PRONUNCIATION-AWARE UNIQUE CHARACTER ENCODING FOR RNN TRANSDUCER-BASED MANDARIN SPEECH RECOGNITION

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ABSTRACT

For Mandarin end-to-end (E2E) automatic speech recognition (ASR) tasks, compared to character-based modeling units, pronunciation-based modeling units could improve the sharing of modeling units in model training but meet homophone problems. In this study, we propose to use a novel pronunciation-aware unique character encoding for building E2E RNN-T-based Mandarin ASR systems. The proposed encoding is a combination of pronunciation-base syllable and character index (CI). By introducing the CI, the RNN-T model can overcome the homophone problem while utilizing the pronunciation information for extracting modeling units. With the proposed encoding, the model outputs can be converted into the final recognition result through a one-to-one mapping. We conducted experiments on Aishell and MagicData datasets, and the experimental results showed the effectiveness of the proposed method.

Index Terms— Unique character encoding, modeling units, RNN Transducer, Mandarin speech recognition

1. INTRODUCTION

Recently, end-to-end (E2E) automatic speech recognition (ASR) techniques have achieved significant progress with the development of system architecture and optimization algorithms [1]. Previous works have shown that the performance of the recently advanced E2E system competes with or even outperforms that of traditional ASR approaches [2, 3]. Among the E2E techniques [3, 4, 5, 6], recurrent neural network Transducer (RNN-T) [6] is one of the most popular E2E models for its natural streaming capability and performance. This work also focuses on using RNN-T models for Mandarin speech recognition tasks.

In traditional hybrid ASR systems, context-dependent phonemes (CD-phone) are widely used as the modeling units. A lexicon-based converter, for example, the weighted finite state transducer (WFST) decoder, is required to convert the predicted outputs to the text sequences [7]. For E2E models, the predicted outputs are expected to be the final recognition results. Therefore, comparing CD-phone and phone, characters, words, and sub-words are more widely used as modeling units [8, 9, 10, 11, 12]. Recently, most of the state-of-the-art ASR system on English use sub-word techniques, for example sentencepiece [10], to extract the modeling units [13, 14].

In Mandarin E2E ASR models, various modeling units, such as character, word, syllable, and CD-phone, have also been explored [15, 16, 17, 18]. Previous works show that models using a combination of characters and syllables outperform those using only characters [15, 17]. However, because of the homophone problem in Mandarin, we need a further process to convert the predicted outputs to final transcriptions when using syllables and phonemes as units [18]. This makes the E2E model lose the end-to-end characteristics. Therefore, how to use pronunciation-aware modeling units for building E2E Mandarin ASR is still an open topic.

Considering the pronunciation information underlying acoustic signal is an essential cue for ASR tasks, therefore, taking the pronunciation information into account when designing modeling units is necessary. In this work, we propose to design a pronunciation-aware unique character encoding method for building E2E Mandarin ASR systems. The proposed encoding consists of three partitions: syllable, tone, and character index (CI). The tonal syllable can be optimized with the acoustic feature, and the character index can be optimized and enhanced with text corpus-based linguistic features. Unlike previous works that need a convertor when using pronunciation-based modeling units, models based on the proposed encoding can run entirely in E2E mode. The contributions of this work can be summarized as follows:

- We analyze the characteristics of the RNN-T and propose a novel pronunciation-aware unique character encoding method for RNN-T-based Mandarin ASR tasks.
- To reduce the prediction difficulty of RNN-T, we propose to use meta symbols rather than integers for tone and CI. The experimental results show that the particular meta symbol-based encoding makes the ASR model perform better.
- We further investigate a CI-based beam searching for external LM rescoring and show the potential of the proposed encoding in solving the low computational efficiency problem of beam searching and the difficulty of exploiting text corpus in the RNN-T approach.
3. RNN-T WITH UNIQUE CHARACTER ENCODING

Unlike the CTC-based models, which predict only one output symbol for every acoustic input, the RNN-T model is a single-input-multiple-output model. This characteristic motivates us to consider whether the RNN-T model can further output information more than symbols related to pronunciation information. In this work, we assume that the RNN-T model can further predict more information after the output related to the acoustic feature. Under this assumption, we define a pronunciation-aware unique character encoding (PUCE) for building RNN-T-based Mandarin ASR systems so that our RNN-T model can run on an E2E mode.

