PM-MMUT: Boosted Phone-Mask Data Augmentation using Multi-Modeling Unit Training for Phonetic-Reduction-Robust E2E Speech Recognition

Guodong Ma\textsuperscript{1}, Pengfei Hu\textsuperscript{2}, Nurmemet Yolwas\textsuperscript{1,3}, Shen Huang\textsuperscript{2}, Hao Huang\textsuperscript{1,3*}

\textsuperscript{1}School of Information Science and Engineering, Xinjiang University, Urumqi, China
\textsuperscript{2}Tencent Minority-Mandarin Translation, Beijing, China
\textsuperscript{3}Xinjiang Key Laboratory of Multi-lingual Information Technology, Urumqi, China

\texttt{hwanghao@gmail.com}

Abstract

Consonant and vowel reduction are often encountered in speech, which might cause performance degradation in 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 the masking unit of PMT (phoneme) and the 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 outperform obviously the pure PMT. We also conduct experiments on the 960-hour Librispeech benchmark using ESPNet1, which achieves about 10% relative WER reduction on all the test set 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) [1–6] based neural networks have achieved large improvements. With the emergence of E2E ASR, researchers [7–16] 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.

Consonant and vowel reduction are often encountered in speech, especially in spontaneous audio, which might cause performance degradation in ASR. This issue is denoted by phonetic reduction (PR). However, few people pay attention to it. To our best knowledge, perhaps our PMT [17] is the first to alleviate the impact of PR on the 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 PR. Although PMT mitigates the impact of PR on E2E ASR to some certain extent, we find that there are some disadvantages of the proposed PMT system. The general modeling unit is based on word-piece [17–24]. Therefore, it will cause granularity mismatch between the masking unit of PMT (phoneme) and the 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 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 structure to eliminate the 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. [13] proposes a decoupling model structure to leverage monolingual data to improve code-switching speech recognition task. Lee et al. [25] 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. [26] point out that combining several segmentation of an utterance transcription in the loss function to optimize the E2E ASR model may be beneficial to the model. Shubham et al. [27] and Krishna et al. [28] proposes phoneme and word-piece CTC loss to joint learning based on BiLSTM model. Kubo et al. [29] proposes to use multi-task learning to improve generalization of the model by leveraging information from multiple labels (phoneme and grapheme). Chen et al. [14] 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. [30] 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 [27,28] 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 2.2), 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 map 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 English task. The main contributions of our work can be summarized as follows: (1) We are the first to publish work on adapting the hierarchical CTC based methods [27, 28] to Conformer-based Encoder-Decoder E2E ASR, especially on Uyghur task. (2) We have boosted our prior work PMT, by managing to eliminate the granularity mismatch between the masking unit of PMT and the modeling unit. (3) Intensive investigations are carried out into the proposed method on both a 1200-hour Uyghur speech dataset and the 960-hour Librispeech English ASR benchmark. The results shows a systematic improvement 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 part 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 [31]. But, 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. Moreover, as for PMT, please refer to our prior work [17] for more details.

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 phone-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. A detailed explanation of the model is 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 phone-level alignment information $X_{ALI}$:

$$X_{PM} = PM(X, X_{ALI}),$$ (1)

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

The AF-to-PLR encoder $\text{ENC}_{AP}(\cdot)$ learns the mapping from the acoustic feature (AF) to phone-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 $X_{PM}$ from the phone mask module to produce PLR representation $H_{PLR}$:

$$H_{PLR} = \text{ENC}_{AP}(X_{PM}).$$ (2)

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

$$L_{PCTC} = \log P_{PCTC}(\mathcal{V}|H_{PLR}),$$ (3)

where $P_{PCTC}$ considers the probability distribution over all the possible alignments based on phone-level label $\mathcal{V}$ and $H_{PLR}$.

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

$$H_{WPLR} = \text{ENC}_{PW}(H_{PLR}).$$ (4)

The WPCTC loss ($L_{WPCTC}$) imposed on $H_{WPLR}$ is to regularize the model similar to general hybrid CTC/attention ASR [4]:

$$L_{WPCTC} = \log P_{WPCTC}(\mathcal{V}|H_{WPLR}),$$ (5)

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

$$L_{CTC} = L_{WPCTC} + \alpha \times L_{PCTC},$$ (6)

