A single speaker is almost all you need for automatic speech recognition

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Abstract

We explore cross-lingual multi-speaker speech synthesis and cross-lingual voice conversion applied to data augmentation for automatic speech recognition (ASR) systems. Through extensive experiments, we show that our approach permits the application of speech synthesis and voice conversion to improve ASR systems on a target language using only one target-language speaker during model training. We managed to close the gap between ASR models trained with synthesized versus human speech compared to other works that use many speakers. Finally, we show that it is possible to obtain promising ASR training results with our data augmentation method using only a single real speaker in a target language.

Index Terms: Speech Recognition, Speech Synthesis, Cross-lingual Zero-shot Voice Conversion, Cross-lingual Zero-shot Multi-speaker TTS, ASR Data Augmentation

1. Introduction

Text-to-Speech (TTS) systems have received a lot of attention in recent years due to the great advances in deep learning, which have allowed for the massive use of voice-based applications such as virtual assistants. These advances have allowed TTS models to achieve naturalness with respect to human speech [1][2][3]. Notably, most TTS systems are tailored for a single speaker, but many applications could benefit from the new-speech synthesis, i.e., not seen during training, employing only a few seconds of the target speech. This approach is called zero-shot multi-speaker TTS (ZS-TTS) as in [4][5][6]. Advances in TTS have motivated works that exploit it as a way to improve Automatic Speech Recognition (ASR) systems. Researchers have explored two different approaches. The first is parallel training of ASR and TTS models; in this approach the TTS and ASR systems can improve themselves, as in [7][8][9]. The second is the use of a pre-trained TTS model to generate new data to train the ASR, such as [10][11] and [12]. In this work, we will focus on the second approach.

All the works that explore a pre-trained TTS model to generate data for ASR explored the use of the LibriSpeech [13] dataset to train the ASR model. For the TTS model training, [10] used 3 speakers from the American English MAILABS [14] dataset, while [11] and [12] trained the TTS model with more than 251 speakers from the LibriSpeech.

In Table 1 we report the Word Error Rate (WER) of the best experiment of each of the related works in the test-other subset of the LibriSpeech dataset. Although the studies contain both test-clean and test-other results, we focus on the results of the most difficult sub-set. Also, [12] reported results using an external language model (LM); however, for fairness, we omit this LM in our comparison.

The ASR model trained with synthesized speech combined with human speech achieved relative improvement of 4.56%, 0.79% and 4.25% than the model trained with human speech alone, respectively, for [10], [11] and [12]. Despite that, the relative difference between the model trained with only human speech and only synthesized speech was 80.17% and 78.98%, respectively, for [10] and [11], which motivates further improvements and research.

Although previous work shows the potential for multi-speaker or zero-shot multi-speaker TTS models for ASR data augmentation, these models still require high-quality datasets with many speakers and hours of speech to converge [12]. Generally, such models are trained on English with big datasets such as VCTK [20] and LibriTTS [21]. This approach is not suitable for low-resource languages. The vast majority of languages do not have an open TTS dataset and the few available are limited in the number of speakers.

In our previous work [6], we presented YourTTS a multi-lingual zero-shot multi-speaker TTS model that showed good results for Portuguese using only a single-speaker dataset in the target language.

In this paper, we combine the power of the YourTTS model with that of Wav2vec 2.0 [22], trained in a self-supervised way on 100 thousand hours of speech in 23 different languages [23], in order to show the viability of the application of TTS data augmentation for ASR systems in languages using just one speaker during TTS training. We also propose a new augmentation approach that uses cross-lingual voice conversion and cross-lingual multi-speaker TTS to alleviate the lack of speakers in a target language. We showed that with our approach, it is possible to train an ASR model using just a single-speaker, achieving promising results.

2. Audio datasets

We used 3 languages/training datasets for the TTS model:

**English**: VCTK [20] dataset, containing 44 hours of speech from 109 speakers, sampled at 48KHz. We divided the VCTK dataset into training, development and test subsets following [6]. To further increase the number of speakers for training, [6] despite relative improvement/difference is not widely used, the improvement achieved in related works is not easily comparable due to approaches’ differences. For this reason, we used this metric, showing the real improvement achieved by related works approaches.

1 although relative improvement/difference is not widely used, the improvement achieved in related works is not easily comparable due to approaches' differences.
we used the subsets *train-clean-100* and *train-clean-360* from LibriTTS [21]. In the end, our TTS model was trained with 1,248 English speakers.

