DATA AUGMENTATION FOR CHILDREN’S SPEECH RECOGNITION
THE “ETHIOPIAN” SYSTEM FOR THE SLT 2021 CHILDREN SPEECH RECOGNITION CHALLENGE

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ABSTRACT

This paper presents the “Ethiopian” system for the SLT 2021 Children Speech Recognition Challenge. Various data processing and augmentation techniques are proposed to tackle children’s speech recognition problem, especially the lack of the children’s speech recognition training data issue. Detailed experiments are designed and conducted to show the effectiveness of each technique, across different speech recognition toolkits and model architectures. Step by step, we explain how we come up with our final system, which provides the state-of-the-art results in the SLT 2021 Children Speech Recognition Challenge, with 21.66% CER on the Track 1 evaluation set (4th place overall), and 16.53% CER on the Track 2 evaluation set (1st place overall). Post-challenge analysis shows that our system actually achieves 18.82% CER on the Track 1 evaluation set, but we submitted the wrong version to the challenge organizer for Track 1.

Index Terms— speech recognition, children’s speech, children’s speech recognition, data processing, data augmentation, neural networks, deep learning

1. INTRODUCTION

Speech recognition has made tremendous progress in the past decade, thanks to the rise of the deep learning techniques and the development of various open-source speech recognition toolkits. To give an example, the original Librispeech paper\textsuperscript{1} in 2015 reports a word-error-rate (WER) of 13.97\% for its test-other evaluation set, while in\textsuperscript{2}, the authors report 2.6\% for the same evaluation set. That is a reduction of 81.4\% in terms of WER in just 5 years!

Most of the efforts, however, have been devoted to adults’ speech recognition systems. Children’s speech recognition, on the other hand, remains very challenging, despite the rising demands from applications such as smart speakers and language learning.

There are a number of reasons why children’s speech recognition remains difficult. First, children typically have shorter vocal tracts and smaller vocal folds, which lead to higher fundamental and formant frequencies. This means that a large part of the children’s speech spectrum will be ignored at the typical speech recognition sampling rate of 16kHz\textsuperscript{3}. Second, children’s speech tend to have higher level of variability\textsuperscript{4}, both acoustically and linguistically, which makes it harder to model. Finally, unlike speech recognition for adults, where training data is generally available and can be easily collected when necessary, collecting speech recognition training data for children is oftentimes laborious and expensive. As a result, children’s speech recognition systems usually trained with limited amount of children’s speech data.

Researchers have proposed various techniques to alleviate the above problems. In\textsuperscript{5} and\textsuperscript{6}, Vocal Tract Length Normalization (VTLN) is used to suppress the acoustic variability introduced by children’s shorter vocal tracts. In\textsuperscript{5} and\textsuperscript{6}, adaptation methods such as Maximum Likelihood Linear Regression (MLLR), Maximum A-Posteriori (MAP) and Speaker Adaptive Training (SAT) are found helpful when dealing with children’s speech. Those methods usually fall into the speaker normalization and adaptation category, which handle the acoustic variability to some degree.\textsuperscript{7} attempts to improve children’s speech recognition from the linguistic variability angle. It adopts language models trained on children’s speech, and finds that it yields better performance than language models trained on adults’ speech.\textsuperscript{4} improves children’s speech recognition from the data insufficiency point of view. It adapts children’s model from adults’ model using transfer learning, and finds it very helpful.

In this paper, we propose data augmentation for children’s speech recognition. Different data augmentation techniques, such as pitch perturbation, speech perturbation, tempo perturbation, volume perturbation, reverberation augmentation, spectral augmentation, are experimented with the SLT 2021 Children Speech Recognition Challenge data. We conduct experiments with both Kaldi’s chain models\textsuperscript{8} and ESPnet’s attention-based encoder-decoder end-to-end models\textsuperscript{9}. We find that data augmentation generally helps to improve model’s robustness towards the acoustic variability in children’s speech, and as a result, improves children’s speech recognition performance across speech recognition toolkits and model architectures. Our final submitted system is trained with ESPnet’s attention-based encoder-decoder end-to-end model, and it achieves 18.82\% CER and 16.53\% CER on the challenge’s Track 1 and Track 2 evaluation sets respectively.

The rest of this paper is organized as follows. In Section 2 we introduce the SLT 2021 Children Speech Recognition Challenge. Section 3 presents our data processing techniques, and Section 4 explains the data augmentation techniques we propose for children’s speech recognition. We describe our speech recognition systems in Section 5, and experiments setup and results in Section 6. Finally, Section 7 concludes the paper and discusses future work.

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2. THE CHALLENGE

We briefly introduce the SLT 2021 Children Speech Recognition Challenge (CSRC) in this section, including datasets and tracks.

