Adding Connectionist Temporal Summarization into Conformer to Improve Its Decoder Efficiency For Speech Recognition

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Abstract

The Conformer model is an excellent architecture for speech recognition modeling that effectively utilizes the hybrid losses of connectionist temporal classification (CTC) and attention to train model parameters. To improve the decoding efficiency of Conformer, we propose a novel connectionist temporal summarization (CTS) method that reduces the number of frames required for the attention decoder fed from the acoustic sequences generated by the encoder, thus reducing operations. However, to achieve such decoding improvements, we must fine-tune model parameters, as cross-attention observations are changed and thus require corresponding refinements. Our final experiments show that, with a beamwidth of 4, the LibriSpeech’s decoding budget can be reduced by up to 20% and for FluentSpeech data it can be reduced by 11%, without losing ASR accuracy. An improvement in accuracy is even found for the LibriSpeech “test-other” set. The word error rate (WER) is reduced by 6% relative at the beam width of 1 and by 3% relative at the beam width of 4.

Index Terms: automatic speech recognition (ASR), Conformer, connectionist temporal classification (CTC)

1. Introduction

End-to-end models have prevailed in ASR in recent years. These directly transform speech feature sequences to label sequences using a single neural network, which smoothly integrates the acoustic model, pronunciation model, and language model into one network. Approaches of this type typically fall into one of three categories. CTC began the trend with its special dynamic programming design by merging alignments with the same label output sequence [1][2]. It considers more decodings paths in the same training data than cross-entropy (CE) training, in which different paths may represent different pronunciations of the same label sequence so as to enhance the robustness of the model. However, CTC still assumes conditional independence and only poorly utilizes the language knowledge of word association. RNN-Transducer follows CTC’s dynamic programming to compute the marginal probability, but adds a label predictor network, conditions on previous output labels, and decides the final output labels jointly with both the original acoustic encoder and the additional linguistic predictor [3]. In this way, it deeply augments the language model into an end-to-end neural model and predicts the next label conditioned on the historical output labels. These models are all based on RNN and a monotonic alignment assumption. The attention-based encoder-decoder architecture includes the previous output labels as decoding conditions as does RNN-Transducer, but also utilizes a special attention scheme that allows the decoder in each step to attend the encoding sequence in full context [4]. This attention broadly expands the context to the sentence level.

Transformer pushes the use of attention from cross attention to self-attention [5][6][7], and Conformer adds convolution network layers into Transformer and improves its robustness and accuracy [8].

The attention-based approach was first invented for translation tasks to great success. Sentence-level attention allows it to translate words from the source language to the target language without word-order constraints: the next word can be predicted by conditioning on any words in the sentence. The multi-head attention mechanism further enhances its dependency modeling. Later CTC/attention multi-target learning (MTL) approaches have proven helpful in training attention-based models, by using CTC loss to constrain the encoder [9][10].

In this paper, we seek to further improve the computational efficiency of Conformer. We propose the CTS segmental representation. For the Conformer model, a mask is used to easily augment CTS into Conformer’s modeling. We describe the algorithm in the next section along with fine-tuning approaches to ensure its accuracy.

For speech modeling, compact speech representations have been developed [11][12][13], including segmental representation [13]. However, these involve training an independent autocoder network to produce speech representations, which may not be optimized for ASR purposes. For example, Wang et al. generate segmental boundaries via special segmentation gates [13]. In contrast, in our approach, as the segmental representations are calculated from the CTC module trained for ASR, there are no complicated autoencoder networks to train. Also, audio word embeddings can be aligned with text word embeddings to broaden the training data to enhance the model [14][15].