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 $H_{WPLR}$ and the textual information $\mathcal{V}$. Generally, it is optimized by Cross Entropy (CE) loss:

$$L_{CE} = \log P_{DEC}(\mathcal{V}|H_{WPLR}),$$ (7)

where

$$P_{DEC}(\mathcal{V}|H_{WPLR}) = \prod_{i=1}^{L} P(y_i|y_1, \ldots, y_{i-1}, H_{WPLR})$$ (8)
Table 1: The datasets

| Data Type | Dur (Hrs) | Domain       |
|-----------|-----------|--------------|
| Uyghur    |           |              |
| Train     | 1200      | Read/Clean   |
| Read-Test | 25.4      | 44.1         |
| Oral-Test | 26.8      | 45.0         |
|             | 25.4      | 44.1         |
| Test/Dev-clean |       |              |
| Test-other | 5.1       | Read/Noisy   |
| Dev-other  | 5.3       | Read/Noisy   |
| Oral-Test  |           |              |
| Test/Dev-clean |       |              |
| Train-960  | 961       | Read/Clear&Noisy |
|             | 24.1      | 39.7         |
|             | 23.9      | 37.5         |
| English    |           |              |
| Train    |           |              |
| Read/Clean | 24.0      | 37.1         |
| Oral-Test | 28.0      | 39.7         |

represents the sequence probability of $Y$ given $H_{WPCTC}$. 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:

$$L = \beta \times L_{CTC} + (1 - \beta) \times L_{CE},$$

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 $[4, 17, 19]$:

$$\hat{Y} = \arg \max_y (\lambda \times \log P_{DEC}(y|H_{WPCTC}) + (1 - \lambda) \times \log P_{WPCTC}(y|H_{WPCTC})),$$

where $\lambda$ is a tunable hyper-parameter controlling score balance between CTC and attention. Following $[17, 19]$, $\lambda$ is set to 0.6 over all experiments.

### 3. Experiments and Results

#### 3.1. Data Description

The proposed method is evaluated on both Uyghur large vocabulary speech recognition and the standard Librispeech speech recognition benchmark $[32]$. For Uyghur speech recognition experiments, we use the same Uyghur speech corpus in our previous work $[17]$. The database contains speech sampled at 16k Hz with a duration of 1 200 hours. And 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 $[33]$ test (THUYG-Test) similar to our previous configurations $[17]$. 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.

#### 3.2. Experiment setup

For Uyghur speech recognition task, following our previous setups $[17]$, 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 $[19]$, we use 80-dimensional logmel spectral energies plus 3 extra features for pitch information as acoustic features input. Following $[17, 19]$, the trade off weight $\beta$ is set to 0.3 over all the tasks. For the E2E configuration, we use a similar setup in our work $[17]$ in the Uyghur ASR experiment, and follow the ESPNet official configuration $[19]$ for the Librispeech task. All the E2E models (Encoders = 12, Decoders = 6, Aheads = 8, $d^{text}=512$) are trained by using ESPNet $[34]$ on 4 P40 GPUs for the Uyghur task and 8 M40 GPUs for the English task. No external language models are used. Then the pre-trained Conformer model $[1]$ from the latest ESPNet

3.3. Results on Uyghur ASR

3.3.1. Base experiments

We experiment with the basic MMUT, PM-MMUT and compare the results with the baselines from our prior work $[17]$. In Table 2, it can be seen that 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 $[17]$. But, when we combine PMT with the basic MMUT, the basic PM-MMUT performs better than both the basic MMUT and PMT. The results suggest that MMUT and PMT are complementary, which is consistent with our expectation.

#### 3.3.2. Results on subdivision of the encoder, $\alpha$ and granularity

The subdivision of the encoder, i.e. the number of $N_{A2P}$, and weight $\alpha$ directly affects phoneme-level representation, and consequently, they indirectly influence the PLR-to-WPLR encoder and the decoder.

We experiment with different $N_{A2P}=3, 6, 8, 10, 11, 12$. The number of layers is closely related to the learning ability of AF-to-PLR and PLR-to-WPLR encoder. Larger $N_{A2P}$ generally means stronger representation learning capability of AF-to-PLR encoder. But this might weaken the PLR-to-WPLR encoder. Therefore, we need a balance in deciding the number of layers in AF-to-PLR and PLR-to-WPLR encoder. As shown in Table 3, $N_{A2P}=10$ shows the best result, which is consistent with our expectation: AF-to-PLR encoder needs a strong representation learning capability in mapping from the acoustic feature to phoneme-level representation, and PLR-to-WPLR encoder is to map phoneme-level representation to word-piece-level representation, which is a relatively easy task.
Table 4: WERs from PM-MMUT, intermediate CTC loss, and word-piece-CTC (PM-MMUT-WP)

| SYSTEM | Read-Test | Oral-Test |
|--------|-----------|-----------|
| Conformer (Word-piece) | 25.4 | 44.1 |
| + PMT | 24.0 | 38.4 |
| + Inter. CTC [25] | 23.7 | 38.0 |
| + PM-MMUT (0.5,10) | 23.7 | 36.8 |
| + PM-MMUT-WP (0.5,10) | 23.9 | 38.3 |

As for $\alpha$, we fix $N_{A2P}$ to 10 and 11. Then, we 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 encoder 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 encoder over-fitting. When $N_{A2P}$ is set to 11, which might weaken PLR-to-WPLR encoder because there is only one layer of Conformer encoder, thus the degraded result is obtained. This further justifies our above analysis. The results is also consistent with our hypothesis that the balance between AF-to-PLR and PLR-to-WPLR encoder is important in the proposed PM-MMUT framework.

