PM-MMUT: BOOSTED PHONE-MASK DATA AUGMENTATION USING MULTI-MODELING UNIT TRAINING FOR ROBUST UYGHUR E2E SPEECH RECOGNITION

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**ABSTRACT**

Consonant and vowel reduction are often encountered in Uyghur speech, which might cause performance degradation in Uyghur automatic speech recognition (ASR). Our recently proposed learning strategy based on masking, Phone Masking Training (PMT), alleviates the impact of such phenomenon in Uyghur ASR. Although PMT achieves remarkably improvements, there still exists room for further gains due to the granularity mismatch between masking unit of PMT (phoneme) and modeling unit (word-piece). To boost the performance of PMT, we propose multi-modeling unit training (MMUT) architecture fusion with PMT (PM-MMUT). The idea of MMUT framework is to split the Encoder into two parts including acoustic feature sequences to phoneme-level representation (AF-to-PLR) and phoneme-level representation to word-piece-level representation (PLR-to-WPLR). It allows AF-to-PLR to be optimized by an intermediate phoneme-based CTC loss to learn the rich phoneme-level context information brought by PMT. Experimental results on Uyghur ASR show that the proposed approaches improve significantly, outperforming the pure PMT (reduction WER from 24.0 to 23.7 on Read-Test and from 38.4 to 36.8 on Oral-Test respectively). We also conduct experiments on the 960-hour Librispeech benchmark using ESPnet1, which achieves about 10% relative WER on all the test sets without LM fusion comparing with the latest official ESPnet1 pre-trained model.

**Index Terms**— Speech recognition, end-to-end, phone masking training, E2E ASR decoupling, multi-modeling unit training

1. INTRODUCTION

Recently, end-to-end (E2E) automatic speech recognition (ASR) \cite{1-6} based neural networks have achieved large improvements. Meanwhile, the E2E ASR simplifies the processing of system construction, which establishes a direct mapping from the acoustic feature sequences to the modeling unit sequences.

With the emergence of E2E ASR, researchers \cite{2-10} explore different E2E ASR scenarios and partly focus on the data augmentation and training strategy due to the nature of data hungry and easy over-fitting. For Uyghur speech recognition, existing works mainly focused on problems such as agglutinative characteristics and low resources, often in conventional structure \cite{11-13}. Until recently, to our best knowledge, we are among the first to publish work on applying E2E ASR to Uyghur using large amount corpus \cite{14}, which is also about data augmentation and learning method. In short, the motivation is to use phone mask training (PMT) to alleviate the impact of phonetic reduction (PR) on the Uyghur E2E ASR system by randomly masking off a certain percentage features of phones and filling with the average value of word where the phone is located during model training, thereby enhancing the robustness of the model to phonetic reduction.

Although PMT mitigates the impact of PR on E2E ASR to some extent, we found that there are some disadvantages of the proposed PMT system. Our recent work \cite{14} shows that the performance of word-piece-based modeling unit in Uyghur Conformer E2E ASR is generally better than grapheme and phoneme based modeling approach. Therefore, it will cause granularity mismatch between the masking unit of PMT (phoneme) and modeling unit (word-piece). We think that this mismatch has limited the effect of PMT to some certain extent. Firstly, it will hinder the model to use more surrounding information to assist the prediction of the weakened part of PR data. Secondly, it will cause that the masking of short phones is meaningless. Because the masking of these phones does not cause too much hindrance to the prediction of the modeling unit and does not encourage the model to learn more information. Moreover, these masking can not achieve the effect of PR data augmentation and even destroy the real PR data. Hence we urgently need a model to eliminate granularity mismatch so that the more information produced by PMT can be considered by our model.