2. CTS-Conformer

The CTS-Conformer adds a single CTS component into the Conformer model to form the following structure, as shown in Fig. 1:

- Self-attention encoder
- CTC loss for encoder
- CTS mask
- Cross-attention decoder
- Attention loss for decoder

Like other end-to-end speech recognizers, Conformer does not need an explicit language model or a finite state transducer to guide its speech inference. Its encoder directly infers from the speech a sequence of acoustic latent representations, $Y = \{y_t; y_t = \text{Enc}(x_t), t = 1 \ldots T \}$, by feeding the Mel-frequency filter bank coefficients $X = \{x_t; t = 1 \ldots T \}$ with $T$ frames into it. Note that although Conformer shrinks to 1/4 in its convolution block, to simplify the presentation, we do not express this in the formula.
To predict the next word $\hat{w}$, the decoder uses cross attentions via $Y = \{y_t | t = 1 \ldots T\}$ conditioned on history words $W^h$ as

$$\hat{w} = \arg \max_{w \in V} \text{Att}(Y|W^h).$$  

(1)

We then apply the CTS mask $M_{CTS}$ to the acoustic encoding sequence $Y$ as

$$\hat{w} = \arg \max_{w \in V} \text{Att}(M_{CTS} \cdot Y|W^h).$$  

(2)

The components are unchanged from the original Conformer except for the CTS function itself and the cross-attention parameters in the decoder, as described in the following sections.

### 2.1. CTS Masking

The purpose of CTS masking is to use the mask function $M_{CTS}$ to change the latent sequence $Y$ from the frame basis to the segment basis, a sequence of boolean values of length $T$. Each boolean value in $M_{CTS}$ indicates whether the latent representation of the frame’s encoder should be used to compute cross-attention softmax values in the decoder. Frames with a negative boolean value are not used in the decoder to predict the next word, reducing the computational effort of the decoder. We expect its affect to accuracy can be resolved; in any case, this can be corrected after fine-tuning. Figure 1 illustrates the concept of CTS masking.

The CTS mask $M_{CTS}$ is generated according to the following algorithm. Firstly, compute softmax distributions for each frame $y_t$ in the acoustic encoding sequence with the help of the linear transformation matrix $H_{CTC}$ in the CTC-loss component. It map $y_t$ from the dimension of latent representation vector for each frame, to the size of word-piece labels in vocabulary $V$, like as in Eq. 3:

$$p_{w,t} = \text{softmax}(H_{CTC} \cdot y_t).$$  

(3)

Then, find out the belonging label which has maximal softmax score for each frame by Eq. 4:

$$\hat{w}_t = \arg \max_{w \in V} (p_{w,t}).$$  

(4)

Then, do the following steps:

- **Segmentation**: for any continuing frames with the same maximum label “$\hat{w}_t = \cdots = \hat{w}_{t+s}$”, aggregate them as one segment.
- **Representation**: for each segment, find the frame $\hat{t}$ with the maximal softmax score by Eq. 5 and select its vector $y_{\hat{t}}$ to represent the whole segment.
- **Masking**: mark frames that are not selected with a negative mask value and skip these during decoder training. $\hat{t} = \arg \max_{\tilde{t} \leq t} (p_{\tilde{t},s})$.  

(5)

Note that CTS masking resembles the max-pooling effect over time for its segmental selection and representation processing as illustrated in Eq. 6:

$$Y' = CTS(Y) \cong \{y'|_{\text{maxpool} (y_i)}, i = 1 \ldots S\},$$  

(6)

where $i$ is the segment index.

After augmenting Conformer training with CTS masking, most encoding frames are skipped among blank segments. This introduces some influences to its decoder performance. To smooth this change, we propose changes to the CTS-Conformer training, as described below.

### 2.2. CTS-Conformer Training

CTS-Conformer attaches a CTS mask to the original Conformer. However, this mask requires a well-trained CTC element to segment and select positive mask values over the frames that are representative of the whole acoustic sequence. Therefore, we train the Conformer with the CTC component, attach the CTS mask, and then refine the CTS-Conformer parameters.

Again, the attachment of the CTS mask changes the input to cross attention of the decoder, leading to increased attention loss. If still using the hybrid losses for training the whole CTS-Conformer parameters, it may introduce errors to affect the well-trained CTC encoder’s parameters. Hence, in the beginning of attaching the CTS mask, the fine-tuning can be applied to the CTS-Conformer with frozen encoder parameters. After training well of decoder’s cross-attention parameters, it may be stable to release encoder’s parameters for fully hybrid-loss training. At this time, there is little change to the encoder parameters, and the CTC loss is also more stable. We call this way a ‘two-step fine-tuning’ approach. It was proven useful in our experiments for CTS-Conformer’s training. We thus adopted the following training procedure for CTS-Conformer parameter training with alternative fine-tuning approaches.