3.1. Definition

Fig. 2 illustrates a modeling unit example for a Chinese word that means "speech." To build a fully E2E system, we can select characters or words as modeling units. However, because of the homophone problem, pronunciation-based units cannot fully support E2E processing mode because one tonal syllable corresponds to one to hundreds of characters in Chinese. Motivated by previous works on sub-character tokenization on NLP tasks [19, 20], we define a syllable-based unique character encoding method to represent the character for ASR tasks. For a Chinese character $\mathbf{C}$, let $p$ be the character’s pronunciation, for example, a syllable, and $TI$ is its tone information since Mandarin is a tonal language. Let $CI$ be the $I$-th character of the corresponding tonal pronunciation $(p, TI)$. Then, the encoding can be described as

$$EC = ((p, TI), CI).$$

In this definition, $p$ can use phonemes, syllables, or IPA-inspired phonemes. Mandarin has five tones: first, second, third, fourth, and neutral; therefore, we define the $TI \in \{1, 2, 3, 4, 5\}$ that corresponds to the five tones. We can remove the $TI$ for languages without tone information.

To reduce the represent confusion of $TI$ and $CI$, rather than using integers, we use meta symbols for $TI$ and $CI$ by referring to the space in sentencepiece. We selected Unicode code points from 10,049 to 10,054 (five tones) for $TI$ and 41,000 to 41,900 (support maximum character index of 900) for $CI$.

3.2. E2E RNN-T pipeline

Fig. 3 illustrates the whole pipeline of RNN-T-based ASR using the proposed encoding method. Firstly, we need to prepare two dictionaries: an encoding dictionary for encoding characters to symbol lists and another for changing the predicted symbols to characters. For Mandarin, not only does a pronunciation correspond to multiple characters, but also some characters have more than one pronunciation. Therefore, the construction of the two dictionaries is described.
as follows: Given a tonal syllable $S_1$ and its corresponding characters $C_1, C_2, \cdots, C_i$, the decoding dictionary is created with \{ $S_1#1 : C_1, S_1#2 : C_2, \cdots, S_1#i : C_i$ \}. Then the encoding dictionary is created by changing the place of key and value of the decoding dictionary to \{ $C_1 : S_1#1, C_2 : S_1#2, \cdots, C_i : S_1#i$ \}. For a character $C_3$ with multiple tonal syllables $S_1, S_2$, its value is represented as \{ $C_3 : S_1#1; S_2#2$ \} in the encoding dictionary. With the proposed decoding dictionary, we change the one-to-many mapping problem to one-to-one mapping in the inference stage to overcome the homophone problem.

With the prepared encoding dictionary, the text of training data is encoded by a simple lookup operation following an operation to split the input sentences into characters. After that, we use tokenization techniques to extract the modeling units for the RNN-T model training. In the inference stage, similar to the process for English, the symbols of RNN-T outputs are first processed with the tokenization model to obtain the proposed encoding. Finally, a lookup operation is done to obtain the final recognition results with the decoding dictionary.

3.3. Modeling units with tokenization

Word piece/sub-word tokenization techniques have been widely used in E2E ASR tasks. Different from the character- and char-word-based methods, the proposed encoding can use tokenization to extract sub-char-based tokens as modeling units. In this work, we apply tokenization on the pronunciation partition, i.e., $(p, T_I)$. With tokenization, the higher frequency syllable is represented as a unique symbol, and the less frequent syllable is split into sub-tokens. This helps the model not to learn less frequent words and is expected to identify the words that do not exist in the training data set.

