CASS-NAT: CTC ALIGNMENT-BASED SINGLE STEP NON-AUTOREGRESSIVE TRANSFORMER FOR SPEECH RECOGNITION

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ABSTRACT

We propose a CTC alignment-based single step non-autoregressive transformer (CASS-NAT) for speech recognition. Specifically, the CTC alignment contains the information of (a) the number of tokens for decoder input, and (b) the time span of acoustics for each token. The information are used to extract acoustic representation for each token in parallel, referred to as token-level acoustic embedding which substitutes the word embedding in autoregressive transformer (AT) to achieve parallel generation in decoder. During inference, an error-based alignment sampling method is proposed to be applied to the CTC output space, reducing the WER and retaining the parallelism as well. Experimental results show that the proposed method achieves WERs of 3.8%/9.1% on Librispeech test clean/other dataset, respectively. Compared to the AT baseline, the CASS-NAT has a performance reduction on WER, but is 51.2x faster in terms of RTF. When decoding with an oracle CTC alignment, the lower bound of WER without LM reaches 2.3% on the test-clean set, indicating the potential of the proposed method.

Index Terms— End-to-end speech recognition, NAT, Single step generation, CTC alignments

1. INTRODUCTION

In recent years, end-to-end (E2E) speech recognition models have shown competitive results [1,2], such as attention-based encoder decoder (AED) [3–5], connectionist temporal classification (CTC) [6] and its variants [7–9].

The decoder in AED generates the output sequence autoregressively. To accelerate it, non-autoregressive transformer (NAT) was proposed for parallel generation of output sequence [10–12]. According to the number of iterations for parallel generation, NAT can be categorized into: (i) iterative NAT, and (ii) single step NAT. Prevailing iterative NATs regard the decoder as a masked language model, where the tokens with low confidence are first masked and then new tokens are predicted from unmasked tokens. The two steps are conducted alternately within a constant number of iterations [13–15]. Length prediction of the decoder input is difficult for NAT models. To address the issue, Higuchi et al. used the length of recognition results of CTC [14], while Chan et al. proposed a model named as Imputer, which directly used the length of input feature sequence [15]. Compared to the left-to-right generation order in an autoregressive transformer (AT), an iterative NAT essentially adopts a different token generation order, where the iterations are still required. Single step NAT, however, can generate the output sequence in one iteration, where the word embedding is substituted with the acoustic representation for each output, assuming that the language semantics can be captured by the acoustic representations [17,18]. Specifically, Bai et al. used a fixed length of decoder input to extract data-driven acoustic representation for decoder input [17]. Tian et al. used only the encoder output with CTC spikes as decoder input [18].

Instead of using a data-driven or incomplete acoustic representation that has no physical meaning, we are trying to extract a token-level acoustic embedding, a more complete acoustic representation for each token, to capture the language semantics more effectively. We, therefore, propose to use CTC alignment as auxiliary information for decoder to extract the token-level acoustic embedding, so as to achieve the goal of single step NAT, referred to as (CASS-NAT). The CTC alignment is first transformed into a trigger mask to specify the time span of the acoustic for each token, as well as the length of a positional encoding. Then the token-level acoustic embedding for each token can be extracted in parallel by using the trigger mask and the positional encoding using encoder-decoder attention. During training, Viterbi-alignment is utilized as a maximum approximation of the objective function. During inference, an error-based alignment sampling method is proposed to improve the performance and retain the parallelism in decoder as well, where the improvements come from the possibility of sampling the candidates who may have more accurate length prediction of the decoder input. From the analysis of the proposed sampling method, we conclude that the accurate length estimation of the decoder input could be essential for the WER reduction of NAT. As a result, the proposed CASS-NAT achieves the state-of-art NAT results on both Librispeech and Aishell1 Mandarin corpus. We also derive a probabilistic framework for the proposed method.

2. ALGORITHM IN CASS-NAT

The proposed CASS-NAT model architecture is based on the hybrid CTC-Attention architecture [19] with transformer structure. The modifications are listed as below.

2.1. Mask in attention

The most basic computation in the transformer, scaled dot-product attention, is modified as:

\[
Attention(Q, K, V, M) = \text{Softmax}(\frac{QK^T}{\sqrt{d_k}}) \odot M \cdot V
\]
where $Q \in R^{n_q \times d_q}$, $K \in R^{n_k \times d_k}$, $V \in R^{n_v \times d_v}$, and $M \in R^{n_m \times n_m}$ are the queries, keys, values and mask matrix, respectively. The mask is used to control the attention range for each output position. In Fig. 1, $M$ represents the Bi-Mask in Encoder, the Trigger Mask in Token Acoustic Extractor, and the Bi-Mask in Decoder.