Recently, many works attempt to decouple the encoder of E2E ASR and by introducing another CTC branch. Zhang et al. \cite{15} proposes a decoupling model structure to leverage monolingual data to improve code-switching speech recognition task. Lee et al. \cite{16} inserts a intermediate CTC loss to regularize the model. In addition, many works try to leverage multi-modeling units to jointly optimize the E2E ASR. Lakomkin et al. \cite{17} point out that combining several segmentations of an utterance transcription in the loss function to optimize the E2E ASR model may be beneficial to the model. Krishna et al. \cite{18} proposes phoneme and word-piece CTC loss to joint learning based on BiLSTM model. Kubo et al. \cite{19} proposes to use multi-task learning to improve generalization of the model by leveraging information from multiple labels (phoneme and grapheme). Chen et al. \cite{20} uses a hybrid of the syllable, Chinese character, and subword as the modeling units for the end-to-end speech recognition system based on the CTC/attention multi-task learning. Nadig et al. \cite{21} explores joint phoneme–grapheme decoding using an Encoder–Decoder network with hybrid CTC/Attention mechanism.

Motivated by the above, we adopt the hierarchical CTC based methods \cite{18} and propose a multi-modeling unit training (MMUT) framework fusion with PMT (PM-MMUT) to explore more context information produced by PMT, whereby to maximize the role of PMT. In our proposed model framework (see Section \cite{22} for more details), we split the encoder into two parts. The first part is inserted in an intermediate phoneme-based CTC loss that allows to learn a mapping from the acoustic feature sequence to phoneme-
level representation (AF-to-PLR). The second part is optimized by word-piece-based CTC and CE loss. It maps the phoneme-level representation to word-piece-level representation (PLR-to-WPLR). All the losses are combined using some tunable weights. Obviously, the modeling unit of AF-to-PLR matches the masking granularity of PMT, so that the rich contextual information will be fully considered by the E2E model. We mainly conduct corresponding experiments on 1200 hours of Uyghur data, but also benchmark Librispeech 960 hours task. Our model demonstrates a significant performance improvements in all the tasks. The main contributions of our work can be summarized as follows:

- We are the first to publish work on adapting the hierarchical CTC based methods [13] to Conformer-based Encoder-Decoder E2E speech recognition, especially on Uyghur ASR task.
- We have boosted our prior work PMT, by managing to eliminate the granularity mismatch between the masking unit of PMT and the modeling unit.
- Intensive investigations are carried out into the proposed method on both a 1200-hour Uyghur speech dataset and the 960-hour Librispeech ASR benchmark. The results show a significant improvements to verify the effectiveness of the proposed method.

2. MODEL DESCRIPTION

2.1. Phone Mask Training

Aiming at reducing the impact of phonetic reduction in Uyghur speech, PMT randomly select a percentage of the phones and mask the corresponding speech segments in each training iteration. The masking parts fill with the average value of word where the selected masked phone is located. The alignment information of each phone and frame is get by force alignment using HMM-DNN (nnet3) model trained by speech recognition toolkit Kaldi [22]. The modeling unit of E2E ASR is based on word-piece, which might cause the granularity mismatch between the masking unit of PMT and modeling unit. As discuss above, this mismatch will limit the effect of PMT to some certain extent. The more detail introductions of PMT are shown in our prior work [13].

Our PMT is based on the follow intuitions: (1) To make E2E model to learn phonetic reduction related lexicon knowledge by simulating the PR data. (2) To encourage E2E model to learn more contextual information brought by PMT.

2.2. PM-MMUT: Multi-Modeling Unit Training Fusion with PM Training

Figure 1 presents the structure diagram of PM-MMUT, which is a Conformer-based E2E system. The model consists of a PM module, an encoder and a decoder. The encoder is composed by an AF-to-PLR encoder which is imposed by a phoneme-based CTC (PCTC) loss, and a PLR-to-WPLR encoder, which is imposed by a word-piece-based CTC (WPCTC) loss. The last part of the model is a standard Transformer decoder. PM-MMUT subdivides the E2E system similar to conventional HMM-DNN structure, so that the model gives full play to the role of each part, and then make the model fully explore the information contained in the data. The detailed explanations of the model are presented as follows.

In the PM module, phone mask operation is applied on the inputs to produce masked features given the input acoustic feature sequence \( X \) and the alignment information \( X_{\text{ALI}} \):

\[
X_{\text{PM}} = \text{PM}(X, X_{\text{ALI}}),
\]

where \( \text{PM}(\cdot) \) denotes the phone mask operation and \( X_{\text{PM}} \) the masked acoustic feature.