2.1. Datasets

CSRC releases three datasets, namely Set A, Set C1 and Set C2. In addition to the three released datasets, external data listed on OpenSLR [11] is allowed for the Track 2 task.

Set A. The Set A dataset consists of 341.4 hours of Mandarin adult reading speech. It has 1999 speakers, with ages between 18 - 60 years old.

Set C1. The Set C1 dataset consists of 28.6 hours of Mandarin child reading speech. It has 927 speakers, with ages between 7 - 11 years old.

Set C2. The Set C2 dataset consists of 29.5 hours of Mandarin child conversational speech. It has 54 speakers, with ages between 4 - 11 years old.

External Data. External data listed on OpenSLR [11] is allowed for the Track 2 task.

2.2. Tracks

CSRC has two separate tasks, namely the Track 1 task and the Track 2 task. Teams can participate in either one of the tracks, or both.

Track 1. In the Track 1 task, only Set A, Set C1 and Set C2 can be used to train the acoustic and language models.

Track 2. In the Track 2 task, in addition to the Set A, Set C1 and Set C2 datasets, external data listed on OpenSLR [11] can be used for acoustic model training. Only the transcripts associated with the provided speech data and the external speech data on OpenSLR [11] can be used for language model training.

2.3. Evaluation

Both tracks share the same evaluation dataset. The evaluation dataset consists of 16.3 hours of Mandarin child reading and conversational speech, with 216 speakers. Character-error-rate (CER) is used to evaluate the model performance.

3. DATA PROCESSING

We split the official datasets into train and dev sets, and then apply text normalization and tokenization for the train and dev sets respectively before we train the speech recognition system.

3.1. Data Partitioning

Since CSRC focuses on children’s speech recognition, our dev set is selected only from the child portion of the datasets, that is Set C1 and Set C2. We randomly choose 20 speakers from Set C1, around 1.4 hours of children’s speech. We call this set dev-011. We also select 5 speakers from Set C2, around 0.6 hours of children’s speech. We call this set dev-018. The rest of the released data is treated as our train set.

3.2. Text Normalization

The transcripts released by CSRC have been properly normalized. In addition to the official text normalization, we also map symbols (e.g., “>”, “@”, etc.) to their corresponding Chinese characters.

3.3. Tokenization

| Table 1. Comparison of different tokenizers (CER) |
|-----------------------------------------------|
| Tokenization | dev-011 | dev-018 |
| mmseg       | 35.96   | 63.15   |
| jieba       | 35.52   | 62.31   |

The official training transcripts are not tokenized. We evaluate both mmseg [12] and jieba [13] tokenizers for this particular task. For each tokenizer, we train a typical triphone system with the Kaldi [14] toolkit, on our train set. We then evaluate the recognition performance on our dev-011 and dev-018 sets. Table 1 reports the CER for both tokenizers on our dev sets. It is clear that jieba outperforms mmseg on both dev sets. For the rest of the task, jieba is used for tokenization.

4. DATA AUGMENTATION

Data augmentation has been proved to be very helpful to speech recognition systems, especially when there is a training data mismatch, or when the training data is insufficient [15, 16]. CSRC’s evaluation data only consists of child reading and conversational speech. Its released training data, on the other hand, is mostly adult speech, with around 340 hours of adult reading speech, plus around 30 hours of child reading speech and another 30 hours of child conversational speech. Given the limited amount of child speech in the training data, we believe data augmentation can play a big role in this particular task.

4.1. Pitch Perturbation

We propose to use pitch perturbation for adult speech to make it closer to child speech, effectively increasing the training data for child speech. We use SoX’s “pitch” option for pitch perturbation, which shifts the original speech’s pitch by “cents”, i.e., 1/100th of a semitone. We experiment with different shift values, and find shifting adult speech’s pitch up by 250 - 370 cents yields the best performance. For each utterance in the adult speech (Set A) dataset, we randomly pick a value between 250 - 370, and shift the utterance’s pitch up by that value. Note that we only intend to apply pitch perturbation to adult speech. But in our experiments, we made a mistake and applied it to the whole dataset.

4.2. Speed Perturbation

Speed perturbation generally improves speech recognition performance [15]. Speed perturbation is usually performed by resampling the original speech signal. As a result, speed perturbation affects both pitch and tempo. For adult speech, when we increase the original speed to a faster rate, it also pushes the pitch higher, making it closer to child speech. So technically, children’s speech recognition should benefit more from speed perturbation. We use SoX’s “speed” option for speed perturbation. For adult speech (Set A), we create 2 additional copies of the original data, at 90% and 110% of
the original speed. For child speech (Set C1 and Set C2), we create 6 additional copies of the original data, at 85%, 88%, 90%, 110% 112% and 115% of the original speed respectively.

