IMPROVING SHORT-VIDEO SPEECH RECOGNITION USING RANDOM UTTERANCE CONCATENATION

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ABSTRACT

One of the limitations in end-to-end automatic speech recognition framework is its performance would be compromised if train-test utterance lengths are mismatched. In this paper, we propose a random utterance concatenation (RUC) method to alleviate train-test utterance length mismatch issue for short-video speech recognition task. Specifically, we are motivated by observations our human-transcribed training utterances tend to be much shorter for short-video spontaneous speech (∼3 seconds on average), while our test utterance generated from voice activity detection front-end is much longer (∼10 seconds on average). Such a mismatch can lead to sub-optimal performance. Experimentally, by using the proposed RUC method, the best word error rate reduction (WERR) can be achieved with around three fold training data size increase as well as two utterance concatenation for each. In practice, the proposed method consistently outperforms the strong baseline models, where 3.64% average WERR is achieved on 14 languages.

Index Terms— random utterance concatenation, data augmentation, short video, end-to-end, speech recognition

1. INTRODUCTION

End-to-end (E2E) automatic speech recognition (ASR) framework has been phenomenal in both academy and industry, thanks to its simple, compact, and more importantly efficacy properties in modeling capacity. However, E2E framework still contains unresolved problems. One of the problems is the learned E2E ASR models tend to overfit to the utterances that have been seen during the training, as a result, it cannot generalize well to unseen utterances. Here, the so-called “unseen” can refers to various noise conditions, out-of-vocabulary or tail words, as well as sequence length mismatch problems.

To alleviate the overfitting problem, many effective solutions have been proposed. One of the earlier pioneer works is dropout, which randomly drops some of the visible or hidden nodes during the training. To date, dropout is widely employed in deep learning to yield robust networks that can generalize to unseen test conditions. Following dropout, another popular technique developed to address train-test data mismatch problem is scheduled sampling, which is crucial for autoregressive attention-based encoder-decoder (AED) framework. This is because ground-truth tokens are used as prior knowledge during the training stage, while during the evaluation the prior tokens might be erroneous. Another group of works focus on front-end data augmentation. Take ASR for instance, to let models see diverse data, speed perturbation, as well as artificial reverberant noise corruptions are applied. Inspired by “Cutout” in computer vision, the recently proposed SpecAugment, that simultaneously masks a small portion of Mel coefficients along both spectral and temporal axes during training, has demonstrated significant efficacy for ASR performance improvement.

More recently, the problem of train-test utterance length mismatch has drawn increased attention in both machine translation (MT) and ASR communities. Specifically, people observed that the models trained using short utterances can result in significantly degraded results (a lot of deletions) when the input test utterances are much longer. To address this problem in MT, proposed a multi-sentence resampling (MSR) method to concatenate sentences, yielding improved translation performance. In ASR task, a series of recipes, such as random state passing to simulate utterance concatenation, attention mechanism manipulation, and overlapping decoding, have been proposed to improve long utterance recognition.

In this paper, we propose a random utterance concatenation (RUC) method to address the train-test utterance length mismatch problem in short-video speech recognition. We are motivated from the observation that our human transcribed utterances are too short (∼3 seconds on average), while the test utterances from the front-end voice activity detection (VAD) are much longer (∼10 seconds on average). The RUC method augments the training data by randomly concatenating two or more utterances. The intention here is to improve the overall recognition performance, particularly on long utterances, by letting the E2E ASR model see much longer utterances during the training. Our main contributions lie in two aspects: 1) to the best of our knowledge, explicit random utterance concatenation for ASR training has not been attempted previously, we are the first to empirically study the effectiveness of the method under ASR scenario; 2) we validate the efficacy of the proposed method on 14-language corpora that contain challenging short-video speech with high spontaneity and diverse background noise.

2. RELATION TO PRIOR WORK

To alleviate the train-test utterance length mismatch problem in MT task, proposed a MSR-based sentence concatenation method that is very close to the proposed RUC here. Although some analyses are conducted on Librispeech data for the ASR task, no actual experiment indicating the efficacy for the ASR task has been performed. Besides, compared with the MT task, utterance concatenation for the ASR task is more complicated, since the concatenated utterances are not only potentially heterogeneous in semantics, they might also be acoustically irrelevant. One cannot know for sure whether it is working without empirical study.