Table 5: WERs by comparing with speed perturbation

| SYSTEM | Read-Test | Oral-Test |
|--------|-----------|-----------|
| Conformer (Word-piece) | 25.4 | 44.1 |
| + SpecAugment | 23.7 | 36.8 |
| + PM-MMUT (0.5,10) | 23.9 | 38.3 |

4. Conclusions

In this paper, aiming at boosting our prior work phone mask training (PMT), we propose a 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. 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.

5. Acknowledgements

This work was supported by the National Key R&D Program of China (2020A2A0107902), Opening Project of Key Laboratory of Xinjiang, China (2020D004047), and Natural Science Foundation of China (61663044, 61761041).
6. References

[1] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, “Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks,” in ICML, ser. ICML ’06, New York, NY, USA: Association for Computing Machinery, 2006, p. 369–376.

[2] A. Graves, “Sequence Transduction with Recurrent Neural Networks,” arXiv e-prints, p. arXiv:1211.3711, Nov. 2012.

[3] W. Chan, N. Jaitly, Q. Le, and O. Vinyals, “Listen,attend and spell: A neural network for large vocabulary conversational speech recognition,” in ICASSP, March 2016, pp. 4960–4964.

[4] S. Kim, T. Hori, and S. Watanabe, “Joint ctc-attention based end-to-end speech recognition using multi-task learning,” in ICASSP, 2017, pp. 4835–4839.

[5] L. Dong, S. Xu, and B. Xu, “Speech-transformer: A no-recurrence sequence-to-sequence model for speech recognition,” in ICASSP, 2018, pp. 5884–5888.

[6] A. Gulati, J. Qin, C.-C. Chiu, N. Parmar, Y. Zhang, J. Yu, W. Han, S. Wang, Z. Zhang, Y. Wu, and R. Pang, “Conformer: Convolution-augmented Transformer for Speech Recognition,” in Proc. Interspeech, 2020, pp. 5036–5040.

[7] D. S. Park, W. Chan, Y. Zhang, C.-C. Chiu, B. Zoph, E. D. Cubuk, and Q. V. Le, “SpecAugment: A Simple Data Augmentation Method for Automatic Speech Recognition,” in Proc. Interspeech, 2019, pp. 2613–2617.

[8] D. S. Park, Y. Zhang, C.-C. Chiu, Y. Chen, B. Li, W. Chan, Q. V. Le, and Y. Wu, “Specaugment on large scale datasets,” in ICASSP, 2020, pp. 6879–6883.

[9] L. Meng, J. Xu, X. Tan, J. Wang, T. Qin, and B. Xu, “Mixspeech: Data augmentation for low-resource automatic speech recognition,” in ICASSP, 2021, pp. 7008–7012.

[10] C. Wang, Y. Wu, Y. Du, J. Li, S. Liu, L. Lu, S. Ren, G. Ye, S. Zhao, and M. Zhou, “Semantic Mask for Transformer Based End-to-End Speech Recognition,” in Proc. Interspeech, 2020, pp. 971–975.

[11] J. Zhang, Y. Peng, V. T. Pham, H. Xu, H. Huang, and E. S. Chng, “E2E-Based Multi-Task Learning Approach to Joint Speech and Accent Recognition,” in Proc. Interspeech 2021, 2021, pp. 1519–1523.

[12] Y. Peng, J. Zhang, H. Xu, H. Huang, and E. S. Chng, “Minimum error word training for non-autoregressive Transformer-based code-switching ASR,” arXiv e-prints, p. arXiv:2110.03573, Oct. 2021.

[13] S. Zhang, J. Yi, Z. Tian, Y. Bai, J. Tao, and Z. wen, “Decoupling pronunciation and language for end-to-end code-switching automatic speech recognition,” in ICASSP, 2021, pp. 6249–6253.

[14] S. Chen, X. Hu, S. Li, and X. Xu, “An investigation of using hybrid modeling units for improving end-to-end speech recognition system,” in ICASSP, 2021, pp. 6743–6747.

[15] E. Tsunoo, K. Shibata, C. Narisety, Y. Kashiwagi, and S. Watanabe, “Data Augmentation Methods for End-to-End Speech Recognition on Distant-Talk Scenarios,” in Proc. Interspeech 2021, 2021, pp. 301–305.

[16] Z. Jin, M. Geng, X. Xie, J. Yu, S. Liu, X. Liu, and H. Meng, “Adversarial Data Augmentation for Disordered Speech Recognition,” in Proc. Interspeech 2021, 2021, pp. 4803–4807.