1. Train standard Conformer model
2. Add CTS mask
3. Fine-tune encoder and decoder parameters. This can be done in three different ways:
   - **Full fine-tuning**: fine-tune the normal way for the whole set of parameters.
   - **Fine-tuning with frozen encoder** (or ‘free-enc’ in short): fine-tune the decoder parameters only.

![Figure 1: CTS-Conformer structure](image)
'Two-step fine-tuning': first fine-tune with the frozen encoder and then do full fine-tuning.

Due to the nature of the CTS algorithm, the effect of fine-tuning depends heavily on the CTC accuracy. Without low CTC loss, segmentation and representation selection perform poorly, which can influence the CTS mask and subsequent cross attentions that depend on the mask. The effect of fine-tuning can also depend on the size of the dataset used for fine-tuning. Many ASR applications have limited training resources, such as in spoken language understanding (SLU). With such small fine-tuning datasets, encoder adaptation may have little effect on the parameters, thus yielding poor fine-tuning results. We conducted experiments on two datasets in order to verify CTS-Conformer performance broadly: LibriSpeech, with around one thousand hours of speech, and the FluentSpeech speech data for SLU research. FluentSpeech includes less than fifteen hours of speech for fine-tuning. For FluentSpeech ASR, we additionally use LibriSpeech to pretrain the Conformer. Below we discuss the difference in their fine-tuning effects.

### 3. Experiments

#### 3.1. Datasets

For our experiments, we used the open-source LibriSpeech ASR corpus[^16], as the major speech dataset with which to train the Conformer. This is a corpus of read speech derived from audiobooks, comprising approximately 1000 hours of 16kHz read English speech. For training, we use the 960-hour training set of clean and noisy speech for training, the 5.4-hour ‘dev-clean’ set for validation, and the 5.4-hour ‘test-clean’ set and 5.3-hour ‘test-other’ set for testing.

We also used the Fluent Speech Commands dataset[^2] or FluentSpeech, as the other data example in our experiments. This is a corpus of SLU data for spoken commands to smart homes or virtual assistants, for instance, “put on the music” or “turn up the heat in the kitchen”. Each audio utterance is labeled with three slots: action, object, and location. A slot takes one of multiple values: for instance, location can take the values “none”, “kitchen”, “bedroom”, or “washroom”. There are few training speech data, and all are spoken based on a very limited vocabulary and sentence expressions. We took the well-trained Conformer (by LibriSpeech) and fine-tuned it with FluentSpeech training data, and then used the resultant Conformer to train our CTS-Conformer models to evaluate our approach on this small dataset.

[^16]: http://www.openslr.org/12/
[^2]: https://fluent.ai/research/fluent-speech-commands/

#### 3.2. CTS-Conformer Fine-tuning

![Figure 2: Effect of CTS masking](image)

Table 1: Datasets

| Dataset   | Spkrs | Utts   | Hours |
|-----------|-------|--------|-------|
| LibriSpeech | train | 5,466  | 281,241 | 960.7 |
|           | dev-clean | 97     | 2,703  | 5.4   |
|           | test-clean | 87     | 2,620  | 5.4   |
|           | test-other  | 90     | 2,939  | 5.3   |
| FluentSpeech | train | 77     | 23,132 | 14.7  |
|           | valid    | 10     | 3,118  | 1.9   |
|           | test     | 10     | 3,789  | 2.4   |

We started with Conformer training. And after adding the CTS mask to the well-trained Conformer, we fine-tuned it to optimize its accuracy. Both models were built with the ESPNet toolkit[^3], using Mel-frequency filter bank (Fbank) feature vectors as input: this is a sequence of 83-dimensional feature vectors with a 25-ms window size and 10-ms window shifts. The model used 2-layer convolutional neural networks (CNN) as the frontend, each of which had 256 filters with $3 \times 3$ kernel size and $2 \times 2$ stride; thus the time reduction of the frontend was $1/4$. Our vocabulary was a list of 5000 byte-pair-encoded[^17] word-piece labels. The above models both contained 12 layers of self-attention encoder blocks and 6 layers of decoder blocks, each of which contained a self-attention layer and an encoder-decoder cross-attention layer. The multi-head attentions in both models had four heads, 256 attention dimensions, and 1024-dimensional feedforward networking. They were trained using hybrid CTC/attention loss with a CTC weight of 0.3.