**Portuguese**: TTS-Portuguese Corpus [24], a single-speaker male dataset in Brazilian Portuguese (pt-BR) containing ca. 10 hrs, sampled at 48KHz. As the authors did not use a soundproof studio, the dataset contains some environmental noise. Following [10], we resampled the audios to 16KHz and used FullSubNet [25] as a denoiser. For development, we randomly selected 500 samples, leaving the rest for training.

**Russian**: ru-RU set of the M-AILABS dataset [14], which is based on LibriVox [3]. The dataset consists of 46 hrs from 1 female and 2 male speakers. In this work, we used samples only from the female speaker for diversity, since we already used a male for pt-BR.

For all TTS datasets, pre-processing was carried out to normalize volume and to remove long silence periods, following [6]. After pre-processing, the datasets contained 8.38 hrs for pt-BR and 14.94 hrs for ru-RU (Russian).

For ASR model training, we used Common Voice version 7.0 [26] for pt-BR and ru-RU. In all experiments, we used the default train, development and test partitions. For pt-BR, these sets have 14.52, 8.9 and 9.5 hours, respectively; and ru-RU has 25.95, 13.06 and 13.75 hours, in the same order.

### 3. Audio augmentation methods

We explore three popular augmentation methods in speech processing – additive noise, pitch shifting and room impulse response (RIR) simulation. For additive noise, we use the MUSAN corpus [27], which is composed of three subsets: (i) the noise subset (ca. 6 hrs.), such as ambient noise and dialtones; (ii) the music subset (ca. 42 hrs.); and (iii) the speech subset (ca. 60 hrs). For RIR, we use the simulated filters provided in [28].

As in [29], for additive noise, we randomly selected the audio and added it to the original signal. For the speech subset, we added it to the original signal with a random signal to noise ratio (SNR) from 13 to 20dB. In a similar fashion, we added from 5 to 15dB SNR for music and from 0 to 15dB SNR for noise. For the RIR filters, we performed speech reverberation via convolution operation with a collection of simulated RIR filters [28]. For pitch shift, we randomly chose a semitone from -4 to 4. All augmentations are randomly selected with a 25% probability of being chosen for each audio in every training step.

For all methods, we use the implementations available in the Python AudioMentations package.

### 4. TTS model setup

We use YourTTS, [6] fine-tuned in English, pt-BR and ru-RU. In the original work, YourTTS was trained using English (LibriTTS and VCTK corpora), French (M-AILABS corpus) and pt-BR (TTS-Portuguese Corpus). The original model was trained using only one male speaker in pt-BR but still produced good results in zero-shot multi-speaker TTS and zero-shot voice conversion for pt-BR. Furthermore, it was able to produce female voices even without being trained on female voices, making it adequate for the objective of this study.

In this work, we use transfer learning from the checkpoints made publicly available by the authors. The dataset in English and pt-BR were the same dataset used in the YourTTS [6] original paper. One difference should be noted: we replaced the French M-AILABS dataset with a female speaker from the Russian M-AILABS dataset to attend the experiment requirements as explained in Section 5.1. Using these datasets, we train the YourTTS model for 100k steps with the same parameters used in the original work. After this, we fine-tuned the model for another 40k steps using the Speaker Consistency Loss (SCL) [6]. Therefore, in this work YourTTS was trained with 1,248 speakers in English, one male speaker in Portuguese and one female speaker in Russian.

YourTTS can synthesize different audios for the same input sentence. During inference, the latent variable predicted by the text encoder is added with a random sample of the standard normal distribution multiplied by a temperature $T$. In this way, diversity can be controlled by the temperature $T$. As shown by [3], the manipulation of $T$ allows generating different pitches; for more details see [30][3][6]. Furthermore, the YourTTS model is trained with the stochastic flow-based duration predictor proposed in [3]. As shown in [3], this duration predictor can produce several different speech rhythms for the same sentence. This happens because during inference, a random sample of the standard normal distribution is multiplied by a temperature $T_{dp}$ and added to the latent variable before it is inverted by the flow. In this way, it is possible to control the variety of rhythms with the temperature $T_{dp}$ [3]. Finally, it is possible to control the speaking rates by multiplying the predicted durations by a positive scalar $L$, thus making the pronunciation faster when $L$ is smaller and slower when $L$ is bigger. During the generation of