[17] G. Ma, P. Hu, J. Kang, S. Huang, and H. Huang, “Leveraging Phone Mask Training for Phonetic-Reduction-Robust E2E Uyghur Speech Recognition,” in Proc. Interspeech, 2021, pp. 306–310.

[18] P. Hu, S. Huang, and Z. Lv, “Investigating the Use of Mixed-Units Based Modeling for Improving Uyghur Speech Recognition,” in Proc. The 6th Intl. Workshop on Spoken Language Technologies for Under-Resourced Languages, 2018, pp. 215–219.

[19] P. Guo, F. Boyer, X. Chang, T. Hayashi, Y. Higuchi, H. Inaguma, N. Kamo, C. Li, D. Garcia-Romero, J. Shi, J. Shi, S. Watanabe, K. Wei, W. Zhang, and Y. Zhang, “Recent developments on esnpt toolkit boosted by conformer,” in ICASSP, 2021, pp. 5874–5878.

[20] P. Wang, T. N. Sainath, and R. J. Weiss, “Multitask Training with Text Data for End-to-End Speech Recognition,” in Proc. Interspeech 2021, 2021, pp. 2566–2570.

[21] T. Hori, N. Moritz, C. Horii, and J. L. Roux, “Advanced Long-Context End-to-End Speech Recognition Using Context-Expanded Transformers,” in Proc. Interspeech 2021, 2021, pp. 2097–2101.

[22] A. Zeyer, A. Merboldt, W. Michel, R. Schütter, and H. Ney, “Librispeech Transducer Model with Internal Language Model Prior Correction,” in Proc. Interspeech 2021, 2021, pp. 2052–2056.

[23] T. N. Sainath, R. Pang, R. J. Weiss, Y. He, C.-c. Chiu, and T. Strohman, “An attention-based joint acoustic and text on-device end-to-end model,” in ICASSP 2020, 2020, pp. 7039–7043.

[24] H. Xu, Y. Huang, Y. Zhu, K. Audhkhasi, and B. Ramabhadran, “Convolutional dropout and wordpiece augmentation for end-to-end speech recognition,” in ICASSP 2021, 2021, pp. 5984–5988.

[25] J. Lee and S. Watanabe, “Intermediate loss regularization for ctc-based speech recognition,” in ICASSP, 2021, pp. 6224–6228.

[26] E. Lakomkin, J. Heymann, I. Skylar, and S. Wiesler, “Subword Regularization: An Analysis of Scalability and Generalization for End-to-End Automatic Speech Recognition,” in Proc. Interspeech, 2020, pp. 3600–3604.

[27] S. Toshniwal, H. Tang, L. Lu, and K. Livescu, “Multitask Learning with Low-Level Auxiliary Tasks for Encoder-Decoder Based Speech Recognition,” in Proc. Interspeech 2017, 2017, pp. 3532–3536.

[28] K. Krishna, S. Toshniwal, and K. Livescu, “Hierarchical Multitask Learning for CTC-based Speech Recognition,” arXiv e-prints, p. arXiv:1807.06234, Jul. 2018.

[29] Y. Kubo and M. Bacchiani, “Joint phoneme-grapheme model for end-to-end speech recognition,” in Proc. ICASSP, 2020.

[30] S. Nadig, V. Ramasubramanian, and S. Rao, “Multi-target hybrid ctc-attentional decoder for joint phoneme-grapheme recognition,” in SPCOM, 2020, pp. 1–5.

[31] D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glembek, N. Goel, M. Hannemann, P. Motlicek, Y. Qian, P. Schwarz, J. Silovsky, G. Stemmer, and K. Vesely, “The kaldi speech recognition toolkit,” Idiap, Rue Marconi 19, Martigny, Idiap-RR Idiap-RR-04-2012, 1 2012.

[32] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: An asr corpus based on public domain audio books,” in ICASSP, 2015, pp. 5206–5210.

[33] A. Rouzi, S. Yin, Z. Zhang, D. Wang, H. Askar, and F. Zheng, “Thuwyg-20: A free uyghur speech database,” Journal of Tsinghua University(Science and Technology), vol. 57, no. 2, p. 182, 2017.

[34] S. Watanabe, T. Hori, S. Karita, T. Hayashi, J. Nishitoba, Y. Unno, N. E. Yalta Soplin, J. Heymann, M. Wiesner, N. Chen, A. Ren, Duchintala, and T. Ochiai, “ESPnet: End-to-End Speech Processing Toolkit,” arXiv e-prints, p. arXiv:1804.00015, Mar. 2018.

[35] T. Kudo and J. Richardson, “SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing,” arXiv e-prints, p. arXiv:1808.06226, Aug. 2018.

[36] T. Ko, V. Peddinti, D. Povey, and S. Khudanpur, “Audio augmentation for speech recognition,” in INTERSPEECH, 2015.