2.2. Encoder

As shown in Fig. 1, the encoder is the same as AT encoder [4]. On the top of the encoder, a CTC loss function is added. In this work, we refer to all the output sequence from CTC as alignment, although the alignment is commonly used for the relationship between frames and the ground truth.

2.3. Token acoustic extractor

The token acoustic extractor is designed to extract token-level acoustic embedding with the CTC alignment as auxiliary information. The first information from CTC alignment is the time span of acoustic information for each token. We use the token sequence by defining a mapping from the CTC alignment to a trigger mask, where the first index of each token in the alignment is considered as its end boundary. For example, if a CTC alignment is $Z = \{\omega, C, C, A, \omega, T_1, \omega\}$, the blank symbol, the end boundary for $C$ and $A$ is $Z_2$ and $Z_3$, and thus the trigger mask for token $A$ is $[0, 0, 1, 1, 0, 0, 0, 0]$. The mapping should be consistent in training and decoding. The trigger mask in this paper is different from that used in [20], where the trigger mask is reused for each token (the trigger mask is consistent in training and decoding). The trigger mask in our framework is different from that used in [20], where the trigger mask should be consistent in training and decoding. The trigger mask in this paper is different from that used in [20], where the trigger mask is reused for each token (the trigger mask is consistent in training and decoding).

The second information from CTC alignment is the number of tokens for decoder input. After removing the blank symbols and repetitions, the number of tokens in $Z$ is regarded as the predicted length of sinusoidal positional encoding, which is also the length of the decoder input. As shown in Fig. 1, the token-level acoustic embedding for each token is then extracted with the trigger mask and the sinusoidal positional encoding using a one-layer source-attention block. Regarding the length of decoder input, the number of CTC spikes is used in [18], resulting in an incomplete training of decoder due to the length mismatch between the CTC spikes and the ground truth. Differently, we use the viterbi-alignment in training to address the length mismatch issue.

2.4. Decoder

The word embedding in AT, which cannot be obtained simultaneously during decoding, is the main obstacle to achieve non-autoregressive mechanism. Instead, the token-level acoustic embedding has a good property of parallel generation and thus is used as a substitution of word embedding for decoder input. Since there is no need to create recurrence in decoder, unidirectional mask in the decoder is not used. We, therefore, utilize a bidirectional mask, trying to model the relations between token-level acoustic embeddings. We assume that the token-level acoustic embedding has the same capability of capturing language semantics with word embedding since they are all token-based embeddings. In the second MHA layer of the mix-attention block, we keep the same bidirectional mask as the one used in the encoder since $K$, $V$ are encoder outputs.

2.5. Training

In our framework, the CTC alignments $Z$ are introduced as latent variables. Suppose the input sequence is $X = \{x_1, \ldots, x_t, \ldots, x_T\}$ and the ground truth is $Y = \{y_1, \ldots, y_u, \ldots, y_U\}$, then the objective function can be decomposed into:

$$\log P(Y|X) = \log E_Z[X][P(Y|Z, X)], \quad Z \in q.$$  \hspace{1cm} (2)

where $q$ is the set of alignments which can be mapped to $Y$, a subset of all the alignments from CTC output space. To reduce computational complexity, the maximum approximation [21] is applied:

$$\log P(Y|X) \geq E_Z[X][\log P(Y|Z, X)] \approx \max_{Z} \log \prod_{u=1}^{U} P(y_u | z_{t_u-1+1:t_u}, x_{1:T}).$$  \hspace{1cm} (3)

where $t_u$ is the end boundary of token $u$ described in Section 2.3 and $t_0 = 0$. The alignment $Z$ tells the decoder where to extract the acoustic representation for each token as auxiliary information. The capability of language modelling for the framework is described in Section 2.4. And the same assumption as in [17] is held that acoustic embedding can also be used to capture the language semantics.

