EFFICIENTLY TRAINABLE TEXT-TO-SPEECH SYSTEM BASED ON DEEP CONVOLUTIONAL NETWORKS WITH GUIDED ATTENTION

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ABSTRACT

This paper describes a novel text-to-speech (TTS) technique based on deep convolutional neural networks (CNN), without any recurrent units. Recurrent neural network (RNN) has been a standard technique to model sequential data recently, and this technique has been used in some cutting-edge neural TTS techniques. However, training RNN component often requires a very powerful computer, or very long time typically several days or weeks. Recent other studies, on the other hand, have shown that CNN-based sequence synthesis can be much faster than RNN-based techniques, because of high parallelizability. The objective of this paper is to show an alternative neural TTS system, based only on CNN, that can alleviate these economic costs of training. In our experiment, the proposed Deep Convolutional TTS can be sufficiently trained only in a night (15 hours), using an ordinary gaming PC equipped with two GPUs, while the quality of the synthesized speech was almost acceptable.

Index Terms— Text-to-speech, deep learning, convolutional neural network, attention, sequence-to-sequence learning.

1. INTRODUCTION

Text-to-speech (TTS) is getting more and more common recently, and is getting to be a basic user interface for many systems. To encourage further use of TTS in various systems, it is significant to develop a handy, maintainable, extensible TTS component that is accessible to speech non-specialists, enterprising individuals and small teams who do not have massive computers.

Traditional TTS systems, however, are not necessarily friendly for them, as these systems are typically composed of many domain-specific modules. For example, a typical parametric TTS system is an elaborate integration of many modules e.g. a text analyzer, an F_0 generator, a spectrum generator, a pause estimator, and a vocoder that synthesize a waveform from these data, etc.

Deep learning [1] sometimes can unite these internal building blocks into a single model, and directly connects the input and the output; this type of technique is sometimes called 'end-to-end' learning. Although such a technique is sometimes criticized as 'a black box,' nevertheless, an end-to-end TTS system named Tacotron [2], which directly estimates a spectrogram from an input text, has achieved promising performance recently, without intensively-engineered parametric models based on domain-specific knowledge. Tacotron, however, has a drawback that it exploits many recurrent units, which are quite costly to train, making it almost infeasible for ordinary labs without luxurious machines to study and extend it further. Indeed, some people tried to implement open

clones of Tacotron [3, 4, 5, 6], but they are struggling to reproduce the speech of satisfactory quality as clear as the original work.

The purpose of this paper is to show Deep Convolutional TTS (DCTTS), a novel, handy neural TTS, which is fully convolutional. The architecture is largely similar to Tacotron [2], but is based on a fully convolutional sequence-to-sequence learning model similar to the literature [7]. We show this handy TTS actually works in a reasonable setting. The contribution of this article is twofold: (1) Propose a fully CNN-based TTS system which can be trained much faster than an RNN-based state-of-the-art neural TTS system, while the sound quality is still acceptable. (2) An idea to rapidly train the attention, which we call 'guided attention,' is also shown.

1.1. Related Work

1.1.1. *Deep Learning and TTS*

Recently, deep learning-based TTS systems have been intensively studied, and some of recent studies are achieving surprisingly clear results. The TTS systems based on deep neural networks include Zen's work in 2013 [8], the studies based on RNN e.g. [9, 10, 11, 12], and recently proposed techniques e.g. WaveNet [13, sec. 3.2], Char2Wav [14], DeepVoice1&2 [15, 16], and Tacotron [2].

Some of them tried to reduce the dependency on hand-engineered internal modules. The most extreme technique in this trend would be Tacotron [2], which depends only on mel and linear spectrograms, and not on any other speech features e.g. F_0. Our method is close to Tacotron in a sense that it depends only on these spectral representations of audio signals.

