When Is TTS Augmentation Through a Pivot Language Useful?

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Abstract

Developing Automatic Speech Recognition (ASR) for low-resource languages is a challenge due to the small amount of transcribed audio data. For many such languages, audio and text are available separately, but not audio with transcriptions. Using text, speech can be synthetically produced via text-to-speech (TTS) systems. However, many low-resource languages do not have quality TTS systems either. We propose an alternative: produce synthetic audio by running text from the target language through a trained TTS system for a higher-resource pivot language. We investigate when and how this technique is most effective in low-resource settings. In our experiments, using several thousand synthetic TTS text-speech pairs and duplicating authentic data to balance yields optimal results. Our findings suggest that searching over a set of candidate pivot languages can lead to marginal improvements and that, surprisingly, ASR performance can be harmed by increases in measured TTS quality. Application of these findings improves ASR by 64.5% and 45.0% character error reduction rate (CERR) respectively for two low-resource languages: Guarani and Suba.

Index Terms: speech recognition, text-to-speech, low-resource learning, multilingual NLP, language revitalization tools

1. Problem statement and motivation

Applications of ASR systems such as digital assistants are becoming increasingly ubiquitous. Despite ASR being a crucial task for low-resource and endangered languages, most existing ASR projects cover high-resource languages and dialects from industrialized nations; most low-resource languages are left behind. This is troubling because speakers of low-resource languages can benefit significantly from ASR. ASR technologies could enable them to access digital information relating to education, politics, health conditions, natural disasters, etc. Endangered languages particularly need ASR for documentation, revitalization, and learning resources, since human audio transcription is prohibitively slow [1, 2].

Most state-of-the-art ASR architectures for high-resource languages require large data sets, which take extensive time and resources to collect [3]. This work explores data augmentation for ASR via TTS for low-resource languages, with Coastal Gloswahili (SWH), Guarani (GRN), and Suba (SXB) as case studies, and Italian (ITA) as an additional example to demonstrate training trends. Gloswahili is a Bantu language and lingua franca in East and Central Africa. It is spoken by ∼200 million people in Africa [4]. Though it is the most spoken African language, few Gloswahili speech technology developments have been made [3, 5]. Guarani is South American language of the Tupi-Guarani family with ∼5.85 million speakers in Paraguay and for which digital resources are becoming increasingly necessary, though they remain limited [6]. Suba is an endangered Bantu language with less than 10000 speakers in Kenya [7], for which speech technologies can help revitalization efforts.

Previous research [8, 9, 10] shows that TTS data can be used to augment ASR training. However, many low-resource languages that can benefit from ASR data augmentation do not have TTS systems. To this end, we ask: Can we use synthesized speech from a high-resource language’s TTS system to improve ASR in a low-resource language?

This question prompts a few others. When augmenting, how much synthesized audio should be used? Which high-resource language should be used for TTS? In initial experiments to address these questions, we noticed that pivot-language TTS audio is noisy to human perception. This led us to experiment with TTS quality improvement. We contribute:

- A novel study on the effects of TTS augmentation through a pivot language for low-resource ASR, with accompanying software and datasets
- Experimentally backed recommendations for augmentation parameters: data amount and duplication, choice of pivot language, and TTS quality, with surprising findings suggesting language relatedness and impressionistic TTS quality may not improve performance
- ASR improvement across languages, including 64.5% and 45.0% CERR¹ for low-resource Guarani and Suba

2. Related work

Multiple data augmentation techniques exist for low-resource ASR. Popular approaches include SpecAugment [11], language models (LM), and incorporating text and untranscribed speech in addition to traditional waveform variation methods such as PSOLA, time-stretching and noise addition [3].

We are not the first to explore cross-lingual transfer for low-resource ASR. Pre-training weights on speech-to-text translation from a high-resource language can reduce ASR error rates [12], and high-resource ASR pre-training can conversely improve low-resource translation [13, 14]. Our work likewise seeks to improve ASR for languages where text data is more available than transcribed speech, but we do so via TTS, without pre-training or requiring translations or translation systems.

Researchers have also explored using TTS to augment ASR training. [8, 9, 15] explored and implemented speaker augmentation to increase variability for synthesized speech, but [16] showed significant improvements in word error rate (WER) from a single speaker. [8] explored how LM, SpecAugment, and TTS augmentation affect WER. They found that these methods are independent of each other and that using TTS data yielded more improvements than LM and SpecAugment, with

¹We use reduction rates calculated as \( \frac{rate_{old} - rate_{new}}{rate_{old}} \)
the best configuration combining them all. In all these works, researchers trained neural TTS models in the target language, requiring more than ten hours of high-quality data [17]. We build upon and differ from these works: because we use TTS systems trained on high-resource languages, our approach may apply to the thousands of low-resource languages for which ten-hour audio data sets are not available [18].

