SYNTH2AUG: CROSS-DOMAIN SPEAKER RECOGNITION WITH TTS SYNTHESIZED SPEECH

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ABSTRACT

In recent years, Text-To-Speech (TTS) has been used as a data augmentation technique for speech recognition to help complement inadequacies in the training data. Correspondingly, we investigate the use of a multi-speaker TTS system to synthesize speech in support of speaker recognition. In this study we focus the analysis on tasks where a relatively small number of speakers is available for training. We observe on our datasets that TTS synthesized speech improves cross-domain speaker recognition performance and can be combined effectively with multi-style training. Additionally, we explore the effectiveness of different types of text transcripts used for TTS synthesis. Results suggest that matching the textual content of the target domain is a good practice, and if that is not feasible, a transcript with a sufficiently large vocabulary is recommended.

Index Terms— Speaker Recognition, Text-To-Speech, Data Augmentation

1. INTRODUCTION

Speaker recognition is the process of recognizing the identity of the speaker from a spoken utterance. Recent work has explored different deep neural network (DNN) architectures [1–8] to produce compact speaker embeddings. In this paper, our work is based on the d-vector model described in [8] for the text-independent speaker recognition task.

DNN speaker recognition has benefited from the use of various data augmentation techniques [2, 9–11]. While speech recognition has also used such techniques [12–14], some recent work has explored the use of TTS for supplementing speech recognition training data [15–17]. These advances are enabled by the fact that synthesizing close-to-human-quality multi-speaker speech has become more mature [18–22].

Likewise, the speaker recognition community has started to explore the use of TTS, but mainly on anti-spoofing. Researchers have worked on determining if speaker recognition systems were vulnerable to TTS techniques and, if so, examining ways to make such systems robust to TTS spoofing attacks [23–27]. While the speech recognition community found some utility in using TTS for data augmentation, we are currently not aware of studies examining TTS for speaker recognition data augmentation. This paper begins to address this gap.

From a speaker recognition perspective, a speech recording can be abstracted into two sources of variability; speaker variability and channel/environment effects. Many data augmentation techniques seek to expand upon the variability observed for channel/environment effects. There is limited work regarding how speaker variability can be augmented. One example is that the time warping component of the SpecAugment technique [28–30] could be considered as a basic form of speech rate perturbation. Interestingly, multi-speaker TTS synthesis seems to be a natural candidate for providing additional speaker-centric variability.

We narrow the scope of this initial work to make performance analysis more tractable (while beginning with perhaps an easier task). In this paper, we study how speech synthesis can be leveraged to improve cross-domain speaker recognition performance with the proposed Synth2Aug approach. As part of this work we assess if TTS as a data augmentation method can provide additional information over a carefully tuned multi-style training setup. We also explore if speech content plays a role in the effectiveness of TTS synthesis for speaker recognition. Note that our experiments are conducted under two main constraints: there is no target domain training data, and our training data consist of a relatively small group of speakers.

The rest of the paper is organized as follows. Section 2 gives a brief introduction on our Synth2Aug approach, followed by detailed explanations of the speaker recognition and TTS systems. In Section 3, we present two sets of experiments; one studying the contribution of TTS synthesis to speaker recognition performance and the other exploring the effect of TTS textual content. This is followed by conclusions and future work in Section 4.

2. DESCRIPTION OF PROPOSED SYSTEM

As mentioned previously, the goal is to build a speaker recognition system that leverages TTS synthesis to potentially improve performance on cross-domain data. While it may be difficult to acquire multi-speaker audio training data for the target domain, it is relatively simple to use similar textual content for speech synthesis such that it better relates to the target domain. We propose Synth2Aug to overcome the cross-domain challenge, as illustrated in Figure 1. Given existing source domain training data, we train a multi-speaker TTS model to synthesize new speech data based on the target domain textual content. We incorporate the synthesized speech, along with the existing training data, into speaker recognition model training. In the following sections, we will walk through the details including: the speaker recognition system, the multi-speaker TTS system, and the specifics of the synthesized speech.

2.1. Speaker recognition system

Our speaker recognition model is a text-independent, d-vector system similar to the model architecture in [8]. While the work could easily be applied to both speaker identification and verification, we are performing a speaker verification task for the discussion in the paper. To aid in reproducibility, we share the system details which cover feature extraction, model architecture, system training and evaluation.
The feature extraction process is implemented based on [31]. The audio is first transformed into frames of 25ms width and 10ms shift, followed by the extraction of 40-dimensional log-Mel-filterbank energy features for each frame. A model-based Voice Activity Detection (VAD) component is integrated to exclude non-speech frames. Finally, we stack adjacent frames of features by concatenating two frames of size 40 into a single frame of size 80, which results in a frame sequence of approximately half the number of original frames.

