THE IMPORTANCE OF ACCURATE ALIGNMENTS IN END-TO-END SPEECH SYNTHESIS

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ABSTRACT

Unit selection synthesis systems required accurate segmentation and labeling of the speech signal owing to the concatenative nature. Hidden Markov model-based speech synthesis accommodates some transcription errors, but it was later shown that accurate transcriptions yield highly intelligible speech with smaller amounts of training data. With the arrival of end-to-end (E2E) systems, it was observed that very good quality speech could be synthesised with large amounts of data. As end-to-end synthesis progressed from Tacotron to FastSpeech2, it has become imminent that features that represent prosody are important for good-quality synthesis. In particular, durations of the sub-word units are important. Variants of FastSpeech use a teacher model or forced alignments to obtain good-quality synthesis. In this paper, we focus on duration prediction, using signal processing cues in tandem with forced alignment to produce accurate phone durations during training.

The current work aims to highlight the importance of accurate alignments for good-quality synthesis. An attempt is made to train the E2E systems with accurately labeled data, and compare the same with approximately labeled data.

Index Terms— end-to-end speech synthesis, accurate alignments, signal processing, FastSpeech2

1. INTRODUCTION

This work explores the importance of accurate alignments in the context of end-to-end (E2E) text-to-speech synthesis (TTS) systems. Specifically, the focus is on improving the duration prediction (and thereby the synthesis quality) of TTS systems by correcting the phoneme alignments of the training data with the aid of signal processing cues.

The E2E approach is the popular state-of-the-art speech synthesis paradigm due to its ease in training systems to obtain high-quality speech. The initial E2E systems were primarily attention-based, such as Tacotron [1], Tacotron2 [2]. The main goal of the attention module in TTS tasks is to learn the alignments between characters/phones and mel-spectrogram frames. The attention module learns soft alignments, in comparison to hard alignments used in traditional TTS approaches such as unit selection synthesis (USS) and hidden Markov model (HMM) based speech synthesis systems (HTS). The attention network is trained to act as a duration predictor during synthesis.

One of the main drawbacks of attention-based networks is that the alignments may not be learnt correctly. Coupled with an auto-regressive decoder, the synthesis output is prone to errors, such as insertion or deletion of phones. Hence, the focus of E2E technology has shifted to improving duration prediction during synthesis. The duration information corresponding to the training data can be learnt in different ways. FastSpeech [3] uses alignments predicted by a teacher model. Some architectures such as Fastspeech2 [4] and DurIAN [5] employ external aligners for this purpose. Other recent works, such as [6 7 8 9] learn the alignments internally.

In the context of HMM-based systems, [10 11] have studied the effect of accurate alignments on synthesis quality and intelligibility, highlighting the importance of accurate boundaries for training. In this paper, we attempt to answer the question of “How relevant are accurate alignments in the context of E2E systems?”. Such a study is very important to produce good quality speech as duration is an important prosody marker. We employ an external aligner, the hybrid segmentation (HS) algorithm, which combines signal processing cues in tandem with deep learning techniques [11], to obtain accurate alignments for the training data. We use the FastSpeech2 architecture [4] and the HiFi-GAN vocoder [12] for E2E training. The synthesis quality of systems trained with different alignment techniques are compared—using a teacher model, Montreal forced aligner (MFA) [13] and hybrid segmentation. We also conduct experiments in a low-resource scenario. Subjective evaluations and qualitative observations indicate that accurate alignments are crucial for generating good-quality speech, especially in low-resource scenarios.

The rest of the paper is organised as follows. Section 2 reviews the related work. The proposed work and related experiments are presented in Sections 3 and 4 respectively. The work is concluded in Section 5.

2. RELATED WORK

This section presents recent literature dealing with duration modeling in E2E training. In FastSpeech [3], duration information is obtained from a transformer TTS [14], which

1In this paper, we refer to the two-stage pipeline of generating mel-spectrograms and then reconstructing waveforms as E2E training.
is considered a teacher model. External aligners are used in a few papers– MFA [13, 4], HMM-based [13], and connectionist temporal classification (CTC) based [16]. TTS systems trained in [6, 8, 9, 17, 18] learn duration information internally using HMM-based approaches. In [6, 8, 9], soft and hard alignments are learnt with monotonicity constraint. Glow-TTS [19] uses normalizing flows and dynamic programming to determine the most probable monotonic alignment between text and the latent representation of the audio. In [20], word-level hard alignments are obtained from an external aligner and soft phone alignments are learnt using a word-to-phoneme attention network. A recently developed network called SoftSpeech [21] proposes a soft length regulator for unsupervised duration modeling within the FastSpeech2 network.