3.4. CI-based beam searching and rescoring

The performance of the ASR model can be further improved by using external LMs trained on text-only data. In traditional hybrid ASR systems, rescoring with a neural network-based language model (NN-LM) on the N-best hypothesis lists is widely used. Because the RNN-T is an autoregressive model, the computational efficiency for extracting the N-best hypothesis is poor, especially with a larger beam width. Therefore, the shallow fusion technique during the inference stage is more widely used \[21, 22\].

In the proposed method, benefitting from the separated definition of pronunciation and the CI, we can implement CI-based beam-searching for extracting N-best lists. In detail, we use the top-1 syllable and tone outputs and execute beam searching on the CI outputs. With the modified N-best list, external LM is used to reorder the hypothesis as

$$
\hat{y} = \log P_{RNN_T}(y|x) + \lambda \log P_{LM}(y),
$$

where $P_{RNN_T}(y|x)$ is the posterior output probability of RNN-T, and $P_{LM}(y)$ is the probability of $y$ generated by external LMs. Because we use unique meta symbols for CI rather than the integer, there is no autoregressive process during the beam searching, and no penalty term on the tokens count since the number of tokens is identical for all the N lists.

4. EXPERIMENTS AND RESULTS

4.1. Dataset

Experiments were conducted on the Aishell-1 \[23\] and MagicData \[24\] Mandarin speech corpus. The Aishell dataset contains about 150 hours of speech recorded by 320 speakers for the training set. The development set includes about 10 hours recorded by 40 speakers and about 5 hours of speech were recorded by 20 speakers as the test set. We applied speed perturbation in the time domain with factors 0.9 and 1.1 to augment the training data to around 450 hours for model building.
The MagicData contains 755 hours of scripted read speech data from 1080 native speakers of Mandarin Chinese spoken in mainland China. The database was split into a training set, validation set, and testing set in a ratio of 51:1:2.

4.2. Experimental setup

Because our target was building a fully E2E ASR system, we built a character-based RNN-T model as a baseline. The number of character modeling units was 4,232 for the Aishell dataset and 4,479 for the MagicData dataset. As previous works showed the effectiveness of char-word units [16], we also built a char-word-unit-based baseline system using the sentencepiece toolkit [25] to prepare tokens with the token number set to 5,000 and 8,000. The same tokenization method was used for the proposed approach to extract the modeling units by taking the TI and CI as special symbols. Performances with the different token numbers (including TI and CI), i.e., 191/208, 300, 500, and 1,000, were compared (The parameter number of the models are from 14.11M to 14.56M). The Char2PUCE and PUCE2Char dictionaries were prepared by referring to previous work [19].

We used the conformer network for the RNN-T encoder and one LSTM layer for the prediction network by referencing to [13]. The conformer encoder consists of 16 conformer blocks with an encoder dimensional of 176, attention heads set to 8, and convolutional kernel number set to 32. Subsampling with factor 4 was processed before the conformer layers. The prediction network consists of 320 LSTM memory cells. The outputs of the encoder and prediction network were transformed to 320 dimension vectors with a linear transform layer of the joint network. The neurons of the final fully-collected layer of the joint network were 320. The input acoustic feature was an 80-dimensional log Mel-based filter-bank feature extracted with 25 ms frame length and 10 ms frameshift. SpecAugment technique was applied during the model training to improve the robustness of the model [26]. All the models were trained from scratch. During model training, we used the Novograd algorithm [27] with a learning rate of 0.03 and a cosine annealing warm restart learning rate scheduler [28] to adjust the learning rate with the minimum learning rate was set to 1e-6. The mini-batch size was 64. The number of training epochs was set to 100.