The model is composed of 3 LSTM layers with projections [32]. For each LSTM layer, the number of hidden nodes is 768 and the output is projected down to 256 dimensions followed by a tanh activation function. A final linear layer of 256 dimensions is appended to the last LSTM layer.

For system training, each mini-batch is constructed with 16 randomly selected speakers with 8 randomly selected utterances per speaker. When there are multiple training datasets, we use the MultiReader technique proposed in [8]. We assign a weight to the batch speaker. When there are multiple training datasets, we use the MultiReader technique proposed in [8]. We assign a weight to the batch speaker.

For system evaluation, we use the L2-normalized output of the last frame from the last 256-dimensional layer to represent the speaker embedding. This speaker embedding is known as the d-vector. The enrollment embedding is calculated by averaging multiple enrollment utterance d-vectors for each speaker and applying L2-normalization again. The test utterance is compared with the enrollment embedding using the cosine similarity metric.

2.2. Text-to-speech model

The Text-To-Speech (TTS) model is based on a Tacotron 2 model [19], which consists of a spectrogram prediction network to convert phoneme sequences to Mel-spectrogram, and a WaveRNN [33] model as a vocoder to convert the Mel-spectrogram to speech waveform. We train a multi-speaker Tacotron 2 model to support multi-speaker speech synthesis. Specifically, every speaker is represented with a d-dimensional embedding vector. We feed it into the decoder of the Tacotron model and concatenate it with the output vector from the attention model. These embedding vectors are trained as parameters together with the main model. To clarify, the speaker embedding vector introduced here is a trainable vector bound to the Tacotron model. It is a different concept from the d-vector speaker embedding in speaker recognition. We will always refer to the speaker embedding in speaker recognition directly as “d-vector” in this paper.

In addition, we introduce a sequence of 32-dimensional latent variables in the decoder (as per [34]) to capture the residual intraspeaker style variations. The latent variables at each output step are sampled independently from a mixture of Gaussian priors. We follow the variational autoencoder method [35], and train a recognition model from the output Mel-spectrogram to infer the posterior distribution of the latent variables during training.

The embedding space when trained with a large number of speakers is expected to capture the unique characteristics of individual speakers. To further increase the diversity of synthesized voices, we train multiple models with different dimensional speaker embedding spaces (of dimension 32, 64, 128) and synthesize speech from all of them.

The training data for the TTS model are audiobook read speech. It is a combination of two proprietary speech corpora and the LibriTTS dataset [36]. There are in total 2,218 speakers, including 55 and 1,080 speakers from the proprietary datasets, and 1,083 LibriTTS speakers (clean-100 and clean-360), with an average of around 500 utterances per speaker. The training process is the same as [19], which involves first training the feature prediction network on its own, followed by the WaveRNN training independently on the outputs generated by the feature prediction network.

2.3. Synthesized speech

When generating the synthesized speech, we consider two approaches for creating a diverse set of voices.

The first approach is to directly use the embedding vectors of the 2,218 training speakers from the TTS model with the 128-dimensional embedding space. The model synthesizes utterances according to each corresponding embedding. Note that we do not include the other two models (i.e. 32d and 64d) because the under-
lying speakers are the same. This approach preserves the genuine characteristics of the speakers with high quality. However, the speaker variability is relatively limited due to us reusing the existing real speakers.

The second approach is to synthesize artificial voices by sampling the speaker embedding in the learned embedding space. An arbitrarily sampled vector in the speaker embedding space may be far from any realistic training voices and this leads to a generalization challenge for the TTS model. To mitigate this, we first fit a mixture of 3 full-covariance Gaussians to the set of training speaker embedding vectors, and then draw samples from the Gaussian Mixture Model. This allows us to extract as many voices as needed with a slightly degraded quality, compared to using the speaker embeddings from real training speakers. As the purpose of data augmentation is to improve the robustness of speaker recognition, the additional noise in the utterance is less of a concern.

