You Do Not Need More Data: Improving End-To-End Speech Recognition by Text-To-Speech Data Augmentation

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Abstract

Data augmentation is one of the most effective ways to make end-to-end automatic speech recognition (ASR) perform close to the conventional hybrid approach, especially when dealing with low-resource tasks. Using recent advances in speech synthesis (text-to-speech, or TTS), we build our TTS system on an ASR training database and then extend the data with synthesized speech to train a recognition model. We argue that, when the training data amount is low, this approach can allow an end-to-end model to reach hybrid systems’ quality. For an artificial low-resource setup, we compare the proposed augmentation with the semi-supervised learning technique. We also investigate the influence of vocoder usage on final ASR performance by comparing Griffin-Lim algorithm with our modified LPCNet. An external language model allows our approach to reach the quality of a comparable supervised setup and outperform a semi-supervised setup (both on test-clean). We establish a state-of-the-art result for end-to-end ASR trained on LibriSpeech train-clean-100 set with WER 4.3% on test-clean and 13.5% on test-other.

Index Terms: Speech Recognition, End-to-End, Speech Synthesis, Data Augmentation

1. Introduction

There are two main approaches to automatic speech recognition (ASR): hybrid (deep neural networks combined with Hidden Markov models (DNN-HMM)) and end-to-end (jointly trained neural network systems). When training data amount is sufficiently large, they perform nearly equal [11]. But for low-resource tasks, end-to-end recognition quality is far behind from the hybrid models [2,3]. However, data augmentation techniques can help to make the end-to-end approach more competitive in the low-resource case [4]. One can augment the data by morphing the training set itself or by obtaining additional data. Semi-supervised learning is one of the external data usage techniques proven to be effective [5]. It consists of using a union of labeled training data and unlabeled data with transcription produced by the initial model to train a new one. However, it might not get the desired improvement if the initial model’s recognition quality is low. There are other approaches, such as transfer and active learning [6], to tackle low-resource challenges, but they are beyond the scope of this paper.

Recent advances in speech synthesis (text-to-speech or TTS) made synthesizing close-to-human speech possible [7]. Apart from human-computer interaction applications, such high-quality artificial speech can be used as a data augmentation for ASR [8]. It can be done either by training a standalone multi-speaker TTS system on in-domain data [2] or by building and training of ASR and TTS systems jointly [10]. It also has been shown that widely used augmentation techniques, specifically speed perturbation [11] and SpecAugment [12], stack effectively with TTS augmentation [13].

This work aims to improve low-resource speech recognition quality by augmenting training data using speech synthesis. Following [13], we use LibriSpeech database [14] to simulate a low-resource task. First, our TTS system and baseline ASR system are trained separately on the same small subset. Then we synthesize utterances from a larger subset and use them as training data for ASR. We compare this approach with a semi-supervised learning technique to determine which one is more suitable for use in the low-resource setup. We also investigate the influence of waveform generation methods in TTS on final ASR performance by using the Griffin-Lim algorithms [15] and our modification of LPCNet [16]. Finally, we present our findings on how the proposed TTS augmentation stacks with the use of a language model and compare our setup with previous works.

2. Related work

There are four prior works similar to ours. All of them use LibriSpeech to train their end-to-end ASR models and employ style modeling in TTS systems.

Li et al. [8] is the earliest of these works. Authors used Global Style Token (GST) [17] to model prosody. Unlike later works, authors trained their TTS model on an external three-speaker dataset (M-AILABS [9]). Authors used Tacotron 2 as synthesizer, WaveNet as vocoder, and Wave2Letter+ ASR model from OpenSeq2Seq toolkit [18].

Rosenberg et al. [9] used a hierarchical version of variational autoencoder (VAE) [19] to model prosody. They also addressed the lexical diversity problem (the number of real transcriptions is limited) by generating new utterances using a language model. The authors used their own Tacotron 2, WaveRNN, and an attention-based ASR model.

Sun et al. [19] suggest modelling style using an autoregressive prior over representations from quantized fine-grained VAE and perform evaluation by synthesizing utterances for training ASR on LibriSpeech. Authors do not consider a low-resource setup and do not report details of their ASR system.

Rosenbach et al. [13] work is the most similar to our research in terms of the experimental setup. It compares GST with i-vectors for style modeling task. The authors used Tacotron 2,
3. ASR system

3.1. Acoustic model

As an ASR model, we chose the Transformer from the ESPnet speech recognition toolkit [20], since it delivers close to state-of-the-art (SotA) results on LibriSpeech [21]. Transformer [22] is a sequence-to-sequence (S2S) architecture that uses self-attention mechanism to employ sequential information. It learns to transform one (source) sequence to another (target). Transformer consists of two neural networks: the Encoder and the Decoder. The Encoder transforms a source sequence into an intermediate sequence. This sequence is used for connectionist temporal classification (CTC) [23] frame-wise posterior distribution computing. The Decoder network also uses this intermediate representation along with previous target frames to predict the next target frame distribution. The final prediction is made using beam search and is computed as a weighted sum of CTC and S2S decoding posteriors.