The AF-to-PLR encoder \( \text{ENC}_{\text{AF2PLR}}(\cdot) \) learns the mapping from the acoustic feature (AF) to phoneme-level representation (PLR). It is similar to the acoustic model in traditional HMM-DNN based speech recognition system, which is made up of Conformer-based encoder in the first a few layers. It accepts \( X_{\text{PM}} \) from the phone mask module to produce PLR representation \( H_{\text{PLR}} \):

\[
H_{\text{PLR}} = \text{ENC}_{\text{AF2PLR}}(X_{\text{PM}}).
\]

The PCTC loss is imposed here to encourage AF-to-PLR encoder to learn more rich phoneme-level context information brought by PMT:

\[
L_{\text{PCTC}} = \log P_{\text{PCTC}}(Y_{\text{PLR}} | H_{\text{PLR}}),
\]

where \( P_{\text{PCTC}} \) considers the probability distribution over all the possible alignments based on phoneme-level label \( Y_{\text{PLR}} \) and \( H_{\text{PLR}} \).

The PLR-to-WPLR encoder \( \text{ENC}_{\text{PLR2WPLR}}(\cdot) \) is applied to learn the mapping from the phoneme-level representation (PLR) \( H_{\text{PLR}} \) to word-piece-level representation (WPLR) \( H_{\text{WPLR}} \), which underlying models the pronunciation lexicon in traditional HMM-DNN based ASR:

\[
H_{\text{WPLR}} = \text{ENC}_{\text{PLR2WPLR}}(H_{\text{PLR}}).
\]

The WPCTC loss (\( L_{\text{WPCTC}} \)) imposed on \( H_{\text{WPLR}} \) is to regularize the model similar to general hybrid CTC/attention ASR [23]:

\[
L_{\text{WPCTC}} = \log P_{\text{WPCTC}}(Y_{\text{WP}}, H_{\text{WPLR}}),
\]

where \( P_{\text{WPCTC}} \) represents the probability distribution over all posible alignments based on word piece-level label \( Y_{\text{WP}} \) and \( H_{\text{WPLR}} \). The total CTC loss (\( L_{\text{CTC}} \)) combines \( L_{\text{PCTC}} \) in Eq. (3) and \( L_{\text{WPCTC}} \) in Eq. (5) using a tunable trade off factor \( \alpha \):

\[
L_{\text{CTC}} = L_{\text{WPCTC}} + \alpha \times L_{\text{PCTC}},
\]
Table 1. The datasets

| Data Type       | Dur (Hrs) | Domain     |
|-----------------|-----------|------------|
| Uyghur          |           |            |
| Train           | 1200      | Read/Clean |
| Read-Test       | 3         | Read/Clean |
| Oral-Test       | 5         | Oral/Noisy |
| English         |           |            |
| Train-960       | 961       | Read/Clear&Noisy |
| Test/Dev-clean  | 5.4       | Read/Clear |
| Test-other      | 5.1       | Read/Noisy |
| Dev-other       | 5.3       | Read/Noisy |

where \( \alpha \) is selected by hand and the sensitive influence of \( \alpha \) on PM-MMUT will be presented in the later experiments.

For the decoder, as previously mentioned, it is a standard Transformer decoder which learns language-related information based on word-piece-level representation \( \text{WLPR} \) and the textual information \( Y \). Generally, it is optimized by Cross Entropy (CE) loss:

\[
\mathcal{L}_{CE} = \log P_{DEC}(Y|\text{WLPR}),
\]

where

\[
P_{DEC}(Y|\text{WLPR}) = \prod_{i=1}^{L} P(y_i|y_1, ..., y_{i-1}, \text{WLPR})
\]

represents the sequence probability of \( Y \) given \( \text{WLPR} \). The final objective is represented as a trade off between the CTC loss in Eq. \( 6 \) and the CE loss in Eq. \( 7 \), as follows:

\[
\mathcal{L} = \beta \times \mathcal{L}_{CTC} + (1 - \beta) \times \mathcal{L}_{CE},
\]

where \( \beta \) is the weight that balances the CTC and the CE loss. In the decoding stage, only the probabilities of the decoder and WPCTC loss are combined to obtain the final output \([14, 23, 24]\):

\[
\hat{Y} = \arg \max_y \{ \lambda \times \log P_{DEC}(y|\text{WLPR}) + (1 - \lambda) \times \log P_{WPCTC}(y|\text{WLPR}) \},
\]

where \( \lambda \) is a tunable hyper-parameter controlling score balance between CTC and attention.