Among the presented literature, [18, 21] demonstrate the capability of their TTS systems in low resource scenarios. In the current work, we use an external aligner, namely, the hybrid segmentation algorithm [11], which is a signal processing aided approach. FastSpeech2 is chosen as the mel-spectrogram generation model as it provides more variance information with pitch and energy.

3. PROPOSED WORK

In this section, we present our proposed approach. We first explain two of the alignment modules that are widely used– (1) the teacher-student approach and (2) MFA, which is an external aligner. Then we present the hybrid HMM-GD-DNN segmentation (HS) approach, the alignment which we propose to be used for FastSpeech2. The E2E system considered in this work has a 2-stage pipeline: (1) text to mel-spectrogram conversion (FastSpeech2), and (2) speech reconstruction using a vocoder (HiFi-GAN). Figure 1 presents the flowchart of systems trained with different alignments.

3.1. Alignment modules

We employ three techniques to obtain the phoneme durations required for FastSpeech2, as described below.

3.1.1. Teacher-student approach (TS)

In the teacher-student approach, phoneme durations from an auto-regressive Tacotron2 teacher model (or transformer network) are fed to FastSpeech2 model training. From a trained teacher model, encoder-decoder attention alignments are extracted for every <text, audio> pair as described in [3].

3.1.2. Montreal forced aligner (MFA)

MFA [13] is an open-source speech-text aligner that provides phone and word boundaries. MFA performs triphone modeling and performs speaker adaptation to model inter-speaker differences. Models are trained in MFA using the Kaldi speech recognition toolkit [22].

3.1.3. Hybrid HMM-GD-DNN segmentation (HS)

Hybrid segmentation is an alignment technique that combines the complementary features of machine learning and signal processing based approaches to generate accurate phone boundaries [10, 11]. HMM-based forced alignment does not accurately model the location of phone boundaries. Hence, in [10], these boundaries are corrected using signal processing based cues. Specifically, a group delay (GD) based algorithm is used to obtain accurate syllable boundaries. However, the drawback of the GD-based technique is that it doesn’t capture the correct number of syllable boundaries as it is agnostic to the text. Hence, spurious GD boundaries are estimated, and the GD boundary closest to an HMM boundary is considered the correct syllable boundary [10]. Then the phone boundaries are re-estimated within these syllable boundaries instead of re-estimating across the entire utterance. Additionally, sub-band spectral flux (SBSF) is used as a cue for correcting boundaries of fricatives, affricates and nasals [23].

In [11], the accuracy of phone boundaries and synthesis quality are compared across TTS systems trained with only deep neural network (DNN) alignments and with DNN alignments employing boundary correction. In the latter, the alignments obtained by the hybrid HMM-GD technique are considered initial alignments for DNN segmentation. Experiments show that the synthesis quality with boundary correction is better than with only DNN alignments. Motivated by this, we use the hybrid HMM-GD-DNN alignments for FastSpeech2 training, and compare systems trained with the other
machine-learning based alignments discussed previously.

Figure 2: An example of a Hindi waveform (bottom panel), its spectrogram (fourth panel), and phone-level alignments obtained from different techniques (top 3 panels). The highlighted regions indicate the alignments in MFA and the correct alignments obtained using hybrid segmentation.

Figure 2 shows a sample Hindi waveform, its spectrogram and phone-level alignments obtained from different techniques. It is clearly seen that the alignments of TS are not correct. Although MFA has better alignments, the boundaries are more refined with HS.

3.2. Text processing

We first convert the text to its phone-based representation using the unified parser for Indian languages [24]. The unified parser takes a word as input and applies relevant language-specific rules to generate the phone-based output in the common label set (CLS) representation. This output is further processed such that each phone is represented by a single character, as described in [25].

Based on the duration information, each phone in the text is assigned a value equal to the number of frames. A comma is included in the text wherever the aligner has predicted a short pause (sp). An additional symbol “S” is included for beginning and end silence regions (SIL) in the audio (if present). Initially, spaces in the text were removed, as they are linguistic units and do not carry any meaning in the acoustic space. However, it was observed that systems trained with spaces still performed better. Hence, spaces were retained in the training text and correspondingly assigned zero duration. An example of a sample Hindi text and its processed version is given in Table 1.

3.3. FastSpeech2 architecture

We use a transformer-based encoder-decoder FastSpeech2 architecture in our work [4]. In FastSpeech2, the text is converted to phoneme embeddings which are then passed through a series of feed-forward transformer (FFT) blocks to generate the phoneme hidden sequence. The phoneme hidden sequence is then expanded to match the length of the mel-spectrogram sequence based on the duration information. Then the expanded phoneme sequence is passed through another set of FFT blocks at the decoder to generate mel-spectrogram frames. To provide more variance information, pitch and energy embeddings are also added to the phoneme hidden state.