3.1.1. Encoder

The Encoder network is a sequential module with two subnetworks and a positional encoding submodule between them. The first network transforms and subsamples an input acoustic feature sequence by using a two-layer CNN with 256 units, kernel size 3, and stride 2, yielding a four times shorter sequence. This subsampled sequence is added to a sinusoidal positional encoding tensor, which maps the position of each feature unit for each timestamp to the corresponding number, thereby allowing the Transformer to operate with the order of the sequence. The second network encodes the sequence by multiple sequential structures of one multi-head self-attention (MHA) layer and two feedforward (FF) layers, according to [22].

3.1.2. Decoder

The Decoder network is a sequential module with an embedding layer, the positional encoding module (same as for the Encoder), a core deep subnetwork, and a posterior distribution prediction layer. The embedding layer transforms a token sequence into a learnable vector representation, and the positional encoding puts temporal information in it. The decoder core subnetwork consists of stacked MHA and FF structures similar to the Encoder but with additional MHA layer between them. Its purpose is to combine the encoder output sequence with the transformed tokens. After this subnetwork completes a step, the last layer yields the next token prediction.

3.2. Language model

Language model (LM) predicts the next token and its weight using only the sequence of previous tokens. In the decoding stage, the LM prediction is added to the CTC and Decoder results using a log-linear combination. The model we used is a recurrent neural network of four LSTM layers with 2048 units each.

3.3. Data preprocessing and augmentation

For each training set used for experiments, we removed utterances that are too short and too long. After that, the data were speed-perturbed with the perturbation factors 0.9 and 1.1 to make the training set 3 times larger. During the training, acoustic features were augmented with SpecAugment.

4. TTS system

We chose a two-network setup, which is prevalent in contemporary neural speech synthesis. The first network (synthesizer) converts input text to a spectrogram. The second network (vocoder) converts input spectrogram to a waveform. The Griffin-Lim algorithm may be used instead of a neural vocoder, but its output usually sounds metallic and less natural.

While ASR takes Mel-spectrograms as an input, converting synthesized spectrograms to waveforms is necessary because of different STFT parameters; unifying them would decrease the quality of either ASR or TTS.

4.1. Preprocessing

As LibriSpeech annotations consist of normalized upper-case texts, the only text preprocessing step is G2P. We used lexicon from OpenSLR⁴. Some of pronunciations in the lexicon were G2P auto-generated.

4.2. Synthesizer

We chose Tacotron [24][7] as a base for our speech synthesizer. It is an RNN-based seq2seq model with attention that converts input text to a log-magnitude 80-band Mel-spectrogram. We used dynamic convolution attention [25] instead of location-sensitive attention [26].

We used framework of VAE to model prosody as a deep latent variable. We followed GMVAE-Tacotron [27] and chose prior and posterior distributions to be a mixture of diagonal Gaussians and a single diagonal Gaussian. For simplicity, we used a single global latent variable to model both intra- and inter-speaker prosody variation.

Loss function is composed of: \( l_1 \) distance between spectrograms, KL-divergence between prior and posterior of the latent variable [27, Eq.3], and CTC loss between spectrogram and input text (following [28]).

4.2.1. Architecture details

Tacotron encoder and decoder hyperparameters follow [29]. Base dimensions are 256 with extensions where concatenation is necessary. For every decoder step, two frames are predicted (r=2). Dynamic convolution attention parameters follow the original paper [25].

Latent variable encoder consists of two 1D convolutional layers (128 and 256 channels, k=3) with ReLUs and batch normalizations followed by two BLSTM layers (d=128). We applied tanh before projecting to posterior means and log-variances. The latent space is 16-dimensional, the number of components in the prior mixture is 10. Sample from the posterior is concatenated to the encoder output.

Before CTC loss, spectrogram is fed through two linear layers (d=512) with dropout (p=0.5) and ReLU in-between.

4.3. Vocoder

Mel-spectrograms produced by Tacotron are smooth and blurry, while the same spectrograms calculated using the output of a

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⁴ https://www.openslr.org/resources/11/
⁵ librispeech-lexicon.txt
⁶ https://github.com/espnet/espnet
⁷ https://github.com/rwth-i6/returnn
neural vocoder are more detailed. The hypothesis is that using a vocoder might be beneficial for the final ASR performance.

![Diagram](image)

**Figure 1: Our LPCNet modification.**

Our vocoder is based on LPCNet. It is a good choice for a multi-speaker TTS [30].