4.3. Tempo Perturbation

Tempo perturbation modifies the speaking rate of the original speech signal without changing its pitch [19]. By adding additional training data at various speaking rate, it makes the speech recognition model robust to different speakers. We use SoX’s “tempo” option for tempo perturbation, which internally implements the waveform-similarity-based synchronized overlap-add (WSOLA) algorithm [20]. For adult speech (Set A), we create 2 additional copies of the original data, at 90% and 110% of the original tempo. For child speech (Set C1 and Set C2), we create 6 additional copies of the original data, at 85%, 88%, 90%, 110% 112% and 115% of the original tempo respectively.

4.4. Volume Perturbation

Volume perturbation is a simple but effective technique to improve speech recognition model’s robustness towards audio volume variations. We use SoX’s “vol” option for volume perturbation. For all the utterances in our training data, including those created from other data augmentation techniques, we perturb the audio volume by a factor between 0.125 and 2.

4.5. Reverberation Perturbation

Reverberation perturbation is critical for far-field speech recognition [16]. We do not expect to see a lot of reverberant speech in the final evaluation set, but we add a small portion of reverberation perturbed data anyways to increase the model robustness. We use SoX’s “reverb” option for reverberation perturbation. We apply reverberation perturbation to all the three datasets Set A, Set C1 and Set C2.

4.6. Spectral Augmentation

Spectral augmentation is typically applied directly to the feature inputs of a neural network [21]. The augmentation policy consists of warping the features, masking blocks of frequency channels, and masking blocks of time steps. We use spectral augmentation in all our systems, which does improve the performance in this task.

5. SYSTEM DESCRIPTION

We use Kaldi [14] for our early experiments, e.g., figuring out what data augmentation techniques to use, and ESPnet [10] for our final submission.

5.1. Kaldi System

Early experiments are based on Kaldi’s multi-cn recipe, which implements a typical chain model [9]. First, a GMM-HMM model is trained to obtain the alignments. Second, data augmentation techniques described in previous sections, such as volume and speed perturbation, are applied. I-vectors [22] are extracted and pasted to the basic acoustic features, as most Kaldi’s recipes [17] do. Finally, a neural network is trained with both cross-entropy and LF-MMI criteria.

Some tiny modifications are made on top of the original multi-cn recipe. We use 80-dimensional FBANK as the basic acoustic features, while the default feature dimension is 40. We increase the number of factorized time-delay neural network (TDNN-F) layers to 17, while the default neural network layout of the multi-cn recipe stacks 6 convolutional neural network (CNN) layers and 12 TDNN-F layers. The re-segmentation step of the original multi-cn recipe is also removed to speed up the overall training.

Other data augmentation strategies are also applied to the recipe. First, spectral augmentation is performed by adding Kaldi’s built-in net3 component spec-augment-layer during the neural network training. Second, for speed perturbation, besides the default speed factors (0.9 and 1.1), we use additional factors 0.8 and 1.15. Third, tempo perturbation is added with the same factors as the speed perturbation. And finally, reverberation perturbation is also performed, as described in previous sections.

As for the language models, we add Recurrent Neural Network Language Model (RNN LM) for rescoring to further improve the performance.

5.2. ESPnet System

The end-to-end flavor system is built using ESPnet [10]. The data augmentation strategies experimented in Kaldi are reused. Convolution-augmented Transformer (Conformer) is applied with relative positional encoding-based self attention [23]. Encoder is constructed using 12 layers of Conformer blocks. Each block consists of a feed-forward module, a multi-head self attention (MHSA)
module and a convolution module followed by another feed-forward module. The hidden dimension of the linear layers in feed-forward modules is 2048. The output dimension of each blocks and the dimension of the MHSA are both 256. Specifically, the number of heads in MHSA is 4. The kernel size of the convolution module is 15.

The input to the encoder goes through a SpecAugment [21] layer followed by a 2-dimensional convolution block with 1/4 subsampling. The block is a stack of 2 2-dimensional convolutions with kernel size 3 and subsampling rate 2, each of which are followed by ReLU activations. Each of the blocks in the encoder begins with a layer-wise normalization.

The decoder is a stack of 6 decoder blocks. Each block consists of 2 MHSA layers and 1 feed-forward layer. The dimension of the MHSA layer is 256, and the hidden dimension of the feed-forward layer is 2048. Each layer begins with a layer-wise normalization. The target of the decoder is represented using embedding of 256. The activation of the decoder goes through another layer-wise normalization and linear transform before output.

The language model (LM) used in this system is token-based 4-gram. For evaluation, hybrid CTC/attention decoding is adopted with CTC weight 0.5 [24]. Besides CTC, ngram score is used with weight 0.5.

