Differentiable Duration Modeling for End-to-End Text-to-Speech

Bac Nguyen, Fabien Cardinaux, Stefan Uhlich

Sony Europe B.V., R&D Center, Stuttgart Laboratory 1, Germany
{Bac.NguyenCong, Fabien.Cardinaux, Stefan.Uhlich}@sony.com

Abstract
Parallel text-to-speech (TTS) models have recently enabled fast and highly-natural speech synthesis. However, such models typically require external alignment models, which are not necessarily optimized for the decoder as they are not jointly trained. In this paper, we propose a differentiable duration method for learning monotonic alignments between input and output sequences. Our method is based on a soft-duration mechanism that optimizes a stochastic process in expectation. Using this differentiable duration method, a direct text to waveform TTS model is introduced to produce raw audio as output instead of performing neural vocoding. Our model learns to perform high-fidelity speech synthesis through a combination of adversarial training and matching the total ground-truth duration. Experimental results show that our model obtains competitive results while enjoying a much simpler training pipeline. Audio samples are available online.

Index Terms: text-to-speech, non-autoregressive, duration

1. Introduction
Text-to-speech (TTS) or speech synthesis is a process of converting written text into speech. Recently, rapid progress has been made in this area, which enables TTS models to synthesize natural and intelligible speech. Many TTS systems are based on autoregressive models such as Tacotron [1, 2], Deep Voice [3, 4], and Transformer TTS [5]. The idea is to learn an encoder-decoder model using a soft attention mechanism. Given a sequence of characters or phonemes as inputs, the encoder learns a sequence of hidden representations, which are passed to the decoder to predict the acoustic parameters, such as fundamental frequencies and (mel-)spectrograms. In addition, a neural vocoder such as WaveNet [6], Parallel WaveGAN [7], or HiFiGAN [8] is used to synthesize the speech waveform from the output of the acoustic model. Despite their satisfactory performance, autoregressive acoustic TTS models typically suffer from robustness (e.g., word repetitions and word skipping) and slow inference speed. The latter limits their applicability in real-time systems that require fast speech generation.

To speed up the inference, non-autoregressive or parallel TTS models have been proposed [9–13]. These models can fully leverage the parallel computation while obtaining reasonably good results. However, learning alignments between text and its corresponding mel-spectrogram becomes challenging for non-autoregressive models. The alignments must satisfy several important criteria [14]: (1) each character/phoneme token should be aligned with at least one spectrogram frame, (2) the aligned spectrogram frames should be consecutive, and (3) the alignment should be monotonic. One common solution is to rely on the attention outputs of a pretrained autoregressive teacher model to extract the alignments [11]. Alternatively, DurIAN [15] and FastSpeech 2 [10] used token durations extracted by forced alignment [16] to obtain alignments. The sequence of hidden representations is expanded according to the duration of each token to match the length of the mel-spectrogram sequence. The main drawback of these models is that they are sensitive to the performance of the teacher model or the external aligner. Therefore, it is important to design a TTS model which can directly learn the alignments.

Despite the significant progress achieved in parallel TTS, the distribution mismatch between the acoustic model and the vocoder often leads to artifacts in synthesized speech [17, 18]. To obtain high-quality speech, two-stage TTS models often require sequential training or fine-tuning. That is, the vocoder is trained with the output generated by the acoustic model. Due to the dependency on the vocoder, the performance of two-stage models is limited. This has motivated the development of fully end-to-end TTS models. The most obvious advantages of end-to-end models include (1) avoiding the error propagation from intermediate steps and (2) reducing the complexity of the training and deployment pipeline. Nevertheless, training an end-to-end TTS system is a difficult task due to the huge difference between text and audio waveform modalities. Besides, it is also hard to learn a meaningful context representation when training only on short audio clips rather than the whole waveforms [10–17] as the end-to-end model is usually bigger and the GPU memory is limited.