Two transformer LMs trained on Aishell and MagidData text were used for N-best list rescoring. The LMs were trained with tokens obtained based on the proposed encoding. The hidden dimension of the transformer LM is 512, except for the feedforward sublayer of size 2048. We set the number of heads to 8 and stack 6 layers in the encoder. The dropout was set to 0.1. The Adam optimizer with a warmup setting with a learning rate of 0.001 was used. The training epochs were set to 200. All the methods were implemented with the NVIDIA NeMo[29] toolkits. The experimental results were reported in character error rate (CER %).

4.3. Investigation and experimental results

4.3.1. Modeling units with characters and words

For building E2E Mandarin ASR, using CD-phone and syllable as modeling units often need a complex converter to convert predicted symbols to characters. In this work, we investigated modeling units with characters and a combination of characters and words for fully E2E ASR baseline systems. Table 1 shows the experimental results for these baselines on both Aishell and MagicData datasets. We also listed some results reported by other researchers for reference. From the results, we can see that compared to using characters, the combination of characters and high-frequency words showed better performance. However, with the increase in the number of words selected, the performance was degraded.

4.3.2. Investigations on TI and CI

The TI and CI of the proposed encoding can use integers. However, because the TI is related to pronunciation information and CI is associated with the character index, therefore, using the same integer to represent may improve confusion between them; for example, the TI = 1 means first tone, but CI = 1 means the second character for a tonal syllable. We compared integers and meta symbols (MS) (as described in section 3.1) for TI and CI to investigate the influence. The investigation results are listed in Table 2. From the results, we can see that using integers for both TI and CI, the RNN-T model worked well even though the number meaning was different. When using integer symbols for CI, performance on both datasets degraded as the number of tokens increased. When using MS for CI, with the increasing of the token number, the performance could be improved on the relatively large dataset, i.e., MagicData, and obtained almost the same error rate on the Aishell dataset.

4.3.3. CI-based beam searching and rescoring

As described in section 3.4, models with the proposed encoding can use CI-based beam searching, and then the extracted

| Table 1. Results (CER %) of the baseline systems on Aishell and MagicData. |
|---------------------------------|-----------|-----------|
| Dataset-ModelingUnits          | Dev       | Test      |
| Aishell char(4232)             | 6.09      | 6.49      |
| Aishell char-word(5000)        | 5.90      | 6.48      |
| Aishell char-word(8000)        | 6.30      | 6.98      |
| Aishell syllable-char-word [16]| 6.02      | 6.73      |
| Aishell char [30]              | -         | 6.84      |
| MagicData char(4479)           | 5.79      | 5.78      |
| MagicData char-word(5000)      | 4.97      | 3.76      |
| MagicData char-word(8000)      | 5.62      | 4.22      |
| MagicData syllable-char-word [16]| 5.38     | 5.51      |
Table 2. Investigation of symbols for TI and CI (INT means integer, MS means meta symbols, TN means token number, MIN means minimum token number).

| Dataset       | TI    | CI    | TN    | Dev | Test |
|---------------|-------|-------|-------|-----|------|
| Aishell       | INT   | INT   | 38(MIN)| 5.63| 6.24 |
| Aishell       | MS    | INT   | 100   | 5.71| 6.32 |
| Aishell       | MS    | MS    | 300   | 5.83| 6.51 |
| Aishell       | MS    | MS    | 191(MIN)| 5.63| 6.24 |
| Aishell       | MS    | MS    | 300   | 5.60| 6.25 |
| Aishell       | MS    | MS    | 500   | 5.76| 6.31 |
| Aishell       | MS    | MS    | 1000  | 5.68| 6.29 |
| MagicData     | INT   | INT   | 54(MIN)| 5.31| 4.06 |
| MagicData     | MS    | INT   | 59(MIN)| 4.95| 3.51 |
| MagicData     | MS    | INT   | 100   | 5.25| 3.81 |
| MagicData     | MS    | MS    | 300   | 5.65| 4.48 |
| MagicData     | MS    | MS    | 208(MIN)| 5.40| 4.08 |
| MagicData     | MS    | MS    | 300   | 5.31| 3.83 |
| MagicData     | MS    | MS    | 500   | 4.86| 3.53 |
| MagicData     | MS    | MS    | 1000  | 4.74| 3.46 |