5.3. Final Track 1 System

Table 3. Final Track 1 System: breakdown of data augmentation

| Data Augmentation | Hours |
|-------------------|-------|
| Set A             | 341.8 |
| Set C1, C2        | 55.1  |
| Set A, C1, C2 + rp + vp | 396.9 |
| Set A, C1, C2 + pp + vp | 396.9 |
| Set A + sp@{0.9,1.1} + vp | 690.6 |
| Set A + tp@{0.9,1.1} + vp | 690.6 |
| Set C1, C2 + sp@{0.85,0.88,0.9,1.1,1.2,1.15} + vp | 342.7 |
| Set C1, C2 + tp@{0.85,0.88,0.9,1.1,1.2,1.15} + vp | 342.7 |
| OpenSLR + sp@{0.9,1.1} + vp | 2776.4 |
| Total             | 7408  |

| pp : Pitch perturbation |
|-------------------------|
| rp : Reverberation perturbation |
| sp : Speed perturbation, values inside the curly braces are different perturbation parameters |
| tp : Tempo perturbation, values inside the curly braces are different perturbation parameters |
| vp : Volume perturbation |

* Datasets SLR-{18, 33, 38, 47, 62, 68} are used

Due to the increased amount of training data in the Track 2 task, the number of tokens in the decoder is increased to 6491. The number of blocks in the encoder and that in the decoder are increased to 18 and 9 respectively, and the attention width is also increased to 512 with 8 multi-heads. The Track 2 model is trained from scratch using all the data in table 3. Instead of checkpointing based on epochs, models are saved every 10000 batches. For the final submission, 8 best models w.r.t. the loss on validation set are averaged as the final output model.

6. RESULTS AND ANALYSIS

6.1. Kaldi Experiments

All data augmentation experiments are conducted with the Kaldi toolkit, as shown in Table 1. We use Kaldi’s multi-cn recipe as our baseline, which gives 16.28% CER on our dev set. By increasing the feature dimension from 40 to 80, we reduce the CER to 16.09%, and by adding spectral augmentation and additional network layers, we further reduce it to 15.81%. From this point, various language models are experimented. We find that a forward Recurrent Neural Network Language Model (RNN LM) with 5-gram rescoring order (Exp9) gives the best result, which bring the CER down to 14.77%. Pitch features are also added to the Exp3 experiment setting, but they do not seem to improve the performance. We therefore do not use pitch features in the rest of the experiments. On top of Exp6, we add speed and tempo perturbation with parameters 0.85, 0.9, 1.1 and 1.15. We also add reverberation perturbation for Set A, Set C1 and Set C2 (Exp9), which reduces the CER from 14.77% to 14.13. We are a little bit concerned that our system is overfitting to the adult speech, so we remove half of the speed and tempo perturbation (with parameters 0.85 and 1.15) data for the adult speech set Set A. We also remove the data re-segmentation and cleaning step as that is becoming very slow. With those two changes, CER improves to 13.95& (Exp10). From there, we add pitch perturbation for all three datasets Set A, Set C1 and Set C2, and we also add more speed and tempo
perturbation for the child speech datasets Set C1 and Set C2. That brings the CER to 13.92% (Exp11). Remember in Exp10 we remove half of the speed and tempo perturbation data for the adult speech set Set A. If we keep the same perturbation for adult speech, and in addition add pitch perturbation and more speech and tempo perturbation for the child speech set, we are able to achieve 13.61% CER on our dev set.

6.2. ESPnet Experiments

Table 5. Kaldi and ESPnet Comparison (CER)

| Systems     | dev-011 | dev-018 | Average |
|-------------|---------|---------|---------|
| Kaldi-Exp3  | 9.95    | 21.66   | 15.81   |
| ESPnet      | 8.3     | 21.60   | 14.95   |

We also run experiments through ESPnet’s attention-based encoder-decoder end-to-end models. Table 5 shows a comparison between ESPnet and Kaldi with the same amount of augmented data (Exp3 augmentation setting). On our dev set, ESPnet’s end-to-end model slightly outperforms Kaldi’s chain model.

6.3. Final Submission

Table 6. Final Submission (CER)

| Track         | evaluation |
|---------------|------------|
| ESPnet-track1 | 18.82      |
| ESPnet-track2 | 16.48      |

From the previous section we learn that ESPnet’s end-to-end model slightly outperforms Kaldi’s chain model. We therefore use ESPnet for our final submission. Our best Kaldi system before the submission is Exp11, so we use Exp11’s augmentation settings, and run it through ESPnet’s end-to-end model. Results on the final evaluation set are shown in Table 6. It is worth mentioning that Exp11 is not our best setting. Post-challenge experiments reveal that Exp12, which has more augmentation data, outperforms Exp11 with a healthy margin on Kaldi’s chain model. We expect the Exp12 setting will further our CERs on the evaluation set.

7. CONCLUSIONS

We have demonstrated that data augmentation is simple and effective for children’s speech recognition. Given the short time window for development, we believe we have not fully utilized the power of data augmentation. Further experiments are encouraged.
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