Train-test utterance length mismatch problem has been extensively studied in ASR community recently. However, the hallmark of the work is to deal with very long-form speech to decode. For instance, the length of their target utterances can be as long as several minutes. Here, our target test utterances are shorter.

1Short video refers to a total duration of less than three minutes.
than 25 seconds. For such utterances, the effectiveness of their methods has not been reported. Besides, all experiments in [12, 13, 15] are conducted on RNN-T ASR framework, while our ASR models belong to the AED. Additionally, the proposed RUC method can be also considered as a data augmentation, and it could be complementary to all approaches proposed in [12, 13, 15] that mainly make efforts on model level.

It is noteworthy to mention random state passing approach [12], which simulates random utterance concatenation. This approach has been shown effective for long-form utterance recognition, however, the “concatenation” is implicit, while it is explicit in this work. Besides, the effort is focused on model level optimization, and thus, the training recipe should be changed accordingly.

3. RANDOM UTTERANCE CONCATENATION

The purpose of the proposed RUC method is to generate longer utterances by randomly concatenating training utterances. Algorithm 1 reveals the implementation details.

**Algorithm 1** Random utterance concatenation

1: $D \leftarrow$ old training set with transcript and feature pairs
2: $N \leftarrow$ maximum number of utterances to concatenate
3: $S = |D| \cdot M \leftarrow$ total utterances in the new training set
4: $R = \emptyset \leftarrow$ new dataset by random utterance concatenation
5: for $i \leftarrow 1$ to $S$ do
6: \hspace{1em} $n \leftarrow$ random integer from 2 to $N$
7: \hspace{2em} $T \leftarrow$ a random utterance id sequence with length $n$
8: \hspace{1em} new_transcript = $\emptyset$
9: \hspace{1em} new_feature = $\emptyset$
10: \hspace{2em} for $k \leftarrow 1$ to $n$ do
11: \hspace{3em} new_transcript.concatenate(transcript $T[k]$)
12: \hspace{3em} new_feature.concatenate(feature $T[k]$)
13: \hspace{1em} end for
14: $R.append(new\_transcript, new\_feature)$
15: end for
16: return $R$

In Algorithm 1 there are following points worth an emphasis. In our experiments, we constrain the length of concatenated utterances to be less than 25 seconds, and it can be adjusted to other values. The “feature” in Algorithm 1 can be either raw waveform or MEL spectral coefficients. In this paper, all concatenations are performed on MEL feature level. Furthermore, the RUC method can be realized either online, as SpecAugment [27] implementation, or offline. The online implementation should be more flexible and simplify the pipeline. In this work, we go with the offline mode for the time being. Next, we always merge the concatenated data set $R$ with the original training set $D$ for the RUC training method. Finally, Algorithm 1 is actually very similar to what is proposed in [31] in terms of both implementation and function.

As an alternative, we also propose a simpler RUC method. Specifically, we first create one copy of the original dataset $D$ and randomly shuffle it, then we do pair-wised random utterance concatenation between the shuffled and the original datasets, yielding approximate 2 times of the original dataset.

To differentiate two variants of RUC method, we denote Algorithm 1 as RUC-A, while the simpler one as RUC-B in what follows. Note that the RUC-B method is equivalent to the RUC-A method with the parameters $N$ and $M$ in Algorithm 1 set to two.

4. DATASET

We employ our anonymized short-video data to verify the efficacy of the RUC approach for ASR training. The data is rather challenging. Not only they are spontaneous, but their genres are also highly diverse. For instance, within a 2-minute video, majority of audios are not speech, but music, ambient noise, and other non-verbal sounds, such as laughter, coughs, breath, etc. Figure 1 presents our video distribution statistics, taking 1k hours of Swedish and 9.5k hours of German as examples. From Figure 1 we can observe that both length and segments/utterances per video distributions of two languages are very similar, where the average video length is around eight seconds and the average number of utterances per video is around three. Over 99 percent of videos are shorter than 50 seconds, and contain less than 10 utterances. The longest videos is around 150 seconds with around 35 utterances for both Swedish and German languages.