However, in the second approach, if two embedding vectors are close to each other, the corresponding synthesized voices will be similar as well. To verify this, we first sample a large set of artificial voices, \( S \), from all three TTS models of different dimensions, then compute d-vector cosine similarities with a pre-trained speaker recognition model \( M^1 \). Specifically, for each sampled voice we synthesize \( N = 100 \) utterances, obtain the d-vector of each utterance from the model \( M \), and then compute the average. We find that while the average cosine similarity between real training voices and sampled voices is only about 0.185, the average similarity between two sampled voices is almost 0.5. The intraspeaker variation in such a case could dominate the interspeaker variation. In order to avoid this problem, we conduct a “speaker selection” process, which aims to build a speaker set where the voices are reasonably distant from each other. We incrementally build a subset of speakers \( T \subseteq S \). At each step, a speaker \( i \) is randomly drawn from \( S \setminus T \), and added to \( T \) if the cosine similarity between \( i \) and each \( j \) of the already selected speakers does not exceed 0.4, as illustrated in Equation 1.

\[
\cos \left( \frac{1}{N} \sum_{n=1}^{N} d_{in}, \frac{1}{N} \sum_{n=1}^{N} d_{jn} \right) \leq 0.4, \quad \forall j \in T, \quad (1)
\]

where \( d_{in} \) is the d-vector computed from the \( n \)th synthesized utterance of the \( i \)th voice.

We construct this speaker set \( T \) in a greedy way, by searching through sampled voices from the TTS models of embedding dimension \( d = 32 \), then 64 and 128 subsequently. As a result, thousands of distinct speaker embeddings are sampled from each model, as shown in Table 1.

For each speaker, real and sampled, we synthesize 10,000 speech utterances. The underlying transcript of the TTS synthesis could contain any text. In Synth2Aug, we collect transcript text which closely matches the target domain text. (We also experiment with different types of transcripts in Section 3.4.)

### 3. EXPERIMENTS

#### 3.1. Overview

Before discussing the experiments, we identify some of the design choices made with regard to data selection and the simplification of experiments. When deciding on the training data for both TTS and speaker recognition systems, we constrain ourselves to using the TTS training data for both tasks to avoid unintended side effects and complexity introduced by multiple training datasets. It is easier for the speaker recognition system to use the TTS system training data than the other way around, because the TTS system training requires high quality speech.

We configure two sets of experiments to better understand how speech synthesis can support speaker recognition.

In the first set of experiments, we explore if TTS synthesis could be valuable for our cross-domain speaker recognition problem. In particular, it is important to understand if it can improve upon a well-tuned multi-style training (MTR) setup [12–14]. The MTR augmentation introduces room reverberation with noise sources including cafes, cars, and ambient noise from quiet environments, as well as music or other types of sounds. The signal-to-noise ratio (SNR) is drawn from a uniform distribution between 3dB and 15dB.

In the second set of experiments, we endeavor to understand how the textual content of the synthesized speech affects the performance of a speaker recognition system trained on this data. We prepare different types of transcripts, including numeric digit sequences, random word concatenation, closely-matched text and exactly-matched text.

#### 3.2. Evaluation data

The evaluation data for all the experiments are the vendor collected speech query data. This dataset was collected via a web service, where 70% of the queries were recorded with mobile phones and 30% with laptops in relatively quieter environments. Gender is balanced and the ages range from 18 to 45 years old. There are various channel effects because of different types of microphones/devices. The mean test utterance duration is 4.4s, and the standard deviation is 1.6s. The average SNR of this entire test dataset is 18.4dB, calculated by following the WADA-SNR algorithm [37]. The audio prompts are from general speech queries and websites such as wikipedia. Note that these speech queries are completely different from the read speech used for training. As a result, this becomes a cross-domain challenge.

The evaluation utterances are divided into into enrollment and test utterance lists. There are 8,069 utterances from 1,434 speakers in the enrollment list and 194,890 utterances from 1,241 speakers in the test list. For this dataset, we have 192,943 target trials and 200,000 non-target trials.

#### 3.3. Impact of TTS synthesized speech

In this section, we prepare various experimental setups to examine the impact of TTS synthesized speech on speaker recognition. The transcript used for speech synthesis is from the 10,000 most popular speech queries. Since our target domain utterances are mainly
speech queries, this transcript could be considered as a close representation. We also investigate whether the synthesized speech is effective when used with MTR. The following models are assessed.

**Baseline:** The baseline training only makes use of the TTS model training data to train the speaker recognition model. There is no data augmentation involved. All setups listed here have these data included for training. We refer to this as `Baseline` training data below.

**TTS-Real:** This corresponds to the approach where, aside from the `Baseline` training data, we additionally include the synthesized speech based on real speaker embeddings using the 128d TTS model. The speaker diversity of the synthesized data is limited because we have a fixed number of real speakers (i.e., 2,218 speakers). We do not apply MTR here.