The framework is then trained by jointly maximizing the decoder loss in Eq. (3) and the CTC loss on the encoder side with a task ratio $\lambda$ [19] and $L_{dec} = \max_{Z} \log \prod_{u=1}^{U} P(y_u | z_{t_u-1+1:t_u}, X)$ as:

$$L_{joint} = L_{dec} + \lambda \cdot \log \sum_{Z \in q} \prod_{i=1}^{T} P(z_i|X)$$  \hspace{1cm} (4)

2.6. Inference: Error-based Sampling Decoding

During decoding, it is essential to obtain a CTC alignment that is close to the hypothetical Viterbi-alignment. Hypothetical Viterbi-alignment is the most probable CTC alignment in Viterbi decoding assuming the transcription is available, referred to as oracle alignment in the experimental results. Three different approaches are
The CTC decoding which retains the tokens with the biggest probability of each frame, referred to as best path alignment (BPA) in this work. The other is beam search decoding over CTC output space, referred to as beam search alignment (BSA). Compared with BPA, BSA is supposed to generate an alignment that is closer to the oracle alignment, which could lead to a lower WER, but the parallelism would be destroyed, resulting in a significant increase of RTF. Considering the expectation in Eq. 3, we use a third alignment generation approach by sampling from CTC output space. Compared to BPA, the sampled alignments have the possibility of being closer to the oracle alignment. Compared to BSA, the sampling can be implemented in parallel, avoiding the increase of RTF. Finally, either the AT baseline or the language models can be used to score and identify the best overall alignment. Sampling from CTC output is not easy due to the large sampling space. However, we observe that BPA tends to make errors in the CTC output where the Top-1 probability is low. We therefore propose an error-based alignment sampling method, which is more effective in terms of WER and RTF compared to the BPA and BSA, referred to as ESA.

To generate ESA, we first select the CTC outputs with low Top-1 probability (the threshold is empirically set to 0.7), shown as blue part in Fig. 2. Then the Top-2 tokens are randomly chosen in each selected output while other outputs keep using the Top-1 token. For instance, the CTC output $z_1$, $z_5$, $z_6$, $z_7$ are selected, and 4 example alignments are sampled as shown in Fig. 2. The reason for sampling within the Top-2 tokens is that the trigger mask of each token is only sensitive to whether the token in the alignment is blank or not, and we observe that most errors in BPA contain blank in Top-2 tokens. ESA significantly reduces the sampling space and aims at correcting the output that is prone to make errors. The sampling in decoding will not affect much of the inference speed because all the alignments can be generated in parallel to compute the decoder input. Note that ESA can have different length for decoder input compared to BPA. As shown in Fig. 2, the length is 4 for BPA, while the lengths are 3, 5, 4, and 5 in the case of ESA. This fluctuation of the token number in the alignment allows the ESA method to possibly sample an alignment that is of the same length as the oracle alignment.

### 3. EXPERIMENTS

#### 3.1. Experimental setup

The experiments were conducted on the 960-hour LibriSpeech English corpus and the 178-hour Aishell Mandaric corpus. All experiments used 80-dim Mel-filter bank features, computed every 10ms with a 25ms window. Every 3 consecutive frames were concatenated to form a 240-dim feature vector as the input. The set of output labels consists of 5k word-pieces obtained by the SentencPece method for Librispeech and 4230 Chinese characters which was obtained from the training set.

A CTC/Attention AT baseline was first trained with the same architecture ($N_e = 12$, $N_d = 6$, $d_{FF} = 2048$, $H = 8$, $d_{MHA} = 512$) as in [25] for Librispeech. For CASS-NAT, the decoder in AT was replaced by $N_s = 3$ self-attention blocks and $N_{mv} = 4$ mix-attention blocks. For Aishell, both the AT baseline and CASS-NAT have the same architecture as their counterparts used for Librispeech except $N_e = 6$. For all methods, each of the two CNN in the encoder has 64 filters with kernel size of 3 and stride of 2, leading to a 4x frame rate reduction. For all models, the Double schedule in [25] was adopted as the learning schedule, where the learning rate is ramped up to and held at 0.001, then be exponentially decayed to 1e-5. Layer normalization, dropout with rate of 0.1 and label smoothing with a penalty of 0.1 were all applied as the common strategies in transformer. We also applied spec-augment [26] for fair comparisons with the results in literature. We additionally applied speed-perturbation for Aishell1. Encoder initialization was used for CASS-NAT training. The task ratio $\lambda$ in Section 2 was set to 1 for all models. We used development sets for early stopping and model averaging for final evaluation. Most of the experiments ended within 90 epochs. The evaluation of the inference speed was conducted on an NVIDIA Tesla V100 GPU with the batch size of one.

