) were used. Both input and output features in the training data for the DNNs were normalized; the input features were normalized to be within 0.00–1.00, and the output features were normalized to be within 0.01–0.99 on the basis of their minimum and maximum values in the training data.

Five-state, left-to-right, no-skip hidden semi-Markov models (HMMs) were used to obtain the time alignment of acoustic features in state for training the DNN-based acoustic models. And the state duration was predicted by FFNNs trained from the time alignment of training data.

The FFNN-based singing voice synthesis was used as the conventional method. The conventional system had 3 layers with 2048 units, and dropout with probability 0.2 was used. The acoustic features and their dynamic features (delta and delta-delta) were output, and the MLPG algorithm was used to obtain the smooth feature sequences. In the proposed system, the first part had the same structure as the conventional system. The second part had 2 layers for down-sampling, 9 layers that have residual structure, and 2 layers for up-sampling. The data were separated into segments of 2000 frames and used for training and generation, and 100 adjacent frames were cross-faded in the generation step. In both systems, the ReLU activation function was used for hidden layers, and the sigmoid one was used for the output layer.

A MLSA-based vocoder [19] and a WaveNet vocoder were used for conversion from acoustic feature sequences to singing voice waveforms. The singing voice signals to train WaveNet were sampled at 48 kHz and quantized from 16 bits to 8 bits by using the $\mu$-law quantizer [27]. Mel-cepstrum-based noise shaping and prefiltering were applied to the quantization step [28]. The parameters for adjusting the intensity in the noise shaping and prefiltering were set as $\gamma = 0.4\beta = 0.2$. The dilations of the WaveNet model were set to 1, 2, 4, 512. Ten dilation layers were stacked three times. The sizes of the channels for dilations, residual blocks, and skip-connections were 256, 512, and 256, respectively.

5.2. Experimental results
The 5-points MOS evaluation (5: natural – 1: poor) for the naturalness was conducted. Fifteen subjects evaluated ten phrases randomly selected from the test data.

Figure 4 shows the results of the MOS evaluation. FFNN+V and FFNN+W represent conventional systems, and CNN+V and CNN+W represent proposed systems. V and W mean MLSA-based vocoder and WaveNet vocoder, respectively.

The CNN-based proposed systems (CNN+V and CNN+W) outperformed the FFNN-based conventional systems (FFNN+V and FFNN+W) as shown in Figure 4. These results indicate that the naturalness of the synthesized singing voice is drastically improved by modeling the time-dependent variation by CNNs. And the WaveNet vocoder (FFNN+W and CNN+W) showed a better score than the MLSA-based vocoder (FFNN+V and CNN+V), respectively.

6. Conclusions
In this paper, a CNN-based acoustic modeling technique has been proposed for singing voice synthesis. Long-term dependencies of singing voices that contain rich expressions were modeled by CNNs. Musical score feature sequences from musical scores were converted to acoustic feature sequences in units of segments, and natural speech parameter trajectories were obtained without the conventional speech parameter generation algorithm. Furthermore, parallel computation can be applied easily because there is no recurrent structure in the proposed architecture. Experimental results show that the proposed system gives more natural synthesized singing voices. Future work includes correcting out-of-tone utterances in singing voices by using prior distribution of tone, evaluations of the proposed architecture on TTS, and parameter tuning for practical use.

7. References
[1] G. Hinton, L. Deng, D. Yu, G. E. Dahl, A. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. N. Sainath et al., “Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups,” IEEE Signal Processing Magazine, vol. 29, no. 6, pp. 82–97, 2012.
[2] H. Zen, A. Senior, and M. Schuster, “Statistical parametric speech synthesis using deep neural networks,” Proceedings of ICASSP, pp. 7962–7966, 2013.
[3] Y. Qian, Y. Fan, W. Hu, and F. K. Soong, “On the training aspects of deep neural network (DNN) for parametric TTS synthesis,” Proceedings of ICASSP, pp. 3829–3833, 2014.
[4] M. Nishimura, K. Hashimoto, K. Oura, Y. Nankaku, and K. Tokuda, “Singing voice synthesis based on deep neural networks,” Proceedings of Interspeech, pp. 2478–2482, 2016.
[5] O. Watts, G. E. Henter, T. Merritt, Z. Wu, and S. King, “From HMMs to DNNs: where do the improvements come from?” Proceedings of ICASSP, pp. 5505–5509, 2016.
[6] A. van den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. W. Senior, and K. Kavukcuoglu, “WaveNet: A generative model for raw audio,” CoRR, vol. abs/1609.03499, 2016.
[7] 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,” *arXiv preprint arXiv:1612.07837*, 2016.