3. DATA DESCRIPTION

The proposed method is evaluated on both Uyghur large vocabulary speech recognition and the standard Librispeech speech recognition benchmark [25]. For Uyghur speech recognition experiments, we use the same Uyghur speech corpus in our previous work [14]. The database contains speech sampled at 16k Hz with a duration of 1 200 hours. The corpus contains 1 198 582 utterances read by 65 089 speakers. As for the evaluation set, we use reading speech (Read-Test), spontaneous speech (Oral-Test) and THUYG-20 [26] test (THUYG-Test) similar to our previous configurations [14]. For English ASR evaluation, we experiment on the Librispeech 960-hour benchmark and test on test-clean/other and dev-clean/other. The details of the datasets are shown in Table 1.

4. EXPERIMENTS AND RESULTS

4.1. Experiment setup

For Uyghur speech recognition task, following our previous setups [14], the experiments use 40 Mel Frequency Cepstral Coefficients (MFCCs) over 25 ms frames with 10 ms stride to each of which cepstral mean and variance normalization (CMVN) is applied. In English tasks, following [24], we use 80-dimensional logmel spectral energies plus 3 extra features for pitch information as acoustic features input. Following [14, 24], the trade off weight \( \beta \) was set to 0.3 over all the tasks.

For the E2E configuration, we use a similar setup in our work [14] in the Uyghur ASR experiment, and [24] for the Librispeech task. All the E2E models are trained by using ESPnet1 [27] on 4 P40 GPUs for the Uyghur task and 8 M40 GPUs for the English task. No external language models were used. The pre-trained Conformer model \([14]\) from the latest ESPNet official version, is used as an important baseline.

4.2. Results on Uyghur speech recognition

4.2.1. Base experiments

We experiment with the basic MMUT and PM-MMUT (both AF-to-PLR and PLR-to-WPLR share the 12 encoder layers) and compare the results with the baselines from our prior work [14]. In Table 2, it can be seen in the basic MMUT, AF-to-PLR alleviates granularity mismatch between the reduction unit (phoneme) and the modeling unit (word-piece), achieves obvious improvements over the baselines. However, it demonstrates inferior performance gain than pure PMT which yield the best results in [14]. When we combine PMT with the basic MMUT, the model performs better than both basic MMUT and PMT. The results suggest that MMUT and PMT are complementary, which is consistent with our expectation.

4.2.2. Results on subdivision of the encoder, \( \alpha \) and granularity

The subdivision of the encoder, i.e., the number of the layers of AF-to-PLR encoder (\( N_{AF2P} \)) and weight \( \alpha \) directly affects phoneme-level representation, and consequently, they indirectly influence the PLR-to-PLR encoder and the decoder.

Table 3. WERs by varying \( N_{AF2P} \) and \( N_{PL2W} \); If \( N_{AF2P} \) is equal to 12, AF-to-PLR and PLR-to-WPLR share the all encoder layers (basic)

| SYSTEM | \( (\alpha, N_{AF2P}) \) | Read-Test | Oral-Test |
|--------|--------------------------|-----------|-----------|
| Chain  | 26.0                     | 47.9      |
| Conformer (Grapheme) | 26.8 | 45.0 |
| Conformer (Word-piece) | 25.4 | 44.1 |
| + SpecAugment | 25.2 | 41.6 |
| + PMT | 24.0 | 38.4 |
| + PM-MMUT | (0.5,12) | 24.9 | 41.6 |
| + PM-MMUT | (0.5,12) | 23.9 | 37.5 |
| + SpecAugment | 25.4 | 44.1 |