Most of the existing methods above use RNN, a natural technique for time series prediction. An exception is WaveNet, which is fully convolutional. Our method is also based only on CNN but our usage of CNN would be different from WaveNet, as WaveNet is a kind of a vocoder, or a back-end, which synthesizes a waveform from some conditioning information that is given by front-end components. On the other hand, ours is rather a front-end (and most of back-end processing). We use CNN to synthesize a spectrogram, from which a simple vocoder can synthesize a waveform.

1.1.2. *Sequence to Sequence (seq2seq) Learning*

Recently, recurrent neural network (RNN) has been a standard technique to map a sequence into another sequence, especially in the field of natural language processing, e.g. machine translation [17, 18], dialogue system [19, 20], etc. See also [1, sec. 10.4].

RNN-based seq2seq, however, has some disadvantages. One is that a vanilla encode-decoder model cannot encode too long sequence into a fixed-length vector effectively. This problem has been

resolved by a mechanism called 'attention' [21], and the attention mechanism now has become a standard idea in seq2seq learning techniques; see also [1, sec. 12.4.5.1].

Another problem is that RNN typically requires much time to train, since it is less suitable for parallel computation using GPUs. In order to overcome this problem, several people proposed the use of CNN, instead of RNN, e.g. [22, 23, 24, 25, 26]. Some studies have shown that CNN-based alternative networks can be trained much faster, and can even outperform the RNN-based techniques.

Gehring et al. [7] recently united these two improvements of seq2seq learning. They proposed an idea how to use attention mechanism in a CNN-based seq2seq learning model, and showed that the method is quite effective for machine translation. Our proposed method, indeed, is based on the similar idea to the literature [7].

2. PRELIMINARY

2.1. Basic Knowledge of the Audio Spectrograms

An audio waveform can be mutually converted to a complex spectrogram $Z = \{Z_{f,t}\} \in \mathbb{C}^{F' \times T'}$ by linear maps called STFT and inverse STFT, where F' and T' denote the number of frequency bins and temporal bins, respectively. It is common to consider only the magnitude $|Z| = \{|Z_{f,t}|\}$, since it still has useful information for many purposes, and that $|Z|$ is almost identical to Z in a sense that there exist many phase estimation ($\sim$ waveform synthesis) techniques from magnitude spectrograms, e.g. the famous Griffin&Lim algorithm [27]; see also e.g. [28]. We always use RTISI-LA [29], an online G&L, to synthesize a waveform. In this paper, we always normalize STFT spectrograms as $|Z| \leftarrow (|Z|/\max(|Z|))^\gamma$, and convert back $|Z| \leftarrow |Z|^{\eta/\gamma}$ when we finally need to synthesize the waveform, where γ, η are pre- and post-emphasis factors.

It is also common to consider a mel spectrogram $S \in \mathbb{R}^{F \times T'}$, ($F \ll F'$), by applying a mel filter-bank to $|Z|$. This is a standard dimension reduction technique in speech processing. In this paper, we also reduce the temporal dimensionality from T' to $\lceil T'/4 \rceil =: T$ by picking up a time frame every four time frames, to accelerate the training of Text2Mel shown below. We also normalize mel spectrograms as $S \leftarrow (S/\max(S))^\gamma$.

2.2. Notation: Convolution and Highway Activation

In this paper, we denote 1D convolution layer [30] by a space saving notation $\mathsf{C}_{k\star\delta}^{o\leftarrow i}(X)$, where i is the sizes of input channel, o is the sizes of output channel, k is the size of kernel, δ is the dilation factor, and an argument X is a tensor having three dimensions (*batch, channel, temporal*). The stride of convolution is always 1. Convolution layers are preceded by appropriately-sized zero padding, whose size is suitably determined by a simple arithmetic so that the length of the sequence is kept constant. Let us also denote the 1D *deconvolution* layer as $\mathsf{D}_{k\star\delta}^{o\leftarrow i}(X)$. The stride of deconvolution is always 2 in this paper. Let us write a layer composition operator as $\cdot \lhd \cdot$, and let us write networks like $\mathsf{F} \lhd \mathsf{ReLU} \lhd \mathsf{G}(X) := \mathsf{F}(\mathsf{ReLU}(\mathsf{G}(X)))$, and $(\mathsf{F} \lhd \mathsf{G})^2(X) := \mathsf{F} \lhd \mathsf{G} \lhd \mathsf{F} \lhd \mathsf{G}(X)$, etc. ReLU is an element-wise activation function defined by $\mathsf{ReLU}(x) = \max(x, 0)$.