Other researchers have asked how much synthetic TTS data is appropriate, since acoustic differences between TTS data and authentic data can make it less effective from the same text [15, 19]. [15] found the best synthetic/authentic data balance on a LibriSpeech task was 50/50. §4.1 shows similar findings in our novel setting of TTS from a high-resource pivot language.

3. Approach

![Visual depiction of our TTS augmentation pipeline](image)

Figure 1: Visual depiction of our TTS augmentation pipeline

3.1. Data setup

**Authentic data** We used Kiswahili audio with transcriptions from the Gamayun Swahili Minitikit [20], which contains 4700 transcribed recordings, for training, validation, and testing. We obtain Italian and Guaraní data from Mozilla Common Voice Corpus 7.0. Our Suba corpus presents an extremely low-resource setting: 1178 sentences (1.7hrs) obtained from AfricanVoices [21].

**TTS Augmentation** We feed authentic text to TTS models to generate synthetic audio which results into a synthetic text-speech pair. We used Microsoft TTS and Google Cloud neural models to obtain synthetic data. We employed this augmentation for ASR in four languages: Kiswahili, Guaraní, Italian, and Suba. We outline the text corpora we used as TTS prompts for each language. **Kiswahili**: 14737 Kiswahili sentences from the Helsinki Swahili corpus [22], which contains news and political text. We selected these sentences to be phonetically diverse using Festvox tools [23]. **Guaraní**: a uniformly random mixture from Guarani Wikipedia and another Guarani corpus [24]. **Italian**: text from unused recordings in the Mozilla data we downsampled from transliterated text. Note that in many experiments we restrict training sets further. Data with train/val/test splits and details about subsets for each experiment are available at [https://github.com/n8rob/Multilingual_TTS_Augmentation](https://github.com/n8rob/Multilingual_TTS_Augmentation).

**Transliteration** We found that pivot language TTS systems make many pronunciation errors and hallucinate phones when Kiswahili text is input. This is not surprising because of orthographic diversity across languages (especially in the case of languages that use different alphabets, such as Kiswahili and Arabic). To remedy this in some experiments, we transliterated text into pivot language orthography using hand-crafted phone maps. This generated empirically higher quality audio with TTS systems for those languages. (See §4.3.) This is represented as the optional step “Transliteration” in Figure 1.

3.2. Experimental Setup

We combine different amounts of TTS data and authentic data to train an ASR system. We evaluate and test on authentic data only. We used ESPNet2 [26] with the default RNNTransducer [27] and RNNLM to train our End-to-End ASR systems. Figure 1 is a visual depiction of our approach.

4. Results

We explored effectiveness of TTS augmentation through a pivot language on three axes: synthetic data amount given authentic data, choice of pivot language, and TTS audio quality.

### 4.1. Synthetic data amount

We began our experiments by probing for the optimal amount of TTS augmented data. For these experiments we augmented Kiswahili speech data with Arabic, Italian, and Kiswahili TTS. We chose Arabic because of its historical influence on Kiswahili and Italian because its output for Kiswahili text sounded reasonably accurate to a proficient Kiswahili speaker. Results are

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The table below shows the data setup for each language.

| Lang. + Corpus | Utterances | train/val/test split | Hours | Speakers | Gender | TTS API |
|-------------|------------|----------------------|-------|----------|--------|---------|
| Kiswahili   | Gamayun SWH | 4700 | 3900/400/0400 | 6.06 | 1 | M | N/A |
| SWH-TTS     | 8465 | 8665/0/0 | 14.5 | 4 | M/F | Microsoft |
| ARA-TTS     | 14737 | 14737/0/0 | 27.7 | 4 | M/F | Google |
| ITA-TTS     | 14737 | 14737/0/0 | 26.2 | 4 | M/F | Google |
| SPA-TTS     | 8000 | 8000/0/0 | 12.6 | 3 | M/F | Google |
| TUR-TTS     | 8000 | 8000/0/0 | 13.1 | 5 | M/F | Google |
| ARA-TTS-trans | 4000 | 4000/0/0 | 8.13 | 2 | M/F | Microsoft |
| SPA-TTS-trans | 3008 | 3008/0/0 | 4.58 | 2 | M/F | Microsoft |