In this paper, we introduce AutoTTS, a parallel end-to-end TTS model, which generates audio waveforms directly from a sequence of phonemes. Unlike most previous methods, AutoTTS does not require extra information extracted by external models to learn the alignments between text and waveform. In particular, the phoneme embeddings are upsampled by an attention matrix, which is derived from a differentiable duration model. Our differentiable duration model allows back-propagation of gradients through the entire network. Importantly, we leverage adversarial training in an end-to-end fashion to improve the perceptual audio quality. Although AutoTTS is trained on short-audio clips, full phoneme sequences are used to learn the context. As a result, AutoTTS can capture the long-term dependencies using its Transformer [19] architecture.

2. Related work
Recent TTS models have exploited the duration prediction of each character/phoneme token to obtain alignments between text and speech. During training, the token durations can be extracted from autoregressive TTS models [17, 20] or external aligner models [10, 12, 15]. Another approach is to explicitly train an internal aligner to extract durations. For instance, AlignTTS [13] considered all possible alignments to align text to mel-spectrogram by using dynamic programming with multi-stage training. JDI-T [21] avoided multi-stage training by jointly training both autoregressive and non-autoregressive models to get the token durations. EATS [17] and Parallel Tacotron 2 [13] used the soft
3. Proposed method

In this section, we present a novel method called AutoTTS that enables prediction of the raw audio waveform from a sequence of phonemes. The overall architecture and training procedure are illustrated in Fig. 1. Essentially, AutoTTS consists of an encoder, an aligner, and a decoder network. The encoder maps a sequence of phonemes into some hidden embeddings. The aligner maps these hidden embeddings to other embeddings which are aligned with the audio output but in a lower resolution. The decoder then upsamples the output embeddings from the aligner to the raw audio waveform. Our method does not require supervised duration signals, which enables back-propagation-based training. In the following, we first introduce our duration modeling to align the text and speech. Then, we describe the adversarial training, followed by some network architecture and implementation details of AutoTTS.

3.1. Duration modeling

We begin by reviewing the length regulator used in FastSpeech [11] for solving the length mismatch problem between the phoneme sequence and mel-spectrogram output. Given a sequence of $N$ phonemes $x = \{x_1, \ldots, x_N\}$, the encoder outputs a sequence of hidden states $H = \{h_1, \ldots, h_N\}$ where $h_i \in \mathbb{R}^T$ for $i = 1, \ldots, N$. The decoder then outputs a sequence of mel-spectrogram frames for a given sequence of hidden states. However, the length of the phoneme sequence is often much smaller than that of the mel-spectrogram. To resolve this problem, a length regulator is used to upsample each hidden state according to its duration. Here, the duration is defined as the number of mel-spectrogram frames corresponding to that phoneme. During training, durations are extracted by an external aligner or teacher-student distillation [1]. Since the length regulator is a non-differentiable function, gradient-based methods cannot be used to find the optimal durations. We will address this issue with a soft duration model, which enables end-to-end training.

Assuming that the duration of a phoneme is a discrete integer in the range of $[0, M]$. We formulate the duration as a stochastic process. In particular, let $w_i$ be a random variable indicating the duration of the $i$-th phoneme and $p_i \in [0, 1]^M$ be a vector containing the parameters of the distribution that characterizes $w_i$, i.e., $w_i \sim P_i(p_i)$. The probability of having a duration of $m \in \{1, \ldots, M\}$ for the $i$-th phoneme is defined as

$$l_{i,m} = p_i[m] \prod_{k=1}^{m-1} (1 - p_i[k]) = p_i[m] \text{cumprod}(1 - p_i[m-1]), \quad (1)$$

where $\text{cumprod}(v) = [v_1, v_1v_2, \ldots, \prod_{j=1}^{m} v_j]$ is the cumulative product operation. We refer to $l$ as the length probability. Given the parameters $p_i$, one can sample the duration following a sequence of Bernoulli$(p_i[m])$ distributions, starting from $m = 1$. As soon as we obtain an outcome being one for some $m$, we stop and set the duration to $m$. If there is no outcome after $M$ trials, the duration is set to zero with a probability of

$$l_{i,0} = \prod_{k=1}^{M} (1 - p_i[k]) = \text{cumprod}(1 - p_i[M]).$$

It is easy to show that $\sum_{m=0}^{M} l_{i,m} = 1$, for every $i \in \{1, \ldots, N\}$. In other words, the length probability is a valid probability distribution.