Convolution layers are sometimes followed by a Highway Network [31]-like gated activation, which is advantageous in very deep networks: $\mathsf{Highway}(X; \mathsf{L}) = \sigma(H_1) \odot H_2 + (1 - \sigma(H_1)) \odot X$, where H_1, H_2 are properly-sized two matrices, output by a layer L as $[H_1, H_2] = \mathsf{L}(X)$. The operator $\odot$ is the element-wise multiplication, and σ is the element-wise sigmoid function. Hereafter let us denote $\mathsf{HC}_{k\star\delta}^{d\leftarrow d}(X) := \mathsf{Highway}(X; \mathsf{C}_{k\star\delta}^{2d\leftarrow d})$.

Fig. 1. Network architecture.

$$\mathsf{TextEnc}(L) := (\mathsf{HC}_{1\star1}^{2d\leftarrow2d})^2 \lhd (\mathsf{HC}_{3\star1}^{2d\leftarrow2d})^2 \lhd (\mathsf{HC}_{3\star27}^{2d\leftarrow2d} \lhd \mathsf{HC}_{3\star9}^{2d\leftarrow2d} \lhd \mathsf{HC}_{3\star3}^{2d\leftarrow2d} \lhd \mathsf{HC}_{3\star1}^{2d\leftarrow2d})^2 \lhd \mathsf{C}_{1\star1}^{2d\leftarrow2d} \lhd \mathsf{ReLU} \lhd \mathsf{C}_{1\star1}^{2d\leftarrow e} \lhd \mathsf{CharEmbed}^{e\text{-dim}}(L).$$

$$\mathsf{AudioEnc}(S) := (\mathsf{HC}_{3\star3}^{d\leftarrow d})^2 \lhd (\mathsf{HC}_{3\star27}^{d\leftarrow d} \lhd \mathsf{HC}_{3\star9}^{d\leftarrow d} \lhd \mathsf{HC}_{3\star3}^{d\leftarrow d} \lhd \mathsf{HC}_{3\star1}^{d\leftarrow d})^2 \lhd \mathsf{C}_{1\star1}^{d\leftarrow d} \lhd \mathsf{ReLU} \lhd \mathsf{C}_{1\star1}^{d\leftarrow d} \lhd \mathsf{ReLU} \lhd \mathsf{C}_{1\star1}^{d\leftarrow F}(S).$$

$$\mathsf{AudioDec}(R') := \sigma \lhd \mathsf{C}_{1\star1}^{F\leftarrow d} \lhd (\mathsf{ReLU} \lhd \mathsf{C}_{1\star1}^{d\leftarrow d})^3 \lhd (\mathsf{HC}_{3\star1}^{d\leftarrow d})^2 \lhd (\mathsf{HC}_{3\star27}^{d\leftarrow d} \lhd \mathsf{HC}_{3\star9}^{d\leftarrow d} \lhd \mathsf{HC}_{3\star3}^{d\leftarrow d} \lhd \mathsf{HC}_{3\star1}^{d\leftarrow d}) \lhd \mathsf{C}_{1\star1}^{d\leftarrow2d}(R').$$