The table above shows the data setup for each language. The columns represent the language and corpus, the number of utterances, the train/val/test split, the total hours of recording, the number of speakers, the gender distribution, and the TTS API used.
in Figures 2 and 3. Because low-resource languages can have varying amounts of transcribed audio data, we ran experiments using three authentic training sets of sizes 300, 1000, and 3900. Our test set of 400 utterances was kept constant throughout the experiments. In each of these settings, increasing the amount of TTS synthetic data improves error rates until it reaches a point where further increase degrades performance. This degradation occurs when the model overfits on the synthetic data and thus performs poorly when tested on authentic data. Figure 2 illustrates that in the case of each authentic data amount, using 4000 augmented pairs improves performance (or stagnates in the highest-resource case), and continuing to add synthetic data beyond that degrades performance.

To avoid this data imbalance and over-fitting, we duplicated authentic data in the setting with 1000 authentic pairs. Results are in Figure 3. We found that when beginning with 1000 transcribed recordings, duplicating authentic data eight times and augmenting with 8000 TTS synthetic pairs works best. This is a relevant example since many low-resource languages have roughly 1000 transcribed recordings, or 1-2 hours of speech, available. (E.g. our Guarani and Suba data, see Table 1.) As shown in Figure 3, this policy reduces CER from 78.2% (no duplication or augmentation) to 20.0% for 74.4% CERR for Kiswahili with an Arabic TTS system. It works well for other language combinations as well: 31.4% CERR for Italian (with Finnish TTS), 64.5% CERR for Guarani (with French TTS), and 45.0% CERR for Suba (with Spanish TTS).

4.2. Choice of pivot language

Before conducting explorations related to pivot language choice, we analyzed the textual outputs from the lowest- and highest-resource experiments featured in Figure 2 beyond error rate. We tested whether there is a relationship between the pivot language or amount and the characters that the system learns to recognize. We did not find any noticeable pattern for phones that was tied to TTS augmentation. The only system that recognized any characters at a rate of ≥ 25% outside the average was the Kiswahili system with 3900 authentic pairs and 4000 Arabic TTS pairs, on 5 of the 26 Kiswahili characters.8

We experimented to test whether choosing a pivot language with high relatedness to the target language can improve results. We tested on three ASR target languages: Italian, Kiswahili, and Guarani. Results are in Table 2. We used pre-computed lang2vec distances from URIEL [28] to determine language relatedness. Following best practice recommendations [29], we relied primarily on geographical and genetic distance. We restricted our similarity search to the languages supported by Google Cloud TTS, and we added some language pairs to test other language characteristics.9

In our experiments featured in Table 2, language similarity did not appear to determine TTS augmentation suitability. The best-performing TTS system for Italian, for example, was Finnish, and for Guarani, French. Arabic performed best for Kiswahili, but this is likely because the data amount configuration was tuned for this pair. (Italian TTS also fares well.) It is possible that having a diversity of language characteristics provided by the TTS system is actually an advantage. We conclude that for any ASR target language, multiple TTS pivot languages should be tried to determine one that works well.

4.3. TTS quality

We sought to improve TTS quality in order to improve augmentation and ASR performance via (1) using Microsoft TTS rather than Google Cloud (higher quality but more time consuming), and (2) transliterating TTS text into pivot language orthography.

8The average described here is the average proportion of substitutions and deletions that occurred for each target language character. The five characters at least 25% outside the norm for one of the data configurations were s, u, i, l, j.

9Google Cloud TTS does not support any languages geographically or genetically close to Guarani or Kiswahili other than Spanish and Arabic, respectively. We selected Italian, Spanish, and Turkish (TUR) for Kiswahili to explore if their straightforward orthography systems would yield an advantage. For Italian, we chose Romanian as they are close geographically and genetically per URIEL and Spanish because of their linguistic proximity. We chose Afrikaans (AFR) for Guarani since URIEL finds them phonologically close. We also tested languages that are closest to the average geographical/genetic distance from the target language: Finnish (FIN) for Italian and French (FRA) for Guarani.
These findings prompted questions as to how much TTS accuracy matters in ASR training. As another ablation, we augmented training data for Kiswahili ASR with 4000 Indonesian (IND) speech files, not resembling Kiswahili at all. Interestingly, in the setting with 3900 authentic pairs, this had a similar effect to using TTS and outscored multiple TTS examples (with CER=7.2% compared to CER=7.8% for ARA-TTS augmentation of the same amount). In the setting of 300 authentic pairs, augmentation quality is more relevant: Indonesian noise does not improve error rates significantly, but TTS audio does.