The duration of several phonemes can be summed over the duration of each individual phoneme. Let $q_{i,j}$ denote the probability that a sequence of the first $i$ phonemes having a duration of $j \in \{0, \ldots, M\}$. For the first phoneme, this is identical to the length probability, i.e., $q_{i,0} = l_{i,0}$. For $i > 1$, $q_{i,j}$ can be recursively formulated with $q_{i-1,j}$ and $l_{i,j}$, as in Eq. (2) by considering all possible durations of the $i$-th phoneme, i.e.,

$$q_{i,j} = \sum_{m=0}^{M} q_{i-1,m} l_{j,m}. \quad (2)$$

This is used to model special characters such as punctuation marks of the input text. It does not contradict the assumptions of alignments.
Attention probability $\mathbf{L}$ is trained based on an adversarial learning scheme [24]. We illustrate how the attention probability $s$ is derived from the cumulative sum operation. Here we consider all possibilities that the $i$-th phoneme aligns the $j$-th output frame. In Fig. 2, we illustrate how the attention probability $s$ is derived from the length probability $l$. By modeling the duration using cumulative summation, we implicitly enforce the alignment being monotonically. After computing the attention probability $s$, we can upsample the hidden states as expected output $E[y_i] = \sum_{i,j} s_{i,j} h_{i,j}$, for $j = \{1, \ldots, M\}$.

### 3.2. Training procedure

**AutoTTS** is trained based on the adversarial learning scheme [25]. A discriminator $D$ is used to distinguish between the real speech waveform $z$ and the audio waveform produced by our network $G(x)$. In particular, the following loss function is used to train AutoTTS

$$\mathcal{L} = \mathcal{L}_{\text{adv-G}} + \lambda_{\text{loss}} \mathcal{L}_{\text{length}} + \lambda_{\text{duration}} \mathcal{L}_{\text{duration}} + \lambda_{\text{recon}} \mathcal{L}_{\text{recon}},$$

where $\mathcal{L}_{\text{adv-G}}$, $\mathcal{L}_{\text{length}}$, $\mathcal{L}_{\text{duration}}$, and $\mathcal{L}_{\text{recon}}$ indicate the adversarial, length, duration, and reconstruction losses, respectively; $\lambda_{\text{loss}}$, $\lambda_{\text{duration}}$, and $\lambda_{\text{recon}}$ are the weighting terms. The discriminator is simultaneously trained using the adversarial loss $\mathcal{L}_{\text{adv-G}}$. The detail of each loss function will be described in the following.

**Adversarial loss.** The least-squares adversarial loss [25] is employed for adversarial training, i.e.,

$$\mathcal{L}_{\text{adv-G}} = \mathbb{E}_{\mathbf{x}}[(D(\mathbf{x}) - 1)^2 + D(G(\mathbf{x}))^2],$$

$$\mathcal{L}_{\text{adv-G}} = \mathbb{E}_{\mathbf{z}}[(D(G(\mathbf{z})) - 1)^2].$$

On one hand, the discriminator forces the output of real samples to be one and that of synthesized samples to be zero. On the other hand, the generator is trained to fool the discriminator by producing samples that will be classified as real samples. This training scheme helps to synthesize realistic speech.

**Length loss.** Based on the length probability, the expected duration of the $i$-th phoneme can be computed as

$$E_{w_i \sim P(w_i|p_j)}[w_i] = \sum_{m=1}^{M} m l_{i,m}.$$
product in Eq. (1) is numerically unstable for the gradient computation. We resolve this issue by computing this product in the log-space. The computation of the probability matrix \( q \) in Eq. (2) and \( s \) in Eq. (3) can be computationally expensive. Fortunately, we can efficiently implement them as convolution operations, which enjoy computational benefits from parallel computing. Another issue is that the attention probability matrix \( s \) might not produce hard alignments as our length probability also produces soft output. Ideally, we would like to have discrete durations, which enable the alignments with the length regulator at inference time. To encourage the discreteness, we simply add zero-mean and unit-variance Gaussian noise before the sigmoid function which produces \( s \) as in [28].