$$\mathsf{SSRN}(Y) := \sigma \lhd \mathsf{C}_{1\star1}^{F'\leftarrow F'} \lhd (\mathsf{ReLU} \lhd \mathsf{C}_{1\star1}^{F'\leftarrow F'})^2 \lhd \mathsf{C}_{1\star1}^{F'\leftarrow2c} \lhd (\mathsf{HC}_{3\star1}^{2c\leftarrow2c})^2 \lhd \mathsf{C}_{1\star1}^{2c\leftarrow c} \lhd (\mathsf{HC}_{3\star3}^{c\leftarrow c} \lhd \mathsf{HC}_{3\star1}^{c\leftarrow c} \lhd \mathsf{D}_{2\star1}^{c\leftarrow c})^2 \lhd (\mathsf{HC}_{3\star3}^{c\leftarrow c} \lhd \mathsf{HC}_{3\star1}^{c\leftarrow c}) \lhd \mathsf{C}_{1\star1}^{c\leftarrow F}(Y).$$

Fig. 2. Details of each component. For notation, see section 2.2.

3. PROPOSED NETWORK

Our DCTTS model consists of two networks: (1) Text2Mel, which synthesize a mel spectrogram from an input text, and (2) Spectrogram Super-resolution Network (SSRN), which convert a coarse mel spectrogram to the full STFT spectrogram. Fig. 1 shows the overall architecture of the proposed method.

3.1. Text2Mel: Text to Mel Spectrogram Network

We first consider to synthesize a coarse mel spectrogram from a text. This is the main part of the proposed method. This module consists of four submodules: Text Encoder, Audio Encoder, Attention, and Audio Decoder. The network $\mathsf{TextEnc}$ first encodes the input sentence $L = [l_1, \ldots, l_N] \in \mathsf{Char}^N$ consisting of N characters, into the two matrices $K, V \in \mathbb{R}^{d \times N}$. On the other hand, the network $\mathsf{AudioEnc}$ encodes the coarse mel spectrogram $S(= S_{1:F,1:T}) \in \mathbb{R}^{F \times T}$, of previously spoken speech, whose length is T, into a matrix $Q \in \mathbb{R}^{d \times T}$.

$$(K, V) = \mathsf{TextEnc}(L). \tag{1}$$

$$Q = \mathsf{AudioEnc}(S_{1:F,1:T}). \tag{2}$$

An attention matrix $A \in \mathbb{R}^{N \times T}$, defined as follows, evaluates how strongly the n-th character l_n and t-th time frame $S_{1:F,t}$ are related,

$$A = \mathsf{softmax}_{n\text{-axis}}(K^\mathsf{T} Q / \sqrt{d}). \tag{3}$$

$A_{nt} \sim 1$ implies that the module is looking at n-th character l_n at the time frame t, and it will look at l_n or l_{n+1} or characters around them, at the subsequent time frame $t + 1$. Whatever, let us expect those are encoded in the n-th column of V. Thus a seed $R \in \mathbb{R}^{d \times T}$, decoded to the subsequent frames $S_{1:F,2:T+1}$, is obtained as

$$R = \mathsf{Att}(Q, K, V) := V A. \text{ (Note: matrix product.)} \tag{4}$$

The resultant R is concatenated with the encoded audio Q, as $R' = [R, Q]$, because we found it beneficial in our pilot study. Then, the concatenated matrix $R' \in \mathbb{R}^{2d \times T}$ is decoded by the Audio Decoder module to synthesize a coarse mel spectrogram,

$$Y_{1:F,2:T+1} = \mathsf{AudioDec}(R'). \qquad (5)$$

The result $Y_{1:F,2:T+1}$ is compared with the temporally-shifted ground truth $S_{1:F,2:T+1}$, by a loss function $\mathcal{L}_{\mathrm{spec}}(Y_{1:F,2:T+1}|S_{1:F,2:T+1})$, and the error is back-propagated to the network parameters. The loss function was the sum of L1 loss and the binary divergence $\mathcal{D}_{\mathrm{bin}}$,