### Table 1: Comparison between related works in the test-other subset.

| Paper | TTS Model | ASR Model | Train data | WER |
|-------|-----------|-----------|------------|-----|
| [10]  | Tacotron  | Wav2Letter | Human      | 16.21 |
|       | GST [15]  |           | Synthesized | 81.78 |
|       |           |           | Human +    | 15.47 |
| [11]  | ZS-Tacotron [4] | LAS [18] | Human      | 13.89 |
|       | + VAE [17] |           | Synthesized | 66.10 |
|       |           |           | Human +    | 13.78 |
| [12]  | GMVAE     | LAS [18][19] | Synthesized | 14.10 |
|       | Tacotron  |           | –          | 13.50 |

2https://librivox.org/  
3https://github.com/iver56/audiomentations
the artificial datasets, diversity is achieved by randomly choosing $L$, $T$ and $T_{dp}$ for $L$, a value between 0.7 and 2, while for temperatures ($T$ and $T_{dp}$) a value between 0 and 0.667.

5. Comparison between human and synthesized speech

Previous works have shown a large gap between ASR models trained with human and synthesized speech [11][12]. In these works, the authors have used a large number of speakers and hours of speech in the target language during the TTS model training. On the other hand, to apply this method here for languages with low/medium resources, we proposed the use of only a single speaker in the target languages during the TTS model training, in order to verify whether being trained even with only a single speaker in the target language, the YourTTS model can be used as the data augmentation for ASR. In this section we compared ASR models trained with synthesized speech and human speech.

5.1. Experiments Setup

For a fair comparison between human and synthesized speech, we have generated a copy of pt-BR and ru-RU Common Voice corpora. For each sentence in Common Voice, we generate the pronunciation of that sentence in the voice of the same speaker, using the pronunciation of that sentence as a reference to extract the speaker embedding. The idea being that if the zero-shot multi-speaker TTS model is good enough, it will generate the same speaker’s voice as in the original audio.

As for the ASR model, we use Wav2vec 2.0 [22], a large model trained in a self-supervised way on the VoxPopuli dataset [23]. We used the model checkpoint provided by the authors at [23] which was trained on 100,000 hours of speech in the following 23 languages: Bulgarian (Bg), Czech (Cs), Croatian (Kr), Danish (Da), Dutch (Nl), English (En), Estonian (Et), Finnish (Fi), French (Fr), German (De), Greek (El), Hungarian (Hu), Italian (It), Latvian (Lv), Lithuanian (Lt), Maltese (Mt), Polish (Pl), Portuguese (Pt), Romanian (Ro), Slovak (Sk), Slovene (Sl), Spanish (Es) and Swedish (Sv). We chose Portuguese and Russian because the Portuguese language was used in the pre-training of this model and Russian was not used, presenting realistic results for both scenarios. Also, these languages are from diverse language families. We carried out four experiments:

- **Experiment 1**: ASR models trained in pt-BR and ru-RU with the Common Voice dataset using the standard training and development subsets. For pt-BR, the model was trained for 140 epochs and ru-RU for 100 epochs;
- **Experiment 1.1**: Transfer learning from experiment 1 and adds in the training audio augmentations (AA) described in Section 3. In this experiment, the ASR is trained with half the number of epochs used in experiment 1.
- **Experiment 2**: Similar to experiment 1, but the model is trained using the synthesized copy of Common Voice in pt-BR and ru-RU. For model training and development, we used synthesized speech.
- **Experiment 2.1**: Transfer learning from experiment 2 and adds the AA described in Section 3. The ASR is trained with half the number of epochs used in experiment 2.

To run the experiments, we use the HuggingFace Transformers framework[4]. The models were trained with a GPU NVIDIA TITAN RTX 24GB using a batch size of 8 and gradient accumulation over 24 steps. We used the optimizer AdamW [31] with a linear learning rate warm-up from 0 to 3e-05 in the first 8 epochs and after using linear decay to zero. During training, the best checkpoint was chosen, using the loss in the development set and used early stopping after the development loss had not improved for 10 consecutive epochs. The code used for all of the experiments, as well as the checkpoints of the trained models are publicly available at: https://github.com/Edresson/Wav2Vec-Wrapper

5.2. Results and Discussion

Table 1 presents the results for our experiments on the pt-BR and ru-RU test subsets from Common Voice.

| Exp. | PT | RU |
|------|----|----|
| 1. Human Speech | 23.50 | 25.47 |
| 1.1 Human Speech + AA | 21.34 | 22.27 |
| 2. Synthesized speech | 50.94 | 55.86 |
| 2.1 Synthesized speech + AA | 43.99 | 50.46 |

The model trained only with human speech (Experiment 1) reached a WER of 23.50% and 25.47%, respectively for pt-BR and ru-RU. The model trained only with synthesized speech (Experiment 2) reached a WER of 56.84% and 65.85%, respectively, for pt-BR and ru-RU. Therefore, without AA, the relative difference between the model trained with only human speech and only synthesized speech is of 58.65% and 61.32% for those two languages.