**Table 1**: Training data statistics of 14 languages

| Language (ID) | Hours (K) | Utterances (M) |
|--------------|-----------|----------------|
| Burmese (MM) | 3.8       | 2.8            |
| Dutch (NL)   | 4.8       | 5.2            |
| Filipino (PH)| 5.0       | 4.8            |
| French (FR)  | 7.0       | 8.4            |
| German (DE)  | 9.5       | 10.6           |
| Indonesian (ID)| 9.8   | 9.4            |
| Italian (IT) | 9.6       | 7.9            |
| Japanese (JP)| 1.7       | 2.2            |
| Korean (KR)  | 2.5       | 2.2            |
| Polish (PL)  | 9.6       | 9.5            |
| Portuguese (BR)| 10.0 | 13.2           |
| Russian (RU) | 9.0       | 6.2            |
| Swedish (SE) | 1.0       | 1.1            |
| Vietnamese (VN)| 9.7   | 11.7           |
Table 1 reports the training data statistics of all 14 languages used in this work. The data size ranges from 1k to 10k hours. Table 2 presents the average utterance length statistics in training and test sets in terms of both time and token units for all languages.

5. EXPERIMENTS AND RESULTS

5.1. Modeling

The E2E ASR models employed in this work are based on AED architecture, and are similar to the ones used in [32]. Specifically, the encoder is modelled using Transformer network, while the decoder is modelled using LSTM. Transformer’s layers, dim, and head parameters are \{18, 512, 8\}, and the feed-forward network dimension is set to 2048 with the GLU activations. The LSTM decoder has four layers with 1024 cells per layer. For robust training, we employed the\footnote{We ignore Mandarin and English for time being, we leave it for future online RUC exploration, since even larger data size is our concern with the present offline method.}\footnote{We attempted different length settings for VAD, and found 3-20 seconds to yield better results on average.} both variational noise (VN) \[33\] and SpecAugment \[34\] methods. The VN training is activated after 10k steps. The SpecAugment is activated after 2k steps, and its frequency \{F, m, p\} and temporal \{W, m_T, p\} parameters are set to \{27, 2\} and \{100, 1, 0.1\}, respectively. During the inference, the beam size is fixed to 10, and the best length normalization factor \[35\] is selected for each language independently from \{0, 2.0\} range. All ASR models employ word piece model \[36, 37\] with the vocabulary size ranging from 3k to 7k.

5.2. Results

Table 3 reports the WER results obtained using RUC-A and RUC-B methods. For RUC-A, parameters N and M in Algorithm 1 are set to two and three, respectively. We chose these configurations without any substantial experiments. The main motivation was to restrict the overall data size as well as processing time, since we are performing the offline RUC.

Table 2: Average utterance length statistics (mean ± std) in training and test sets for 14 languages

| ID | Train Duration (s) | #Tokens | Test Duration (s) | #Tokens |
|----|--------------------|---------|------------------|---------|
| MM | 4.62 ± 3.49 | 13.47 ± 11.87 | 10.67 ± 4.51 | 29.2 ± 18.9 |
| NL | 3.19 ± 2.63 | 9.12 ± 7.76 | 10.93 ± 4.72 | 24.2 ± 17.1 |
| PH | 3.51 ± 2.82 | 9.88 ± 8.46 | 9.98 ± 4.26 | 21.3 ± 13.3 |
| FR | 2.82 ± 2.44 | 11.30 ± 10.08 | 10.47 ± 4.64 | 34.1 ± 23.1 |
| DE | 3.08 ± 2.86 | 9.74 ± 9.44 | 10.22 ± 4.21 | 26.7 ± 15.9 |
| ID | 3.57 ± 3.15 | 9.09 ± 8.23 | 11.35 ± 4.54 | 20.8 ± 13.9 |
| IT | 4.14 ± 3.22 | 11.53 ± 10.11 | 10.85 ± 4.71 | 26.6 ± 17.5 |
| JP | 2.63 ± 2.56 | 14.95 ± 14.58 | 12.39 ± 4.11 | 78.0 ± 39.6 |
| KR | 3.89 ± 3.28 | 8.95 ± 8.59 | 10.33 ± 4.80 | 17.7 ± 13.9 |
| PL | 3.50 ± 2.88 | 11.81 ± 10.39 | 10.41 ± 4.61 | 32.7 ± 20.9 |
| BR | 2.73 ± 2.08 | 8.76 ± 7.09 | 10.07 ± 3.97 | 29.8 ± 15.7 |
| RU | 5.11 ± 3.99 | 14.45 ± 12.52 | 11.11 ± 4.54 | 23.9 ± 15.4 |
| SE | 3.35 ± 2.70 | 10.30 ± 9.06 | 10.59 ± 4.58 | 29.0 ± 19.4 |
| VN | 2.88 ± 2.58 | 12.47 ± 11.28 | 10.70 ± 4.73 | 35.8 ± 25.5 |