## 4. Experiments

### 4.1. Experimental setups

We evaluate our model AutoTTS on the LJSpeech data set [29], which consists of 13,100 English audio clips at the sampling rate of 22,050. LJSpeech contains 24 hours of high-quality speech data with a single speaker. The data set is split into two sets, a set of 12,588 samples for training and another set of 512 samples for testing. Texts are normalized to sequences of phonemes using phonemizer [30]. To better model the prosody, all punctuation marks are preserved in the output of text normalization.

Our model is trained for 3,000 epochs with a batch size of 22 using 8 NVIDIA A100 GPUs. Training takes about 1.8 minutes per epoch. We use the AdamW optimizer [31] with \( \beta_1 = 0.8, \beta_2 = 0.99 \), and a learning rate of \( 2 \times 10^{-5} \). During training, we randomly extract 128 frames (~1.5 seconds) of the hidden representation to feed to Upsampler to alleviate the memory constraint of GPUs. Training targets are then defined as the corresponding audio segments extracted from the ground truth audio waveforms.

We compare the mean opinion score (MOS) of audio generated by AutoTTS with other systems, including Tacotron 2 [2], FastSpeech 2 [10], HiFi-GAN+Mel (where the ground truth audio are converted to mel-spectrograms, then converted back to audio waveforms using the pre-trained HiFi-GAN vocoder [8]), and the ground-truth audio. For a fair comparison, we also use HiFi-GAN as the vocoder for Tacotron 2 and FastSpeech 2. All audio samples for the MOS study are generated by randomly choosing transcripts from the test set. We normalize all audio waveforms to avoid the effect of amplitude differences. The subjective test was conducted internally by 20 participants. For each utterance, each listener assigns a score in a five-point Likert scale (where 1: Bad, 2: Poor, 3: Fair, 4: Good, and 5: Excellent) with a rating increment of 0.5.

### 4.2. Experimental results

The subjective evaluation results are shown in Table 1. AutoTTS achieves the best performance among the competing TTS models. More importantly, it outperforms the baseline FastSpeech 2 by a large margin even without any variance information such as pitch, energy, and duration. These results show that end-to-end adversarial training improves the audio quality. Compared to the ground-truth audio, AutoTTS gives slightly worse results. It is also important to mention that end-to-end TTS systems such as FastSpeech 2 [10] and EATS [17] performed worse than two-stage TTS systems as reported in their studies.

Furthermore, we report the model size and inference speed of the competing methods in Table 2. The last two columns denote the real time (in seconds) required to synthesize ten seconds of speech waveforms on CPU and GPU, respectively. Real time is measured on an Intel(R) Xeon(R) CPU @ 3.40GHz with one NVIDIA GTX 1080 Ti GPU. Additionally, the vocoder parameters are listed for Tacotron 2 and FastSpeech 2 because both need a vocoder for speech generation. AutoTTS has slightly more parameters compared to these acoustic models since they output mel-spectrograms instead of raw audio waveforms. We can see that AutoTTS is faster than other competing methods on both CPU and GPU due to the fully end-to-end generation.

### 5. Conclusions

In this paper, we have proposed AutoTTS, a parallel end-to-end TTS method, which enables high-quality speech generation. Instead of relying on external aligners or teacher-student distillation techniques, AutoTTS can learn the alignments between text and speech from raw data, making the training pipeline simpler. We have shown that AutoTTS is fast at inference, while being competitive in terms of speech quality to other state-of-the-art TTS systems. For future work, we will further reduce the model size, while keeping the audio quality to ensure fast speech synthesis on small devices. Another promising direction is to apply our duration-based mechanism in other domains.
6. References

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