Additionally, a transformer-based language model was trained with the provided text in Librispeech. Both the settings of the model and ctc-attention decoding were the same as in ESPNet [27]. When NAT decoding with the language model, the beam size was set to 5.

#### 3.2. Accuracy and speed analysis

Table 1 presents the results of AT baseline and Non-AT models on the Librispeech dataset. First, in the proposed CASS-NAT method, the ESA decoding reduced WER significantly compared to both BPA and BSA, while had a moderate increase of RTF over BPA. Thus, we use the results of ESA for CASS-NAT by default unless otherwise stated. Then in the case of no external LM, compared to the AT baseline, the WER of the proposed CASS-NAT was 6% higher relatively, but was 51.2x faster in terms of RTF, which is expected. Compared to the iterative NAT-based Imputer, the CASS-NAT achieved a better performance on WER, and theoretically was faster than the Imputer, which needs 8 iterations during decoding. When decoding with an external LM, the gap of WER between AT baselines and the proposed CASS-NAT was increasing. The reason could be that AT benefited more from the external LM due to the same autoregressive mechanisms in AT and the LM.

\[\text{Espnet just updated the AT structure to Conformer [28]. We would like to update the CASS-NAT structure as well in the future work.}\]
Table 1. A comparison of accuracy and speed of Autoregressive Transformer (AT) and non-AT (NAT) algorithms on Librispeech. BPA: decoding with the best path alignment. BSA: beam search alignment. ESA: the proposed error-based sampling alignment in which 50 alignments are sampled. RTF: Real-time factor. The LM used in CASS-NAT and AT are the same but trained with fewer epochs than the LM used in ESPNet.

| Alignment | Type | WER (%) | RTF |
|-----------|------|---------|-----|
|            | dev-clean | dev-other | test-clean | test-other |
| Without LM |          |          |          |          |
| RETURNN [1] | AT    | 4.3     | 12.9    | 4.4     | 13.5 |
|             | ESPNet | AT    | 3.2     | 8.5    | 3.6   | 8.4 |
|             | AT (ours) | AT    | 3.4     | 8.5    | 3.6   | 8.5 | 0.562 |
|             | Imputer [18] | NAT | -      | -      | 4.0   | 11.1 |
| CASS-NAT | BPA | NAT | 4.4 | 10.6 | 4.5 | 10.7 | 0.005 |
|            | BSA | NAT | 3.9 | 9.6 | 3.9 | 9.6 | 0.655 |
|            | ESA | NAT | 3.7 | 9.2 | 3.8 | 9.1 | 0.011 |
| With LM | | | | | |
| RETURNN [1] | AT | 2.6 | 8.4 | 2.8 | 9.3 | - |
| ESPNet | AT | 2.3 | 5.6 | 2.6 | 5.7 | - |
| AT (ours) | AT | 2.5 | 5.7 | 2.7 | 5.8 | - |
| CASS-NAT | ESA | NAT | 3.3 | 8.0 | 3.3 | 8.1 | - |

Table 2. A comparison of WERs on Aishell1 with the existing works.

| CER(%) | NAT Type | Dev | Test |
|--------|----------|-----|------|
| AT (ours) | n/a | 5.5 | 5.9 |
| Masked-NAT [13] | iterative | 6.4 | 7.1 |
| Insertion-NAT [15] | iterative | 6.1 | 6.7 |
| ST-NAT [18] | single step | 6.9 | 7.7 |
| LASO [17] | single step | 5.8 | 6.4 |
| CASS-NAT (ours) | single step | 5.3 | 5.8 |

On Aishell1 Mandarin task, Table 2 shows that the CASS-NAT had a lower WER than the AT (ours) and WERs reported in other NAT methods, which suggests the effectiveness and generalizability of the proposed method.

3.3. Analysis of the CTC Alignments

Further, we analyzed the alignments obtained from different decoding strategies and hopefully to comprehend why ESA can improve the accuracy. Two metrics were evaluated on the test sets of Librispeech, mismatch rate (MR) and length prediction error rate (LPER), measured between the generated alignments and the oracle alignment. The two metrics were computed after the blank and repetitions in the alignment were removed because of the mapping rule in Section 2.3. For MR, only deletion and insertion errors were counted as mismatch since substitution errors will not change the end boundaries and the number of predicted tokens. If the number of tokens in an alignment is different from that in the oracle alignment, this alignment is considered as a case of length prediction error.