4.4. Application to low-resource languages

For many low-resource languages, only a small set of transcribed audio is available: on the order of 1000 utterances or 1-2 hours. Two such datasets are the CommonVoice Guarani and African Voices Suba datasets. Employing our findings in practice, we augmented both of these datasets by duplicating the authentic data eight times and adding an equal amount of TTS synthetic data, following the recommended procedure based on Figure 3. See Table 4. This augmentation results in better ASR, with word error reduction rates (WERR) of 27.0% and 19.2% and CERR 64.5% and 45.0%.

5. Conclusion

We show that synthetic audio from a high-resource pivot language TTS system can be used to augment authentic datasets and improve ASR for low-resource languages. Our experiments suggest that performance improves best when several thousand TTS-generated synthetic pairs are used and authentic data is replicated to an equal amount, and when a search over potential pivot languages is conducted. Our experiments suggest, surprisingly, that measured TTS audio quality may not affect suitability for ASR training augmentation. These techniques improve ASR for low-resource languages Kiswahili, Guarani, and Suba (74.4%, 64.5%, and 45.0% CERR, respectively). They are also broadly applicable to the thousands of other low-resource languages often overlooked in speech technologies. This has promising implications of increased information access for speakers of these languages and for documentation and revitalization efforts for endangered languages like Suba.

Future work may involve methodological advances, such as including authentic speech from the TTS pivot language in training; or pretraining steps, such as training a model on noisy TTS synthetic data and then tuning on authentic data. This process could theoretically be enhanced by using pre-trained representations from multilingual self-supervised models such as XLSR [30]. Further investigation may also involve more rigorous analyses of optimal pivot languages, including comparisons of language recording acoustic features.

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Table 2: Language choice results. All of these models were trained with 1000 authentic pairs copied eight times and 8000 synthetic TTS pairs, the optimal amounts for starting with 1000 authentic pairs, per our experiments in Figure 3. All synthetic audio was generated by Google Cloud with standard settings. Best results are bold: note that the SWH-ARA combination was tuned for this data configuration.

| Target lang. | Pivot lang. | WER   | CER   |
|--------------|-------------|-------|-------|
| ITA          | RON         | 98.8% | 73.1% |
| ITA          | SPA         | 91.7% | 53.9% |
| ITA          | FIN         | 92.5% | 53.5% |
| SWH          | ARA         | 51.6% | 20.0% |
| SWH          | ITA         | 53.3% | 24.3% |
| SWH          | SPA         | 62.8% | 22.7% |
| SWH          | TUR         | 69.3% | 29.9% |
| GRN          | AFR         | 79.6% | 34.4% |
| GRN          | SPA         | 74.1% | 30.0% |
| GRN          | FRA         | 73.0% | 30.0% |

Table 3: TTS quality experiments. Models were trained using 4000 Arabic TTS synthetic pairs or 3008 Spanish; no authentic data duplication.

| Target lang. | Auth. pairs | Aug. data | WER   | CER   |
|--------------|-------------|-----------|-------|-------|
| SWH          | 300 poor ARA| 83.1%     | 46.6% |
| SWH          | 300 trans ARA| 87.7%     | 53.2% |
| SWH          | 300 poor SPA| 93.6%     | 43.8% |
| SWH          | 300 trans SPA| 82.2%     | 45.1% |
| SWH          | 1000 poor ACA| 56.6%     | 24.2% |
| SWH          | 1000 trans ARA| 61.2%     | 27.1% |
| SWH          | 1000 poor SPA| 77.4%     | 32.9% |
| SWH          | 1000 trans SPA| 54.6%     | 21.7% |
| SWH          | 3900 poor ARA| 22.7%     | 7.7%  |
| SWH          | 3900 trans ARA| 23.0%     | 7.8%  |
| SWH          | 3900 poor SPA| 24.9%     | 8.0%  |
| SWH          | 3900 trans SPA| 20.5%     | 6.5%  |

Table 4: We achieve significant error rate reductions in low-resource Guarani and Suba ASR by applying findings.

| Augmentation | WER   | CER   |
|--------------|-------|-------|
| GRN: no aug. | 100%  | 84.4% |
| FRA TTS      | 73.0% | 30.0% |
| SXB: no aug. | 86.3% | 51.6% |
| SPA TTS      | 69.7% | 28.4% |

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