As expected, fine-tuning the models with AA (Experiment 1.1 and Experiment 2.1) improved performance. The model trained with human speech only improved its result by 1.96% and 3.20% WER for pt-BR and ru-RU after the addition of AA. The model trained only with synthesized speech improved by 12.85% and 15.39% WER, respectively. Therefore, using AA benefits the model trained with synthesized speech much more than the model trained with human speech. This can be explained by the absence of noise diversity in the synthesized speech. Common Voice is a dataset composed of a lot of environmental noises, whereas the synthesized speech just has some artifacts, but not environmental noises. Therefore, with the use of AA, the gap between models trained only with human and only synthesized speech is reduced to a relative difference of 51.03% and 55.86% for those two languages.

Our results are interesting because, despite using only a single speaker dataset for training the TTS model for pt-BR and ru-RU, our ASR model trained only with synthesized speech achieves a comparable result to related works. For comparison, considering the results reported by [11], the relative difference between models trained only with human and only synthesized speech was of 78.98%. Even though this work explores the English language in a setting with many available speakers and it is not directly comparable, we believe that our results indicate that our approach requiring just one speaker in the target language, can be used for low-resource languages.

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4https://github.com/huggingface/transformers
6. Is only one speaker in the target language sufficient for learning?

In section 5 we applied the YourTTS model, trained with a single speaker in pt-BR and ru-RU, to create datasets for ASR. Although the TTS model was trained with only one speaker, we made a copy of the Common Voice dataset in order to gain many in the target languages. This approach has shown promising results, but many languages do not have datasets with many available speakers. For that reason, we explore the use of a single-speaker in the target language, for training both TTS and ASR. To make up for the lack of speakers during the creation of the synthesized dataset, we explored the use of voice conversion, using English speakers, rather than cloning speakers from the target languages.

6.1. Experiments Setup

We created the GEN\textsubscript{TTS} dataset by synthesizing all the sentences in Common Voice using English speakers. Furthermore, we created the GEN\textsubscript{VC} dataset which consists of the single-speaker used for training the TTS model in the target language converted to a multi-speaker dataset using cross-lingual voice conversion with English speakers. For voice conversion, we also use the YourTTS model. Each sample of the dataset used in the TTS model training was converted to the voice of 5 speakers, chosen at random from the 1,248 English speakers used to train the YourTTS model. The value of 5 transfers per sample was chosen in preliminary experiments. We would like to note that, in preliminary experiments, we explored increasing the number of speakers per sentence in the GEN\textsubscript{TTS} dataset; however, this did not bring significant improvements. We carried out three experiments:

- **Baseline**: ASR models trained with the single-speaker dataset used during the TTS model training on pt-BR and ru-RU.
- **Upper Bound**: ASR models trained on pt-BR and ru-RU with Common Voice plus the single-speaker TTS dataset.
- **Baseline + DA**: explores the use of human speech from a single-speaker in the target language (TTS dataset), with data augmentation (DA) being accomplished by the YourTTS model. For the data augmentation we merge the GEN\textsubscript{TTS} and GEN\textsubscript{VC} datasets, detailed above.

All 3 experiments use AA and the same training parameters used in Section 5.

6.2. Results and Discussion

Table 3 presents our experiments’ results on the test subsets of the pt-BR and ru-RU Common Voice datasets.

| Experiment          | Train data                          | PT   | RU   |
|---------------------|-------------------------------------|------|------|
| Baseline            | TTS dataset (single-speaker)        | 63.90| 74.02|
| Upper Bound         | Common Voice + TTS dataset          | 20.39| 24.80|
| Baseline + DA       | TTS dataset + GEN\textsubscript{TTS} + GEN\textsubscript{VC} | 33.96| 36.59|

Comparing the results with the SOTA English ASR system on the Common Voice dataset (7.7% achieved by [32]) these results do not look so remarkable. However, for comparison in pt-BR, [33] used ca. 158 hrs of speech and a non-self-supervised model without an external LM and achieved a WER of 47.41% on the test set of BRSD v2 dataset. Despite being different datasets, [34] showed that the Common Voice test set is more challenging than the test set of BRSD v2, and for this reason, the model proposed by these authors reached a higher WER on the Common Voice dataset. In ru-RU, [35] used transfer learning from 5 large English datasets, they trained the QuartzNet [36] model on Common Voice, obtaining a WER of 32.20% on the test set of the same dataset. Therefore, 33.96% WER achieved by our model is probably superior to the SOTA for pt-BR, before the introduction of self-supervised learning approaches. Also, the WER of 36.59% achieved in Russian is comparable with the SOTA.