**TTS-Sampled:** The alternative to generating speech using real speaker embeddings is to use the sampled embeddings. Here we include all the utterances synthesized from the 32d, 64d and 128d models. New speakers are introduced, and the total number of speakers after speaker selection is much larger than the number of real speakers we had originally. As a result, `TTS-Sampled` also has more utterances than `TTS-Real`. We do not apply MTR here.

**TTS-Sampled-Small:** In this experiment, we only use the 64d-Sampled dataset from the 64d TTS model. It has a similar number of speakers to `TTS-Real`. Therefore, the effect of using a different number of speakers is minimized. The main difference is whether we are introducing new speakers, or simply supplementing the existing training data with more utterances for each existing speaker. No MTR is applied.

**Baseline-MTR:** We augment the `Baseline` training data with MTR to improve coverage. Since this represents an important baseline, it is imperative to optimize its performance. We found that to maximize the performance of the MTR setup we needed to apply MTR to each utterance 15 times. This expands the amount of training data by 15 times as well.

**TTS-Sampled-MTR:** In this setup MTR is applied to the synthesized speech in `TTS-Sampled`. Both the clean and the MTR synthesized speech are used, along with the `Baseline` training data, to train the speaker recognition model. Note that the `Baseline` training data does not have MTR applied.

**Combined-MTR:** We combine both MTR and TTS synthesis data augmentation techniques by reusing the optimized data setup from `Baseline-MTR` and appending to it the clean and MTR copies of the synthesized speech data from `TTS-Sampled-MTR`. We have not fine-tuned the weight of each training data source to be optimal in the MultiReader configuration. Instead we assign weights proportional to the size of each training dataset.

The experimental results are displayed in Table 2. As shown, using any sort of synthesized data (`TTS-Real`, `TTS-Sampled-Small` or `TTS-Sampled`) in addition to the original training data provides improvement over the `Baseline`. In addition, `TTS-Sampled-Small` outperforms `TTS-Real`. It indicates that extending the existing speaker set with newly sampled voices is helpful. Also, the ability to synthesize new speakers outweighs the slight degradation in voice quality from not using existing real speaker embeddings. Furthermore, when we compare `TTS-Sampled` against `TTS-Sampled-Small`, there is noticeable benefit from introducing additional new speakers.

By analyzing the MTR related experiments, we observe that the optimized `Baseline-MTR` system already shows significant improvement over the non-MTR `Baseline` system. When MTR is applied to the `TTS-Sampled` dataset (`TTS-Sampled-MTR`), the EER is reduced. More interestingly, when these two data augmentations are combined (`Combined-MTR`), the performance is improved further.

| Model                  | With MTR? | EER (%) |
|------------------------|-----------|---------|
| Baseline               | N         | 6.3     |
| TTS-Real               | N         | 5.6     |
| TTS-Sampled-Small      | N         | 4.8     |
| TTS-Sampled-MTR        | N         | 4.6     |
| Baseline-MTR           | Y         | 4.3     |
| TTS-Sampled-MTR        | Y         | 4.0     |
| Combined-MTR           | Y         | 3.5     |

This shows that TTS synthesis can complement a well-tuned MTR setup. It may be that while MTR addresses the sparsity of channel/environment effects in the speech data, TTS synthesis helps expand speaker-centric variability.

### Table 2. Performance of different data augmentation techniques evaluated on vendor provided speech query data. The first column lists models trained with different types of data augmentation techniques. The second column indicates if MTR data augmentation makes up part of the training data. The third column shows the performance of each model.

#### 3.4. Impact of textual content on performance

The main focus of this section is to assess the impact of different textual content on speaker recognition performance. We synthesize speech with the same number of speakers and utterances, but with different types of transcripts. The transcript contents studied include random digit/word sequences, top speech queries, target domain test dataset text and its word-shuffled variant:

- **Random-Digits:** We prepare text with a very limited vocabulary of numeric digits (zero through nine, plus an additional "oh"). The digits are randomly drawn and concatenated into utterances of 3 to 7 words.

- **Random-Words-100:** The transcript is constructed from the concatenation of random words drawn from a subset of the TIMIT dataset dictionary [38]. The subset consists of 100 words chosen randomly from the full dictionary. Utterances of 3-7 words are created from this subset.

- **Random-Words-Full:** This transcript extends the vocabulary subset in Random-Words-100 to use all the words in the TIMIT dictionary. We do the same random word concatenation to construct utterances of 3-7 words.