1https://github.com/espnet/espnet/tree/master/egs/librispeech/asr1
We experiment with different $N_{A2P}=3, 6, 8, 10, 11, 12$ ($N_{A2P}=12$ mean the basic PM-MMUT). The number of layers is closely related to the learning ability of AF-to-PLR and PLR-to-WPLR. Larger $N_{A2P}$ generally means stronger representation learning capability of AF-to-PLR. But this might weaken the PLR-to-WPLR. Therefore, we need a balance in deciding the number of layers in AF-to-PLR and PLR-to-WPLR. As shown in Table 4, $N_{A2P}=10$ shows the best result, which is consistent with our expectation: AF-to-PLR needs a strong representation learning capability in mapping from the acoustic feature to high-level phonetic representation, and PLR-to-WPLR is to map high-level phonetic representation to word-piece-level representation, which is a relatively easy task.

As for $\alpha$, we fix $N_{A2P}$ to 10 and 11 and conduct experiments with $\alpha$ varying from 0.3, 0.5 and 0.7 to 1.0. The results are shown in Figure 2. When $N_{A2P}$ is set to 10, the performance becomes worse with the increasing of $\alpha$. This might be because the two layers of PLR-to-WPLR is still stronger. If $\alpha$ increases, the AF-to-PLR encoder pays more attention to the learning of phoneme-level representation, which is more likely to make the PLR-to-WPLR layers over-fitting. When $N_{A2P}$ is set to 11, which might weaken PLR-to-WPLR because there is only one layer of PLR-to-WPLR encoder, thus the degraded result is obtained. This further justifies our above analysis. The results are also consistent with our hypothesis that the balance between AF-to-PLR and PLR-to-WPLR is important in the proposed PM-MMUT framework.

We further carried out an experimental comparison of intermediate CTC [16], the proposed PM-MMUT, and PM-MMUT-WP (replacing the phoneme-based CTC of PM-MMUT with word-piece-based CTC). The intermediate CTC [16] inserts an intermediate CTC loss to regularize the model. As shown in Table 5, the intermediate CTC can improve on PMT, but is still worse than PM-MMUT. When we replace the phoneme-CTC with word-piece-CTC, there appears to be no help on PMT. This further verified that PM-MMUT alleviates the granularity mismatch between masking unit of PMT and modeling unit. The proposed PM-MMUT makes the modeling unit more compatible with PMT to achieve improved performance.

4.2.3. Results on PM-MMUT with speed perturbation

As we have mentioned in our prior work [14], it is naturally to consider the utilization of the standard speed perturbation [28] to augment the speech data of variant speed. In [14], we demonstrate that PMT and speed perturbation are complimentary. Here we also experiment on PM-MMUT after speed perturbation. We can see in Table 6 that a significant improvements using PM-MMUT comparing with PM after speed perturbation.

4.3. Results on Librispeech English ASR

To further demonstrate the effectiveness of the proposed method, we present the results on a popular ASR benchmark Librispeech 960 hours task. Table 6 shows the results. We can see that PMT is still useful in Librispeech due to phonetic reduction phenomenon exists on English yet. And PMT, PM-MMUT are both complementary with SpeAugment [7]. Finally, our model achieves the best performance without external language model.

5. CONCLUSIONS

In this paper, aiming at boosting our prior work phone mask training (PMT), we propose an effective multi-modeling unit learning architecture fusion with PMT (PM-MMUT) for E2E speech recognition. During training, we will split Encoder into two parts including acoustic feature sequences to phoneme-level representation (AF-to-PLR) and phoneme-level representation to word-piece-level representation (PLR-to-WPLR). Therefore, it allows AF-to-PLR to be enforced by an intermediate phoneme-based CTC loss to learn the rich phoneme-level contextual information brought by PMT. We have carried out Uyghur ASR experiments on both reading and spontaneous speech. Results show that the proposed method improves the performance of Uyghur ASR obviously, especially on the spontaneous speech. Extensive investigations into ASR benchmark Librispeech 960 hours have also been carried out and confirm the effectiveness of the proposed method. According to the analysis, the PM-MMUT is helpful in improving the phonetic-reduction-robustness of Uyghur and English E2E ASR.
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