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

[9] Z. Jin, A. Finkelstein, G. J. Mysore, and J. Lu, “FFTnet: A real-time speaker-dependent neural vocoder,” *Proceedings of ICASSP*, pp. 2251–2255, 2018.

[10] R. Prenger, R. Valle, and B. Catanzaro, “WaveGlow: A flow-based generative network for speech synthesis,” *arXiv preprint arXiv:1811.00002v1*, 2018.

[11] A. Tamamori, T. Hayashi, K. Kovayashi, K. Takeda, and T. Toda, “Speaker-dependent WaveNet vocoder,” *Proceedings of ICASSP*, pp. 1118–1122, 2017.

[12] A. Robinson and F. Fallside, “Static and dynamic error propagation networks with application to speech coding,” *Proceedings of NIPS*, pp. 632–641, 1988.

[13] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, pp. 1735–1780, 1997.

[14] K. Tokuda, T. Yoshimura, T. Masuko, T. Kobayashi, and T. Katamura, “Speech parameter generation algorithms for HMM-based speech synthesis,” *Proceedings of ICASSP*, vol. 3, pp. 1315–1318, 2000.

[15] H. Zen and H. Sak, “Unidirectional long short-term memory recurrent neural network with recurrent output layer for low-latency speech synthesis,” *Proceedings of ICASSP*, pp. 4470–4474, 2015.

[16] W. Wang and B. Xu, “Combining unidirectional long short-term memory with convolutional output layer for high-performance speech synthesis,” *Proceedings of ICASSP*, pp. 5500–5504, 2017.

[17] Y. Hono, S. Murata, K. Nakamura, K. Hashimoto, K. Oura, Y. Nankaku, and K. Tokuda, “Recent development of the DNN-based singing voice synthesis system - Sinsy,” *Proceedings of AP-SIPA ASC*, pp. 1003–1009, 2018.

[18] K. Hashimoto, K. Oura, Y. Nankaku, and K. Tokuda, “The effect of neural networks in statistical parametric speech synthesis,” *Proceedings of ICASSP*, pp. 4455–4459, 2015.

[19] S. Imai, K. Sumita, and C. Furuichi, “Mel log spectral approximation filter for speech synthesis,” *IECE Translations on Fundamentals (Japanese Edition)*, vol. J66-A, pp. 122–129, 1983.

[20] T. Yamada, S. Muto, Y. Nankaku, S. Sako, and K. Tokuda, “Vibrato modeling for HMM-based singing voice synthesis,” *Proceedings of Information Processing Society of Japan*, vol. 2009-NUS-80, no. 5, pp. 1–6, 2009.

[21] H. Zen, K. Tokuda, and A. W. Black, “Statistical parametric speech synthesis,” *Speech Communication*, vol. 51, no. 11, pp. 1039–1064, 2009.

[22] Y. Fan, Y. Qian, F. Xie, and F. K. Soong, “TTS synthesis with bidirectional LSTM based recurrent neural networks,” *Proceeding of Interspeech*, pp. 964–1968, 2014.

[23] R. Fernandez, A. Rendel, B. Ramabhadren, and R. Hoory, “Prosody contour prediction with long short-term memory, bidirectional, deep recurrent neural networks,” *Proceedings of Interspeech*, pp. 2268–2272, 2014.

[24] K. Hashimoto, K. Oura, Y. Nankaku, and K. Tokuda, “Trajectory training considering global variance for speech synthesis based on neural networks,” *Proceedings of ICASSP*, pp. 5600–5604, 2016.

[25] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” *Proceedings of CVPR*, pp. 3431–3440, 2015.

[26] H. Kawahara, M. K. Bayo, and A. Cheveigne, “Restructuring speech representations using the pitch-adaptive time-frequency smoothing and an instantaneous-frequency-based f0 extraction: Possible role of a repetitive structure in sounds,” *Speech Communication*, vol. 27, no. 3, pp. 187–207, 1999.