During training, the phoneme durations are obtained from a teacher model (such as Tacotron2) or an external aligner. Pitch and energy values are extracted from the ground-truth audio files. Duration, pitch and energy predictors are trained and optimized with mean square error (MSE) loss. During synthesis, these prosodic features are predicted by the network.

3.4. HiFi-GAN vocoder

HiFi-GAN is a GAN-based vocoder capable of producing high-fidelity speech from mel-spectrograms [12]. It is a non-autoregressive vocoder that models periodic patterns in speech audio. HiFi-GAN has a smaller footprint size and a higher synthesis speed compared to most neural vocoders.

4. EXPERIMENTS AND RESULTS

Systems are trained on Hindi male dataset (8.5 hours) from the open-source Indic TTS database [26]. Three systems are trained based on the alignments used– (1) from Tacotron2 as the teacher model (TS), (2) with MFA, and (3) using hybrid HMM-GD-DNN alignments (HS). We also compare these models in a low-resource scenario, i.e., using only 1 hour of training data.

For training Tacotron2 and FastSpeech2 models, the ESPNet toolkit was used [27], with the default parameters. HiFiGAN models were trained using an open-source code[2]. The hybrid segmentation code[3] implemented using HTK [28] and Kaldi [22] toolkits, was used. For the low-resource scenario, corresponding models were trained using only 1 hour of data.[4]
We conduct pairwise comparison (PC) tests to assess the performance across different systems. In PC test, listeners are presented with a pair of audio files in random order of systems, and asked to give their preference. The test sentences were selected from the web, ensuring coverage of different domains—news, sports, entertainment, and technical lectures. 14 native Hindi listeners participated in each PC test and evaluated 10 pairs of audio files. Results of the PC test comparing TS vs. HS and MFA vs. HS systems with full data are presented in Table 2. On average, the system with HS is preferred in more than 56% of the cases, with an equal preference of 34% across the competing systems.

Table 2: PC test results for full data (preference in %)

| System pairs | TS/MFA | HS | Equal |
|--------------|--------|----|-------|
| TS vs. HS    | 10.99  | 51.65 | 37.36 |
| MFA vs. HS   | 7.69   | 61.54 | 30.77 |

Further, a PC test is also conducted in the low-resource scenario. The system with TS is excluded from the experiments as the training of the Tacotron2 (1 hour) teacher model failed due to lack of adequate data. Consequently, the FastSpeech2 student model also did not train well. 14 native listeners evaluated a set of 10 audio pairs. Results of the PC test comparing MFA and HS systems are presented in Table 3. Although the preference for the HS system in the low-resource scenario has reduced, the system still outperforms the MFA (1 hour) model.

Table 3: PC test results with 1 hour data (preference in %)

| System pairs | MFA | HS | Equal |
|--------------|-----|----|-------|
| MFA vs. HS   | 16.48 | 36.26 | 47.25 |

To demonstrate that HS provides more accurate boundaries, we manually align 10 ground truth utterances at the phone level. The average of absolute boundary differences with different alignments (of full data) is given in Table 4. It is clearly seen that HS provides better alignments compared to MFA.

Table 4: Alignment accuracy

| Alignment technique | MFA | HS |
|---------------------|-----|----|
| Duration difference (in ms) | 11.88 | 4.40 |

Figures 3 and 4 show spectrograms of utterances in which the MFA systems have errors (highlighted regions). In Figure 3, the MFA system produces the affricate “c” instead of voiceless stop consonant “t” in “tarika”. In Figure 4, the aspirated voiced stop consonant “dxh” in “dxhang” is missed by the MFA system, while uttered correctly by the HS system (as evidenced by the voice bar).

Our observations from the experiments in this work are summarised here. Although the alignments from the teacher model are not correct in most places, the FastSpeech2 student model still learns to generate good-quality speech, given enough amount of training data. But to further improve the pronunciation of sounds in the generated output, more accurate alignments are required. Experiments show that accurate alignments are especially important in low-resource scenarios.

5. CONCLUSION

In this work, we have studied the role of accurate alignments in the context of training FastSpeech2 based E2E system. We show that systems trained with the hybrid HMM-GD-DNN technique with refined boundaries produce better quality speech compared to the popularly used MFA aligner, even in a low-resource scenario. This work can be further explored in the context of direct text-to-wave E2E systems.

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