Table 3. Summary of the baselines and the proposed method (PUCE) on in- and cross-domain datasets (CER %).

| Method(Training data - units) | InDomain | CrossDomain |
|------------------------------|----------|-------------|
|                              | Dev      | Test        | Dev      | Test        |
| Aishell-char(4232)           | 6.09     | 40.29       | 5.98     | 30.98       |
| Aishell-char-word(5000)      | 5.90     | 35.39       | 5.81     | 30.43       |
| Aishell-PUCE(191)            | 5.63     | 33.72       | 5.53     | 27.66       |
| + CI-based rescoring         | 5.33     | 30.88       | 5.26     | 24.38       |
| MagicData-char(4232)         | 5.79     | 24.63       | 5.78     | 26.96       |
| MagicData-char-word(5000)    | 4.97     | 25.24       | 3.76     | 27.76       |
| MagicData-PUCE (208)         | 5.40     | 20.78       | 4.08     | 22.88       |
| + CI-based rescoring         | 5.26     | 17.25       | 3.93     | 19.20       |
| MagicData-PUCE (1000)        | 4.74     | 21.97       | 3.46     | 24.05       |
| + CI-based rescoring         | 4.60     | 18.35       | 3.32     | 20.37       |

N-best can be reordered with an external language model. Different from the beam searching of the vanilla RNN-T, the proposed CI-based beam searching does not need an autoregressive operation; therefore, the searching has the same computational complexity as the CTC-based beam searching. We listed the rescoring results in Table 3. For Aishell test data, we used the transformer LM that trained on Aishell text data. And rescoring on MagicData test data, the LM trained on MagicData text was used. The λ was determined based on the dev datasets, which were 1.16 and 2.08 for the in- and cross-domain dataset of Aishell-PUCE(191), and were 0.55 and 1.85, 0.61 and 1.50 for MagicData-PUCE(208) and MagicData-PUCE(1000), respectively. From the results, we can see that rescoring the CI-based N-best could further improve the performance on both the in-domain and the cross-domain datasets.

4.3.4. Performance on cross-domain datasets.

In Table 3, we listed the investigation on the cross-domain tasks. We evaluated the MagicData test data with the model trained on the Aishell dataset and evaluated Aishell test data with the model trained on MagicData. Using a combination of characters and words could improve the performance on the in-domain dataset; however, for the unseen domain, the performance even changed worse. The proposed method outperformed the two baseline systems on both the in and cross-domain datasets. Experimental results also show that as the number of tokens increases, the performance decreases on cross-domain dataset.

4.4. Summary and discussion

In this work, considering the autoregressive characteristics of RNN-T, we defined a pronunciation-aware unique character encoding method for building E2E Mandarin ASR systems. To reduce the confusion and improve the efficiency of model optimization, we further enhanced the encoding by using meta symbols for both TI and CI. We evaluated the proposed method and showed the effectiveness of the proposed method for the Mandarin ASR tasks. Further investigations on cross-domain datasets and CI-based N-best rescoring illustrated the robustness and the potential of exploiting the external text corpus of the proposed method.

In this work, we implemented CI-based N-best rescoring with the transformer LMs. The popular shallow fusion [21, 22] can also be used with the proposed modeling units. And CI-based rescoring based on the results with shallow fusion could further improve the performance. As the char-word baseline system showed, taking high-frequency words as tokens could improve the performance on in-domain tasks. Therefore, further designing word-based encoding will be one of our future works.