From Table 2, we can see that the average utterance length of our train data is much shorter than the test data in terms of both time and token units. On average, the test utterances are 2-3 times of the training utterances. Among them, Russian has the longest utterances, around 5.11 seconds on average, while Japanese has the shortest utterances, around 2.08 seconds on average. The length mismatch here mainly attributes to two reasons. On the one hand, as was mentioned earlier, our short-video data is mostly non-speech. Consequently, human transcribers tend to make short utterances. On the other hand, our VAD front-end tends to split the videos into longer utterances, though the utterance length is restricted to be within 3-20 seconds. The VAD front-end is also used to filter out the non-speech part, and therefore, it should be adjusted to minimize the incorrect segment elimination. It is applied only during the test utterance recognition to be consistent with our real business application. In other words, the test video is first segmented using VAD, and then, each segment (or utterance) is decoded using ASR. Lastly, the recognized outputs are joined together to produce whole video transcripts.

Note that the test sets given in Table 2 contain from 100 up to 2,000 short-videos, and the utterance length statistics are calculated after splitting them using VAD.

Table 3: The WER (%) results obtained using random utterance concatenation method. AVE - average result.

| ID | Baseline | RUC-A | RUC-B |
|----|----------|-------|-------|
| WER | WER | WERR | WER | WERR |
| MM | 19.62 | 19.0 | 3.16 | 19.30 | 1.63 |
| NL | 23.90 | 23.79 | 0.46 | 23.50 | 1.67 |
| PH | 26.27 | 26.00 | 1.0 | 25.89 | 1.45 |
| FR | 19.35 | 18.80 | 2.84 | 18.66 | 3.57 |
| DE | 15.05 | 13.78 | 8.44 | 14.11 | 6.25 |
| ID | 21.93 | 21.47 | 2.10 | 21.08 | 3.88 |
| IT | 18.47 | 17.65 | 4.44 | 17.69 | 4.22 |
| JP | 17.40 | 17.12 | 1.61 | 17.86 | -2.64 |
| KR | 18.86 | 18.02 | 4.45 | 18.51 | 1.86 |
| PL | 13.12 | 12.60 | 3.96 | 12.89 | 1.75 |
| BR | 12.72 | 12.17 | 4.32 | 12.46 | 2.04 |
| RU | 19.22 | 19.11 | 0.57 | 19.96 | -3.85 |
| SE | 24.88 | 24.01 | 3.50 | 23.99 | 3.58 |
| VN | 23.04 | 20.34 | 11.72 | 21.52 | 6.60 |

The WER results in Table 3 show that RUC methods achieve obvious performance improvements over the baseline. The average WERRs for RUC-A and RUC-B methods are 3.64 and 2.34, respectively. Specifically, for RUC-A, the WERR ranges from 0.46 (on NL) to 11.72 (on VN), while the RUC-B WERR is between -3.85 (on RU) and 6.60 (on VN). By analyzing the recognition outputs, we also observed that proposed RUC method consistently reduces the deletion errors.

The WERR gains are marginal or even negative for some languages (NL, PH, JP, and RU). Presumably, it might be due to the following factors. First, we applied the same RUC setting (N and M values) to all languages. However, the optimal setting might vary from one language to another, and thus, it should be tuned for each language independently. For example, in JP, the test utterances are almost five times longer than training utterances. To achieve better results, we might need to concatenate around five utterances. Second, by concatenating training utterances, we increase the average utterance length. This results in smaller mini-batches, which might lead to sub-optimal learning. For example, the training utterances of RU is longer than utterances of other languages, and to achieve better result using RUC, we might also need to tune other hyperparameters.
such as learning rate, number of steps, etc. Lastly, the size of final dataset produced by RUC is also important, since the RUC-A with M set to three yields better results than the RUC-B with M equal to two.

6. ANALYSIS

In this section, we briefly analyze the WER performance of proposed RUC-A method. All experiments were conducted using Swedish language only. Note that we also report WER performance on special Test2 set. The Test2 set contains around 1k short-videos and is similar to the training set as it was segmented and labelled by human transcribers (i.e., average utterance length matches the training data).