- **Close-Match:** We collect 10,000 of the most popular speech queries as the transcript. The same transcript is used in the previous experiments in Table 2. We denote this as Close-Match, because the texts are close representations of the target domain speech queries.

- **Exact-Match:** In this setup, we directly extract the text from the speech query test dataset. This represents an exact match of the textual content from the target domain. Since the test dataset contains more utterances than what we have in the Section 3.3 experiments, we limit the set to 10,000 utterances.

- **Exact-Match-Shuffled:** This transcript is the same as Exact-Match, except that there is the additional step of shuffling to reordering the words within each utterance.

Now that the individual models are described, we discuss the results in Table 3. We note that the experiments included here are based on the same configuration as Combined-MTR in Table 2, except that the transcripts being used for TTS synthesis are specific to the models. In the Orig & TTS column of Table 3, the Exact-Match model has the best performance. Although Random-Digits performs...
Table 3. Table showing evaluation results and vocabulary sizes for different transcript types. Column Orig & TTS lists the results of the models trained with the original TTS training data included, while column TTS-only relates to the models trained with only the synthesized speech. Note that the Orig & TTS column result of the Close-Match model is the same as the Combined-MTR in Table 2.

| Model               | Vocab Size | Orig & TTS EER (%) | TTS-only EER (%) |
|---------------------|------------|--------------------|------------------|
| Random-Digits       | 11         | 3.7                | 6.9              |
| Random-Words-100    | 100        | 3.6                | 5.6              |
| Random-Words-Full   | 6,222      | 3.5                | 5.1              |
| Close-Match         | 3,194      | 3.5                | 4.8              |
| Exact-Match         | 10,101     | 3.4                | 4.3              |
| Exact-Match-Shuffled| 10,101     | 3.5                | 4.7              |

the worst, it is still relatively comparable to the others. In fact, all the results are within a narrow range. Since the original TTS training data (with MTR applied) already produces a relatively low EER, the expected effect of different textual content is thereby reduced.

In order to fully test the validity of these transcripts, we exclude the original TTS training data, and train our model only on the synthesized data. Results of these revised experiments are shown in the TTS-only column of Table 3.

Not surprisingly, the Exact-Match model again has the lowest EER. Here, the synthesized utterances for training share the exact same textual content with the evaluation utterances. The Close-Match model outperforms the Random-Words-Full model, mostly likely due to the fact that the synthesized data for Close-Match is more similar to the evaluation textual content than solely random word concatenations. More interestingly, the Exact-Match-Shuffled model, which was trained with semantically meaningless synthesized utterances, is worse than the Exact-Match model, but better than the Close-Match model by a very small margin. This may indicate that the benefits of matching the target domain text stem from not only similar vocabularies and word frequencies, but also similar word sequences.

In addition, from Random-Words-Full to Random-Words-100 to Random-Digits, there is a clear trend of an increased error rate when the vocabulary size is reduced. Initial observations suggest that a sufficiently large vocabulary (of the order of thousands of unique words) is required to provide close to optimal performance.

In summary of our experiments, it is recommended that speech synthesis uses textual content which: 1) matches the target domain text, and 2) if that is not feasible, uses a comprehensive vocabulary. That said, further work would be required to understand if the same conclusion generalizes to other data sources, data augmentation approaches, or system configurations.

4. CONCLUSIONS AND FUTURE WORK

This paper proposed and studied a novel approach, Synth2Aug, to use TTS synthesis as a data augmentation technique for improving cross-domain speaker recognition. When the training data were constrained to a limited number of speakers, using synthesized speech generated from a multi-speaker TTS system improved our cross-domain speaker recognition significantly. TTS synthesis may reduce the sparsity of the training speakers by generating additional artificial speakers. We also found that TTS based augmentation could further improve an optimized MTR augmentation setup.

Additionally, we explored the effect of speech synthesis textual content on model performance. Results indicated that it was helpful to generate transcripts that were matched with the target domain text. Having a sufficiently large vocabulary was also key in the absence of matched transcripts. We also observed that the influence of different textual content was reduced when other non-target domain data was also used in training.

As for future work, one could expand the scope of this work and explore the effect of TTS synthesized data for the in-domain scenario. In particular, it would be useful to understand the performance trade-offs as the quantity of in-domain data increases. From a broader perspective, this paper represents an initial study into how we can use data augmentation to better model the speaker-centric aspects of the speech data. In contrast, past speaker recognition research focused more on environment-centric factors such as channel and noise effects. We challenge the community to examine other ways in which speaker-centric data augmentation can be applied using TTS synthesis or other approaches.
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