$$\mathcal{D}_{\mathrm{bin}}(Y|S) := \mathbb{E}_{ft}[-S_{ft} \log Y_{ft} - (1 - S_{ft}) \log(1 - Y_{ft})]$$
$$= \mathbb{E}_{ft}[-S_{ft}\hat{Y}_{ft} + \log(1 + \exp \hat{Y}_{ft})], \qquad (6)$$

where $\hat{Y}_{ft} = \mathrm{logit}(Y_{ft})$. Since the binary divergence gives a non-vanishing gradient to the network, $\partial \mathcal{D}_{\mathrm{bin}}(Y|S)/\partial \hat{Y}_{ft} \propto Y_{ft} - S_{ft}$, it is advantageous in gradient-based training. It is easily verified that the spectrogram error is non-negative, $\mathcal{L}_{\mathrm{spec}}(Y|S) = \mathcal{D}_{\mathrm{bin}}(Y|S) + \mathbb{E}[|Y_{ft} - S_{ft}|] \geq 0$, and the equality holds iff $Y = S$.

3.1.1. Details of TextEnc, AudioEnc, and AudioDec

Our networks are fully convolutional, and are not dependent on any recurrent units. Instead of RNN, we sometimes take advantages of *dilated convolution* [32, 13, 24] to take long contextual information into account. The top equation of Fig. 2 is the content of TextEnc. It consists of the character embedding and the stacked 1D *non-causal* convolution. A previous literature [2] used a heavier RNN-based component named 'CBHG,' but we found this simpler network also works well. AudioEnc and AudioDec, shown in Fig. 2, are composed of 1D *causal* convolution layers with Highway activation. These convolution should be causal because the output of AudioDec is feedbacked to the input of AudioEnc in the synthesis stage.

3.2. Spectrogram Super-resolution Network (SSRN)

We finally synthesize a full spectrogram $|Z| \in \mathbb{R}^{F' \times 4T}$, from the obtained coarse mel spectrogram $Y \in \mathbb{R}^{F \times T}$, by a spectrogram super-resolution network (SSRN). Upsampling frequency from F to F' is rather straightforward. We can achieve that by increasing the convolution channels of 1D convolutional network. Upsampling in temporal direction is not similarly done, but by twice applying deconvolution layers of stride size 2, we can quadruple the length of sequence from T to $4T = T'$. The bottom equation of Fig. 2 shows SSRN. In this paper, as we do not consider online processing, all convolutions can be non-causal. The loss function was the same as Text2Mel: sum of binary divergence and L1 distance between the synthesized spectrogram $\mathsf{SSRN}(S)$ and the ground truth $|Z|$.

4. GUIDED ATTENTION

4.1. Guided Attention Loss: Motivation, Method and Effects

In general, an attention module is quite costly to train. Therefore, if there is some prior knowledge, it may be a help incorporating them into the model to alleviate the heavy training. We show that the simple measure below is helpful to train the attention module.

In TTS, the possible attention matrix A lies in the very small subspace of $\mathbb{R}^{N \times T}$. This is because of the rough correspondence of the order of the characters and the audio segments. That is, if one reads a text, it is natural to assume that the text position n progresses nearly linearly to the time t, i.e., $n \sim at$, where $a \sim N/T$. This is
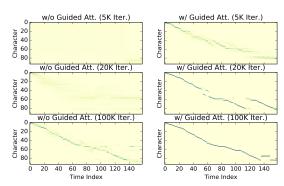
the prominent difference of TTS from other seq2seq learning techniques such as machine translation, in which an attention module should resolve the word alignment between two languages that have very different syntax, e.g. English and Japanese.

Based on this idea, we introduce another constraint on the attention matrix A to prompt it to be 'nearly diagonal,' $\mathcal{L}_{\mathrm{att}}(A) = \mathbb{E}_{nt}[A_{nt} W_{nt}]$, where $W_{nt} = 1 - \exp\{-(n/N - t/T)^2/2g^2\}$. In this paper, we set $g = 0.2$. If A is far from diagonal (e.g., reading the characters in the random order), it is strongly penalized by the loss function. This subsidiary loss function is simultaneously optimized with the main loss $\mathcal{L}_{\mathrm{spec}}$ with equal weight.