5. CONCLUSIONS

In this work, we proposed to use a novel pronunciation-aware unique character encoding for building E2E RNN-T-based Mandarin ASR systems. The proposed encoding was a combination of pronunciation-base syllable and character index (CI). By introducing the CI, the RNN-T model can overcome the homophone problem while utilizing the pronunciation information for extracting modeling units. With the proposed encoding, we changed the one-to-many mapping problem to one-to-one mapping in the inference stage so that the model outputs can be converted into the final recognition result through a simple lookup operation. We conducted experiments on Aishell and MagicData datasets, and the experimental results showed the effectiveness of the proposed method.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] Jinyu Li, “Recent advances in end-to-end automatic speech recognition,” APSIPA Transactions on Signal and Information Processing, April 2022.

[2] Tara N. Sainath, Yanzhang He, Bo Li, Arun Narayanan, Ruoming Pang, Antoine Bruguier, Shuo yiin Chang, Wei Li, Raziel Alvarez, Z. Chen, Chung-Cheng Chiu, David Garcia, Alexander Gruenstein, Ke Hu, Minho Jin, Anjuli Kannan, Qiao Liang, Ian McGraw, Cal Peyser, Rohit Prabhavalkar, Golan Pundak, David Rybach, Yuan Shangguan, Yash Sheth, Trevor Strohman, Mirkó Visontai, Yonghui Wu, Yu Zhang, and Ding Zhao, “A streaming on-device end-to-end model surpassing server-side conventional model quality and latency,” in Proc. IEEE ICASSP, 2020, pp. 6059–6063.

[3] Jinyu Li, Rui Zhao, Zhong Meng, Yanqing Liu, Wenning Wei, Sarangarajan Parthasarathy, Vadim Mazalov, Zhenghao Wang, Lei He, Sheng Zhao, and Yifan Gong, “Developing rnn-t models surpassing high-performance hybrid models with customization capability,” in Proc. Interspeech, 2020.

[4] Jan Chorowski, Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio, “End-to-end continuous speech recognition using attention-based recurrent NN: First results,” in Proc. NeurIPS, 2014.

[5] William Chan, Navdeep Jaitly, Quoc V. Le, and Oriol Vinyals, “Listen, attend and spell: A neural network for large vocabulary conversational speech recognition,” in Proc. IEEE ICASSP, 2016, pp. 4960–4964.

[6] Graves Alex, “Sequence transduction with recurrent neural networks,” in Proc. ICML, 2012.

[7] Dong Yu and Li Deng, “Automatic speech recognition: A deep learning approach,” in Springer, 2014.

[8] Alex Graves and Navdeep Jaitly, “Towards end-to-end speech recognition with recurrent neural networks,” in Proc. ICML, 2014.

[9] Awni Y. Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, and Andrew Y. Ng, “Deep speech: Scaling up end-to-end speech recognition,” ArXiv, vol. abs/1412.5567, 2014.

[10] Rico Sennrich, Barry Haddow, and Alexandra Birch, “Neural machine translation of rare words with subword units,” in Proc. ACL, 2016, pp. 1715–1725.

[11] Kartik Audhkhasi, Brian Kingsbury, Bhuvana Ramabhadran, George Saon, and Michael Picheny, “Building competitive direct acoustics-to-word models for english conversational speech recognition,” in Proc. IEEE ICASSP, 2018, pp. 4759–4763.

[12] Thomas Zenkel, Ramon Sanabria, Florian Metze, and Alexander H. Waibel, “Subword and crossword units for ctc acoustic models,” in Proc. Interspeech, 2018.

[13] Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, and Ruoming Pang, “Conformer: Convolution-augmented transformer for speech recognition,” in Proc. Interspeech, 2020, pp. 5036–5040.

[14] Rui Zhao, Jian Xue, Jinyu Li, Wenning Wei, Lei He, and Yifan Gong, “On addressing practical challenges for rnn-transducer,” in Proc. IEEE ASRU, 2021, pp. 526–533.

[15] Shiliang Zhang, Ming Lei, Yuan Liu, and Wei Li, “Investigation of modeling units for mandarin speech recognition using dfsmn-ctc-smbr,” in Proc. IEEE ICASSP, 2019, pp. 7085–7089.