Results are presented in Table 3. We can see that the CASS-NAT had a lower bound with WER of 2.3% when using oracle alignment, showing that the framework is promising. For ESA, no further gains were observed when the number of sampled alignment is greater than 50. We can also observe from the table that the WER was more correlated to the LPER other than MR. It suggests that a correct estimation of the decoder input length is important for NAT, which is also mentioned in [13]. Fig. 3 again shows the importance of length prediction accuracy. We can see that the WER was lower than 2% when the length of the decoder input was estimated correctly. The analysis suggests a possible guideline on how to find a more effective alignment sampling strategy besides ESA. It also shows the potential of CASS-NAT to get a more promising result.

Fig. 3. Length prediction error distributions and corresponding WERs with ESA(s=50) decoding on the test-clean dataset.

Table 3. A comparison of different alignment generation methods in CASS-NAT decoding without LM. Oracle: Viterbi-alignment with ground truth. MR: mismatch rate; LPER: length prediction error rate. S: the number of alignments sampled in ESA.

| Alignment | S | WER (%) | MR (%) | LPER (%) |
|-----------|---|---------|--------|---------|
|           | test-clean | test-other | test-clean | test-other |
| Oracle    | n/a | 2.3 | 5.8 | n/a | n/a | n/a | n/a | n/a |
| BSA       | n/a | 3.9 | 9.6 | 2.2 | 5.8 | 27.9 | 48.3 |
| BPA       | n/a | 4.5 | 10.7 | 2.1 | 4.9 | 31.0 | 51.8 |
| ESA       | 10 | 3.9 | 9.4 | 2.9 | 5.7 | 26.4 | 42.8 |
|          | 50 | 3.8 | 9.1 | 3.1 | 5.8 | 25.3 | 41.9 |
|          | 100 | 3.8 | 9.0 | 3.0 | 5.8 | 25.1 | 41.8 |
|          | 300 | 3.8 | 9.0 | 3.1 | 5.8 | 25.1 | 41.9 |

4. CONCLUSIONS

This work presented a novel CASS-NAT framework which leverages the CTC alignment to extract the token-level acoustic embedding as a substitution of the word embedding in autoregressive models. During the training, Viterbi-alignment was considered as a maximum approximation of the posterior probability. During the inference, we proposed an error-based alignment sampling method to reduce the mismatch between the generated alignment and the oracle alignment. We also showed the importance of the prediction for the length of decoder input in NAT through the analysis of the alignments. As a result, the proposed CASS-NAT had ~50x faster inference speed than autoregressive transformer. To the best of our knowledge, the results of CASS-NAT are the best-reported ones for single step NAT methods so far on both the Librispeech (WERs of 3.8%/9.1%) and Aishell1 (a CER of 5.8%) when no external LM is used.
5. REFERENCES

[1] Christoph Lüscher, Eugen Beck, Kazuki Irie, Markus Kitza, Willfried Michel, Albert Zeyer, Ralf Schlüter, and Hermann Ney, “Rwth asr systems for librispeech: Hybrid vs attention–w/o data augmentation,” Interspeech, pp. 231–235, 2019.

[2] Jinyu Li, Yu Wu, Yashesh Gaur, Chengyi Wang, Rui Zhao, and Shujie Liu, “On the comparison of popular end-to-end models for large scale speech recognition,” arXiv preprint arXiv:2005.14327, 2020.

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

[4] Linhao Dong, Shuang Xu, and Bo Xu, “Speech-transformer: a no-recurrence sequence-to-sequence model for speech recognition,” in ICASSP. IEEE, 2018, pp. 5884–5888.

[5] Pan Zhou, Ruchao Fan, Wei Chen, and Jia Jia, “Improving generalization of transformer for speech recognition with parallel schedule sampling and relative positional embedding,” arXiv preprint arXiv:1911.0203, 2019.

[6] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in ICML. 2006, pp. 369–376.

[7] Kanishka Rao, Hasim Sak, and Rohit Prabhavalkar, “Exploring architectures, data and units for streaming end-to-end speech recognition with rnn-transducer,” in ASRU, 2017, pp. 193–199.

[8] Hasim Sak, Matt Shannon, Kanishka Rao, and François Beaufays, “Recurrent neural aligner: An encoder-decoder neural network model for sequence to sequence mapping,” in Interspeech, 2017, vol. 8, pp. 1298–1302.