Although this measure is based on quite a rough assumption, it improved the training efficiency. In our experiment, if we added the guided attention loss to the objective, the term began decreasing only after $\sim$100 iterations. After $\sim$5K iterations, the attention became roughly correct, not only for training data, but also for new input texts. On the other hand, without the guided attention loss, it required much more iterations. It began learning after $\sim$10K iterations, and it required $\sim$50K iterations to look at roughly correct positions, but the attention matrix was still vague. Fig. 3 compares the attention matrix, trained with and without guided attention loss.

4.2. Forcibly Incremental Attention in Synthesis Stage

In the synthesis stage, the attention matrix A sometimes fails to look at the correct characters. Typical errors we observed were (1) it occasionally skipped several characters, and (2) it repeatedly read a same word twice or more. In order to make the system more robust, we heuristically modify the matrix A to be 'nearly diagonal,' by a simple rule as follows. We observed this device sometimes alleviated such misattentions. *Let n_t be the position of the character to be read at t-th time frame; $n_t = \mathrm{argmax}_n A_{n,t}$. Comparing the current position n_t and the previous position n_{t-1}, unless the difference $n_t - n_{t-1}$ is within the range $-1 \leq n_t - n_{t-1} \leq 3$, the current attention position forcibly set to $A_{n,t} = \delta_{n,n_{t-1}+1}$ (Kronecker's delta), to forcibly make the attention target incremental, i.e., $n_t - n_{t-1} = 1$.*

5. EXPERIMENT

5.1. Experimental Setup

To train the networks, we used LJ Speech Dataset [33], a public domain speech dataset consisting of $\sim$13K pairs of text&speech, $\sim$24 hours in total, without phoneme-level alignment. These speech are a little reverbed. We preprocessed the texts by spelling out some of

Table 1. Parameter Settings.

Sampling rate of audio signals	22050 Hz
STFT window function	Hanning
STFT window length and shift	1024 ($\sim$46.4 [ms]), 256 ($\sim$11.6[ms])
STFT spectrogram size $F' \times 4T$	$513 \times 4T$ (T depends on audio clip)
Mel spectrogram size $F \times T$	$80 \times T$ (T depends on audio clip)
Dimension e, d and c	128, 256, 512
ADAM parameters $(\alpha, \beta_1, \beta_2, \varepsilon)$	$(2 \times 10^{-4}, 0.5, 0.9, 10^{-6})$
Minibatch size	16
Emphasis factors (γ, η)	(0.6, 1.3)
RTISI-LA window and iteration	100, 10
Character set, `Char`	`a-z,.'-` and `Space` and `NULL`

Table 2. Comparison of MOS (95% confidence interval), training time, and iterations (Text2Mel/SSRN), of an open Tacotron [5] and the proposed method (DCTTS). The digits with * were excerpted from the repository [5].

Method	Iteration	Time	MOS (95% CI)
Open Tacotron [5]	877K*	12 days*	2.07 ± 0.62
DCTTS	20K/ 40K	$\sim$2 hours	1.74 ± 0.52
DCTTS	90K/150K	$\sim$7 hours	2.63 ± 0.75
DCTTS	200K/340K	$\sim$15 hours	2.71 ± 0.66
DCTTS	540K/900K	$\sim$40 hours	2.61 ± 0.62

abbreviations and numeric expressions, decapitalizing the capitals, and removing less frequent characters not shown in Table 1, where `NULL` is a dummy character for zero-padding.

We implemented our neural networks using Chainer 2.0 [34]. The models are trained on a household gamine PC equipped with two GPUs. The main memory of the machine was 62GB, which is much larger than the audio dataset. Both GPUs were NVIDIA GeForce GTX 980 Ti, with 6 GB memories.