[16] Shunfei Chen, Xinhui Hu, Sheng Li, and Xinkang Xu, “An investigation of using hybrid modeling units for improving end-to-end speech recognition system,” in Proc. IEEE ICASSP, 2021, pp. 6743–6747.

[17] Wei Zou, Dongwei Jiang, Shuailiang Zhao, and Xianggang Li, “Comparable study of modeling units for end-to-end mandarin speech recognition,” in Proc. ISCSLP, 2018, pp. 369–373.

[18] Xiong Wang, Zhuoyuan Yao, Xian Shi, and Lei Xie, “Cascade RNN-Transducer: Syllable based streaming on-device mandarin speech recognition with a syllable-to-character converter,” in Proc. IEEE SLT, 2021, pp. 15–21.

[19] Chenglei Si, Zhengyan Zhang, Yingfa Chen, Fanchao Qi, Xiaozi Wang, Zhiyuan Liu, Yasheng Wang, Qun Liu, and Maosong Sun, “Sub-character tokenization for chinese pretrained language models,” ArXiv, vol. abs/2106.00400, 2021.

[20] Longtu Zhang and Mamoru Komachi, “Using sub-character level information for neural machine translation of logographic languages,” Transactions on Asian and Low-Resource Language Information Processing, vol. 20, pp. 1 – 15, 2021.

[21] Rodrigo Cabrera, Xiaofeng Liu, Mohammad Reza Ghodsi, Zebulun Matteson, Eugene Weinstein, and Anjuli Kannan, “Language model fusion for streaming end to
end speech recognition,” *ArXiv*, vol. abs/2104.04487, 2021.

[22] Suyoun Kim, Yuan Shangguan, Jay Mahadeokar, Antoine Bruguier, Christian Fuegen, Michael L. Seltzer, and Duc Le, “Improved neural language model fusion for streaming recurrent neural network transducer,” in *Proc. IEEE ICASSP*, 2021, pp. 7333–7337.

[23] Hui Bu, Jiayu Du, Xingyu Na, Bengu Wu, and Hao Zheng, “AIShell-1: An open-source mandarin speech corpus and a speech recognition baseline,” in *Proc. Oriental COCOSDA*, 2017.

[24] Magic Data Technology Co. Ltd., “MAGIC-DATA: Mandarin chinese read speech corpus,” in *OpenSLR.org/68*, 2019.

[25] Taku Kudo and John Richardson, “Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing,” in *Proc. EMNLP*, 2018.

[26] Daniel S. Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D. Cubuk, and Quoc V. Le, “SpecAugment: A simple data augmentation method for automatic speech recognition,” in *Proc. Interspeech*, 2019, pp. 2613–2617.

[27] Boris Ginsburg, Patrice Castonguay, Oleksii Hrinchuk, Oleksii Kuchaiev, Vitaly Lavrukhin, Ryan Leary, Jason Li, Huyen Nguyen, and Jonathan M. Cohen, “Stochastic gradient methods with layer-wise adaptive moments for training of deep networks,” *ArXiv*, vol. abs/1905.11286, 2019.

[28] Ilya Loshchilov and Frank Hutter, “SGDR: Stochastic gradient descent with warm restarts,” in *Proc. ICLR*, 2017.

[29] Oleksii Kuchaiev, Jason Li, Huyen Nguyen, Oleksii Hrinchuk, Ryan Leary, Boris Ginsburg, Samuel Krizman, Stanislav Beliaev, Vitaly Lavrukhin, Jack Cook, et al., “NeMo: A toolkit for building ai applications using neural modules,” *arXiv preprint arXiv:1909.09577*, 2019.

[30] Haoneng Luo, Shiliang Zhang, Ming Lei, and Lei Xie, “Simplified self-attention for transformer-based end-to-end speech recognition,” in *Proc. IEEE SLT*, 2021, pp. 75–81.