We modified it to take Mel-spectrograms as an input, as opposed to originally used bark-frequency cepstrum (Figure 1). Original LPCNet uses pitch correlation to control sampling temperature, requiring pitch as an input feature. To free Tacotron from predicting pitch and simplify the pipeline, we approximate pitch correlation through spectral flatness. This modification has been successfully used in prior work [31].

The size of the main GRU hidden state was set to 384. We did not apply sparsification. We used the data preparation pipeline from reference implementation with simplifications stated above.

## 5. Experiments

### 5.1. ASR setup

We took only train-clean-100 (a hundred-hour portion of the “clean” speech) and train-clean-360 (the rest of the “clean” data) for the training, dev-clean for tuning of the models, and test-clean and test-other for the evaluation. Language model was trained on external text data. The acoustic features are cepstral mean and variance normalized 80-dimensional log-Mel filterbank coefficients with 3-dimensional pitch features (bank-pitch). The text data were tokenized by SentencePiece byte-pair-encoding [22] with 5000 vocabulary size.

We mostly used the Transformer architecture setup from [21], but our Transformers were trained for 48 epochs with early stopping after five epochs of non-best accuracy for the development set. Also, the parameters averaging was performed over five best-on-devset models, and the beam size was set to 20.

### 5.2. TTS setup

We used 80-band Mel-spectrogram calculated with window of 50 ms and hop of 12.5 ms as an intermediate acoustic representation between synthesizer and vocoder.

#### 5.2.1. Speech synthesizer

We trained our TTS on force-aligned train-clean-100 subset. Input vocabulary consists of English phonemes, a pause break token, and a stop token.

The augmentation process is as follows: we synthesize every text from train-clean-360 with prosody variable being sampled from the prior. We used one sample per text due to time and computing constraints. We also did not predict pause breaks, which resulted in non-stop continuous speech even for long utterances.

#### 5.2.2. Vocoder

Our LPCNet was trained on train-clean-100 subset for 250k steps, with a batch size of 64 and with each training sequence consisting of 1600 samples (100ms frame).

We found that for very low-pitched or high-pitched samples the quality of speech signal decreased.

### 5.3. Experimental setup

To establish a low-resource baseline, we trained our ASR model on train-clean-100. Next, we augmented the data with the speech synthesized from train-clean-360 texts and trained our TTS-augmented model (tts-aug-360). The semi-supervised model was trained on waveforms from the same train-clean-360 set with the transcripts produced by the baseline model (semi-sup-360). To compare our technique with with the supervised “oracle” setup, we trained the model ontrain-clean-100 combined with train-clean-360 (train-clean-460).

### 5.4. Results

First of all, we compared our end-to-end system with the best hybrid Kaldi baseline [2]. Since our system employs sequential information (via attention decoding mechanism), we compared it with 4-gram LM decoding of the DNN-HMM inference. As shown in Table 1 hybrid system is clearly superior to ours in both clean and other conditions for train-clean-100, while for train-clean-460 the end-to-end model is competitive in clean and better in other conditions. We also put results for train-clean-100 from RETURNN [13] as the strongest hybrid baseline known to us.

| Training set | ASR system | WER [%] |  |  |
|--------------|------------|---------|---|---|
|              |            | clean   | dev | clean | other | test | other |
| clean-100    | Kaldi      | 5.9     | 20.4 | 5.6  | 22.5  |
|              | RETURNN    | 5.0     | **19.5** | 5.8  | **18.6** |
|              | E2E (our)  | 10.3    | 24.0 | 11.2 | 24.9  |
| clean-460    | Kaldi      | 5.3     | 17.7 | 5.8  | 19.1  |
|              | E2E (our)  | 5.1     | **14.1** | 5.9  | **14.1** |

After establishing baselines, we evaluated different ways of converting TTS spectrograms to waveforms. The question was: when synthesized utterances are used for ASR training, are there benefits of choosing neural vocoder over the Griffin-Lim algorithm in terms of final ASR performance? A comparison of Griffin-Lim algorithm with our modification of LPCNet

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[http://www.openslr.org/resources/11/librispeech-lm-norm.txt.gz](http://www.openslr.org/resources/11/librispeech-lm-norm.txt.gz)

[https://github.com/kaldi-asr/kaldi/blob/master/egs/librispeech/s5/RESULTS](https://github.com/kaldi-asr/kaldi/blob/master/egs/librispeech/s5/RESULTS)
is presented in Table 2. As the proposed vocoder delivered 5-6% relative WER improvement, all synthesized utterances for further experiments were made using the neural vocoder.