For simplicity, we trained Text2Mel and SSRN independently and asynchronously, using different GPUs. All network parameters are initialized using He's Gaussian initializer [35]. Both networks were trained by ADAM optimizer [36]. When training SSRN, we randomly extracted short sequences of length $T = 64$ for each iteration, to save the memory usage. To reduce the frequency of disc access, we only took the snapshot of the parameters, every 5K iterations. Other parameters are shown in Table 1.

As it is not easy for us to reproduce the original results of Tacotron, we instead used a ready-to-use model [5] for comparison, which seemed to produce the most reasonable sounds among the open implementations. It is reported that this model was trained using LJ Dataset for 12 days (877K iterations) on a GTX 1080 Ti, newer GPU than ours. Note, this iteration is still much less than the original Tacotron, which was trained for more than 2M iterations.

We evaluated mean opinion scores (MOS) for both methods by crowdsourcing on Amazon Mechanical Turk using crowdMOS toolkit [37]. We used 20 sentences from *Harvard Sentences* List 1&2. We synthesized the audio using 5 methods shown in Table 2. The crowdworkers evaluated these 100 clips, rating them from 1 (Bad) to 5 (Excellent). Each worker is supposed to rate at least 10 clips. To obtain more responses with higher quality, we set a few incentives shown in the literature. The results were statistically processed using the method shown in the literature [37].

5.2. Result and Discussion

In our setting, the training throughput was $\sim$3.8 minibatch/s (Text2Mel) and $\sim$6.4 minibatch/s (SSRN). This implies that we can iterate the updating formulae of Text2Mel, 200K times only in 15 hours. Fig. 4
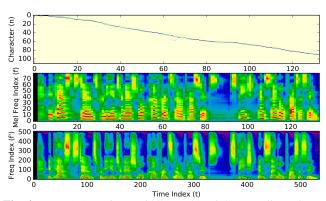

Fig. 4. (Top) Attention, (middle) mel, and (bottom) linear STFT spectrogram, synthesized by the proposed method, after 15 hours training. The input is *"icassp stands for the international conference on acoustics, speech and signal processing."*

shows an example of attention, synthesized mel and full spectrograms, after 15 hours training. It shows that the method can almost correctly look at the correct characters, and can synthesize quite clear spectrograms. More samples will be available at the author's web page.[1]

In our crowdsourcing experiment, 31 subjective evaluated our data. After the automatic screening by the toolkit [37], 560 scores by 6 subjective were selected for final statistics calculation. Table 2 compares the performance of our proposed method (DCTTS) and an open Tacotron. Our MOS (95% confidence interval) was 2.71 ± 0.66 (15 hours training) while the Tacotron's was 2.07 ± 0.62. Although it is not a strict comparison since the frameworks and machines are different, it would be still concluded that our proposed method is quite rapidly trained to the satisfactory level compared to Tacotron.

6. SUMMARY AND FUTURE WORK

This paper described a novel text-to-speech (TTS) technique based on deep convolutional neural networks (CNN), as well as a technique to train the attention module rapidly. In our experiment, the proposed Deep Convolutional TTS can be sufficiently trained only in a night ($\sim$15 hours), using an ordinary gaming PC equipped with two GPUs, while the quality of the synthesized speech was almost acceptable.

Although the audio quality is far from perfect yet, it may be improved by tuning some hyper-parameters thoroughly, and by applying some techniques developed in deep learning community. We believe this handy method encourages further development of the applications based on speech synthesis. We can expect this simple neural TTS may be extended to other versatile purposes, such as emotional/non-linguistic/personalized speech synthesis, singing voice synthesis, music synthesis, etc., by further studies. In addition, since a neural TTS has become this lightweight, the studies on more integrated speech systems e.g. some multimodal systems, simultaneous training of TTS+ASR, and speech translation, etc., may have become more feasible. These issues should be worked out in the future.

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