Comparing the results of the Baseline + DA experiment with the Upper Bound (20.39% and 24.80% for pt-BR and ru-RU). Our results are still a little far from the Upper Bound. However, the results are remarkable since our model was trained with just one real speaker in the target language.

7. Conclusions and future work

In this work, we present a novel data augmentation approach for ASR training by using cross-lingual speech synthesis and voice conversion. We show that it is possible to achieve promising results for ASR model training with just a single-speaker dataset in a target language, making it viable for a low-resource scenario. Finally, our approach works both in a language (pt-BR) present in the Wav2Vec 2.0 model pre-training, as well as for an unseen language (Russian).

In future work, we intend to explore the use of the self-supervised model feature extractor as a discriminator during the training of the YourTTS model. In this way, the YourTTS model may produce even more human-like speech in the self-supervised model.

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A. Upper Bound + DA

To verify how data augmentation using speech synthesis and voice conversion can improve the results of ASR models trained with multiples humans speakers, even when the TTS/voice conversion model was trained with only a single speaker in the target language. We train the ASR models with the merged datasets from GEN_TTS, GEN_VC, TTS dataset and Common Voice. We called this experiment as Upper Bound + DA.

Table 4 presents results of the experiments Upper Bound (reported previously on Section 6) and Upper Bound + DA experiments on the test subsets of the pt-BR and ru-RU Common Voice datasets.

Table 4: WER of Upper Bound and Upper Bound + DA experiments on the test subsets of the pt-BR and ru-RU Common Voice datasets

| Experiment         | Train data                       | PT  | RU  |
|--------------------|----------------------------------|-----|-----|
| Upper Bound        | Common Voice + TTS dataset       | 20.39 | 24.80 |
| Upper Bound + DA   | Common Voice + TTS dataset + GEN_TTS + GEN_VC | 20.20 | 19.46 |

The model trained with Common Voice and a single-speaker TTS dataset in the target languages (Upper Bound) achieved a WER of 20.39% and 24.80% for pt-BR and ru-RU, respectively. The model trained with Common Voice, a single-speaker TTS dataset and our data augmentation approach in the target languages (Upper Bound + DA) achieved a WER of 20.20% and 19.46%, respectively. Therefore, the ASR model’s trained with our data augmentation approach achieved a relative improvement of 0.93% and 21.53%, respectively, for those languages. The relative improvement achieved in pt-BR is consistent with the results reported in [11], where a relative improvement was of 0.79%. However, it is lower than the result reported by [10] (4.56%) and [12] (4.25%). On other hand, the relative improvement achieved in ru-RU is significantly superior than that which was reported in related works.

Unlike related works, we use AA and only one target-language speaker in the training of the TTS/voice conversion model. AA can make the ASR model more robust and improve generalization; however, these approaches may have overlapping contributions. To verify this hypothesis, we did an ablation study by re-training the Upper Bound and Upper Bound + DA experiments in pt-BR without AA. The Upper Bound achieved a WER of 22.96% and the Upper Bound + DA achieved a WER of 21.41%. That is, without the use of AA as in the related works, the relative difference between ASR models trained only with human and only synthesized speech in pt-BR is 6.75%. Thus, in pt-BR and ru-RU, our approach achieves results better than related works in English, using only one speaker for training the TTS/voice conversion model in the target language. In this way, we have shown that it is possible to apply TTS systems to ASR dataset generation even for languages where just a single-speaker dataset is available.

We believe that the difference between the results achieved for pt-BR and ru-RU, can be explained by the characteristics of the datasets. In Common Voice, the amount of hours available for training the ASR model for the ru-RU is 25.95 hrs as opposed to 14.52 hrs for pt-BR. Furthermore, the ru-RU TTS dataset has approximately 6.5 more hours after preprocessing than pt-BR and the ru-RU TTS dataset is high-quality. In our experiments, we use voice conversion to transform the TTS dataset into a multi-speaker dataset using 5 transfers for each sample, thus the difference in the number of hours is a multiple as well.