Table 2: Comparison of waveform synthesis methods. Both ASR models are trained on train-clean-100 plus tts-aug-360.

| Vocoder   | WER[\%] | dev | test |
|-----------|---------|-----|------|
|           |         | clean | other | clean | other |
| Griffin-Lim | 6.6     | 20.8 | 7.2  | 21.2  |
| LPCNet     | 6.3     | 19.8 | 6.8  | 19.9  |

We carefully studied the influence of TTS-augmentation versus semi-supervised learning on the system's performance. Table 3 contains an extensive study on how these approaches perform depending on whether our external LM was used in decoding. Results for dev-clean and dev-other are omitted.

Additionally, there is a "medium-resource" setup in which tts-aug-360 is combined with train-clean-460 instead of train-clean-100. The goal of this experiment was to check whether the synthesized speech variability is wide enough to effectively use it with the source utterances of the same text. Although two augmentation approaches without LM usage performed equally and worse than the supervised for test-clean and dev-other, our medium-resource setup benefited from using TTS-augmented data, especially for test-clean when LM was employed.

Table 3: Comparison of different ASR training setups against LM usage.

| LM  | Core data | Additional data | WER[\%] | dev | test |
|-----|-----------|-----------------|---------|-----|------|
|     |           |                 |         | clean | other | clean | other |
| No  | -         | -               | 11.2    | 24.9 |
|     | clean-100 | tts-aug-360    | 6.8     | 19.9 |
|     | clean-100 | semi-sup-360   | 6.8     | 17.1 |
|     | clean-460 | -               | 5.9     | 14.1 |
|     | clean-460 | tts-aug-360    | 4.8     | 13.5 |
| Yes | clean-100 | -               | 7.0     | 17.0 |
|     | clean-100 | tts-aug-360    | 4.3     | 13.5 |
|     | clean-100 | semi-sup-360   | 5.2     | 13.0 |
|     | clean-460 | -               | 4.7     | 9.1  |
|     | clean-460 | tts-aug-360    | 3.2     | 9.1  |

For low- and medium-resource setups, we compared our best results with ones from papers mentioned in Section 2. We also provided a large-resource results overview for previous works, although we were unable to successfully train a model on a comparable amount of data due to a lack of computing resources. Note that the partition into resource tasks may not be accurate due to not exactly matching data setups. In Table 4 we considered the final WER and the relative WER improvement from non-augmented setup as two main indicators of good system performance. Our best system outperformed previous works for both test-clean and test-other in the low-resource. Our best system a new SotA on train-clean-100 since our approach surpassed any system known before. While superior in the medium-resource setup, the result for test-other did not improve. For large-resource setups, the improvement decreased.

Table 4: Comparison of our system performance against the results of other works for different simulated setups. "Impr" stands for relative WER improvement.

| Setup       | Paper | WER[\%] | Imp\%[\%] |
|-------------|-------|---------|-----------|
|             |       | test-clean | test-other | test-clean | test-other |
| low-resource|       | 4.3     | 13.5     | 38.6 | 20.6 |
|             | [9]   | 9.3     | 30.6     | 22.8 | 10.1 |
|             | [13]  | 5.4     | 22.2     | 33.3 | 9.4  |
| medium-resource | 3.2 | 9.1 | 31.9 | 0.0 |
|             | [9]   | 6.3     | 22.5     | 0.3  | -0.5 |
| large-resource |     | 4.7     | 15.5     | 8.6  | 4.6  |
|             | [9]   | 4.6     | 13.6     | 4.6  | 1.8  |
|             | [13]  | 2.5     | 7.2      | 4.9  | 2.4  |

Difference in improvements on test-clean and test-other subsets may be attributed to data partition made by LibriSpeech authors. They used ASR performance as the main partition criterion, with ASR being trained on a speech corpus of mostly North American English. As a result, clean subset should be, on average, closer to NA accent, and other should be farther. Using augmented NA speech is expected to be less effective on non-NA test data due to the domain shift.

6. Conclusions

In this work we investigated data augmentation for low-resource speech recognition using text-to-speech. A low-resource setup was simulated with 100-hour subset of LibriSpeech. Using GMVAE-Tacotron as a speech synthesizer and modified LPC-Net as a vocoder, we generated 360 hours of synthetic speech with random prosody, modelled by a variational autoencoder. Adding synthesized speech allowed us to improve a powerful end-to-end ASR baseline by 39% relative WER on test-clean and by 21% on test-other. Our approach outperformed similar setups in both absolute WER and relative WER improvement and thereby established a new LibriSpeech low-resource SotA with 4.3% WER on test-clean and 13.5% WER on test-other. Our experiments also showed that usage of TTS augmentation was more successful than semi-supervised learning on test-clean, and less successful on test-other.

In future work we plan to address the accent domain shift to improve performance on test-other and close the gap to test-clean on both low- and large-resource tasks. We also plan to evaluate our approach on non-simulated low-resource setups.

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