[9] Ehsan Variani, David Rybach, Cyrill Allauzen, and Michael Riley, “Hybrid autoregressive transducer (hat),” in ICASSP. IEEE, 2020, pp. 6139–6143.

[10] Jiatao Gu, James Bradbury, Caiming Xiong, Victor OK Li, and Richard Socher, “Non-autoregressive neural machine translation,” in ICLR. 2018.

[11] Raphael Shu, Jason Lee, Hideki Nakayama, and Kyunghyun Cho, “Latent-variable non-autoregressive neural machine translation with deterministic inference using a delta posterior,” arXiv preprint arXiv:1908.07181, 2019.

[12] Chitwan Saharia, William Chan, Saurabh Saxena, and Mohammad Norouzi, “Non-autoregressive machine translation with latent alignments,” arXiv preprint arXiv:2004.07437, 2020.

[13] Nanxin Chen, Shinji Watanabe, Jesús Villalba, and Najim Dehak, “Non-autoregressive transformer automatic speech recognition,” arXiv preprint arXiv:1911.04908, 2019.

[14] Yosuke Higuchi, Shinji Watanabe, Nanxin Chen, Tetsuji Ogawa, and Tetsunori Kobayashi, “Mask ctc: Non-autoregressive end-to-end asr with ctc and mask predict,” arXiv preprint arXiv:2005.08700, 2020.

[15] Yuya Fujita, Shinji Watanabe, Motoi Omachi, and Xuancai Chan, “Insertion-based modeling for end-to-end automatic speech recognition,” arXiv preprint arXiv:2005.13211, 2020.

[16] William Chan, Chitwan Saharia, Geoffrey Hinton, Mohammad Norouzi, and Navdeep Jaitly, “Imputer: Sequence modelling via imputation and dynamic programming,” arXiv preprint arXiv:2002.08926, 2020.

[17] Ye Bai, Jiangyan Yi, Jianhua Tao, Zhengkun Tian, Zhengqi Wen, and Shuai Zhang, “Listen attentively, and spell once: Whole sentence generation via a non-autoregressive architecture for low-latency speech recognition,” arXiv preprint arXiv:2005.04862, 2020.

[18] Zhengkun Tian, Jiangyan Yi, Jianhua Tao, Ye Bai, Shuai Zhang, and Zhengqi Wen, “Spike-triggered non-autoregressive transformer for end-to-end speech recognition,” arXiv preprint arXiv:2005.07903, 2020.

[19] Shinji Watanabe, Takaaki Hori, Suyoun Kim, John R Hershey, and Tomoki Hayashi, “Hybrid ctc/attention architecture for end-to-end speech recognition,” IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1240–1253, 2017.

[20] Niko Moritz, Takaaki Hori, and Jonathan Le, “Streaming automatic speech recognition with the transformer model,” in ICASSP. IEEE, 2020, pp. 6074–6078.

[21] Albert Zeyer, André Merboldt, Ralf Schlüter, and Hermann Ney, “A new training pipeline for an improved neural transducer,” arXiv preprint arXiv:2005.09319, 2020.

[22] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, “Librispeech: an asr corpus based on public domain audio books,” in ICASSP. IEEE, 2015, pp. 5206–5210.

[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 20th O-COCOSDA. IEEE, 2017, pp. 1–5.

[24] Taku Kudo and John Richardson, “Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing,” arXiv preprint arXiv:1808.06226, 2018.

[25] Shigeki Karita, Nanxin Chen, Tomoki Hayashi, Takaaki Hori, Hirofumi Inaguma, Ziyian Jiang, Masao Someki, Nelson Enrique Yalta Soplín, Ryuichi Yamamoto, Xiaofei Wang, et al., “A comparative study on transformer vs rnn in speech applications,” in ASRU. IEEE, 2019, pp. 449–456.

[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,” Proc. Interspeech 2019, pp. 2613–2617, 2019.

[27] Shinji Watanabe, Takaaki Hori, Shigeki Karita, Tomoki Hayashi, Jirofumi Inaguma, Ziyian Jiang, Masao Someki, Nelson Enrique Yalta Soplín, Jahn Heymann, Matthew Wiesner, Nanxin Chen, et al., “Espnet: End-to-end speech processing toolkit,” Proc. Interspeech 2018, pp. 2207–2211, 2018.

[28] Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, et al., “Conformer: Convolution-augmented transformer for speech recognition,” arXiv preprint arXiv:2005.08100, 2020.