We first study the impact of parameters N and M on the WER performance of RUC-A method. Table 4 presents WER results with different settings for N and M. The obtained results show that RUC-A method outperforms the baseline for all the settings of parameters N and M. Specifically, when the N is fixed to two, the best WER is obtained for M equal to three. On the other hand, when the M is fixed to three, the best WER is achieved for N equal to three, which is better than the one reported in Table 1. Overall, the analysis shows the robustness of proposed RUC-A method to different values of parameters N and M, where consistent WER improvement over the baseline is achieved. Moreover, from the WER results on Test2 set, we can also notice that RUC-A method’s performance on short utterances is stable. We leave the more extensive analyses using other languages as a future work due to the space and time constraints.

Table 4: Impact of parameters N and M on the WER performance of RUC-A method for Swedish language.

| N  | M  | Test | Test2 | N  | M  | Test | Test2 |
|----|----|------|-------|----|----|------|-------|
| -  | -  | 24.88| 8.93  | -  | -  | 24.88| 8.93  |
| 2  | 2  | 24.06| 9.06  | 2  | 3  | 24.01| 9.06  |
| 2  | 3  | 24.01| 8.86  | 3  | 3  | 23.59| 8.85  |
| 2  | 4  | 24.02| 9.02  | 4  | 3  | 24.16| 8.91  |
| 2  | 5  | 24.05| 8.93  | 5  | 3  | 24.24| 8.98  |
| 2  | 6  | 24.57| 8.80  | 6  | 3  | 23.67| 8.94  |

To analyze the performance of the proposed RUC-A method on utterances of various lengths, we increased the Test2 set size by applying our RUC-A method with N=6 and M=3 (maximum utterance length is around 25 seconds). Next, we computed the WER on various portions of Test2 limited by the utterance length using baseline ASR and ASR trained on data produced by RUC-A (with N=2 and M=3). In other words, we first computed WER on Test2 set’s utterances containing less than 10 tokens, then on utterances containing less than 20 tokens, and so on.

The experiment results are shown in Figure 2. We can observe that the WER performance of both models are almost identical for short utterances containing less than 20 tokens. Starting from the utterance length of 20 tokens the WER gap between two models starts to increase, though the overall performance of both models is still improving. The baseline model’s performance drops sharply after 60-token length, while the performance of RUC-A method remains stable. These results indicate that proposed RUC-A method is effective for recognizing long utterances.

7. DISCUSSION

Train-test utterance length mismatch problem can always happen, and this is particularly true in real-world application scenarios, where the incoming test data is unpredictable. Although we have successfully verified the efficacy of the proposed RUC method by achieving noticeable WERR on majority of 14 languages, our effort is still rather preliminary.

First, we report the data concatenation results using offline mode, which is restricted by two factors: 1) the multiple of original dataset to generate, and 2) the number of utterances to concatenate. That is, the M and N parameters in Algorithm 1. For online concatenation, as in SpecAugment implementation, the effects of both parameters should be further explored. Currently, we are performing online RUC experiments, and the preliminary results show better WERR than the offline method used in this work.

Secondly, we only verify the method on the attention-based encoder-decoder ASR architecture, while leaving the most popular RNN-T ASR models untouched. [15] has already shown that RNN-T is not immune to the train-test data mismatch problem either. Therefore, we believe the RUC method should be also working for the RNN-T models. Besides, the RUC method itself is not particularly related to a specific modeling framework.

Thirdly, the RUC method might not bring direct WER reduction, but training assisted with it could yield robust ASR models for longer utterance recognition, which could be potentially crucial in real-world applications.

8. CONCLUSION

In this work, we proposed a RUC method to improve short-video speech recognition. Specifically, the proposed method addresses train-test utterance length mismatch originated from the differences between training and test data preparation stages. We demonstrated its efficacy using AED-based ASR on 14 languages, where average WERR of 3.64% has been achieved, with the maximum WERR being 11.72% on Vietnamese language. The improvements are achieved by concatenating two utterances, and increasing the original dataset size three times. We observed that RUC method is more effective on longer utterances, and it helps to reduce deletion errors. In addition, we also found that RUC method is robust to different parameter settings, where consistent WER improvement over the strong baseline is achieved. In future work, we plan to implement the online version of our method to simplify the pipeline. Additionally, we plan to exploit the full potential of proposed method by investigating other configurations of concatenation using more languages. We will also study its effectiveness in combination with other data augmentation techniques.
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