First, we used the LibriSpeech ‘test-clean’ and ‘test-other’ sets to compare the different models; the results are presented in Table 2. The best CTS-Conformer results are obtained by the two-step fine-tuning approach. Virtually no loss of accuracy for CTS-Conformer fine-tuned with the method, except on ‘test-clean’ WER was reduced from 3.63% to 3.73% as decoding at a beamwidth of 10. No accuracy loss at all for ‘test-other’ set. Larger improvements were found for both test sets at a beamwidth of 1, relative word error rate (WER) reductions of 10% and 6% respectively were seen on ‘test-clean’ and ‘test-other’ sets.

We then performed the same comparison on FluentSpeech, as shown in Table 3. Note that FluentSpeech’s Conformer...
**Table 2**: ASR WER (%) on LibriSpeech with different models using various beamwidths

| Beamwidth | 1   | 4   | 10  |
|-----------|-----|-----|-----|
| **CTS-Conformer** |     |     |     |
| w/ full fine-tuning | 4.41 | 3.98 | 3.78 |
| w/ frozen-enc fine-tuning | 4.74 | 4.08 | 3.98 |
| w/ 2-step fine-tuning | 4.27 | 3.77 | 3.73 |
| **Conformer** |     |     |     |
| w/ full fine-tuning | 4.75 | 3.78 | 3.63 |

**Table 3**: Same comparison as in Table 2 but on FluentSpeech

| Beamwidth | 1   | 4   | 10  |
|-----------|-----|-----|-----|
| **CTS-Conformer** |     |     |     |
| w/ full fine-tuning | 9.55 | **8.85** | 8.75 |
| w/ frozen-enc fine-tuning | 9.93 | 8.99 | 8.96 |
| w/ 2-step fine-tuning | **9.47** | **8.85** | **8.74** |
| **Conformer** |     |     |     |
| w/ full fine-tuning | 10.08 | 9.11 | 8.79 |

was derived from the Conformer listed in Table 2 which was pre-trained with LibriSpeech and then fine-tuned with FluentSpeech. CTS-Conformer was trained with the same steps as above, i.e., fine-tuning CTS-Conformer model based on the Conformer parameters well-trained already. Its all WERs are almost small, likely because the FluentSpeech corpus is relatively simple, with its small vocabulary and limited expressions. Only small gain and loss of 0.02% absolute values were seen in the table as comparing WERs of two-step fine-tuned CTS-Conformer with those of Conformer.

To further understand the effect of CTS masking on cross attention, we used the CTS mask on the Conformer model without fine-tuning and indeed noted a significant change in accuracy. Table 4 presents the results: clearly, in addition to the additional substitution errors, there were also far more insertion errors. Such results demonstrate that the refinement of parameters is thus important after changing the input to the decoder.

**Table 4**: Results by attaching the CTS mask to Conformer but without fine-tuning of parameters, compared with the one decoding with no CTS masking. Beamwidth = 4.

| Data Model | WER (%) | LibriSpeech Conf. | FluentSpeech Conf. | Decoding Time |
|------------|---------|-------------------|--------------------|---------------|
| Conf.      | 3.78    | 61.12             | 1.09               | 3.64          |
| +CTS       | 2.62    | 13.27             | 0.38               | 0.39          |
| sub        | 0.76    | 4.00              | 0.07               | 0.11          |
| del        | 0.41    | 43.58             | 0.64               | 3.14          |

**Table 5**: Real-time factor (RTF) of CPU decoding of LibriSpeech and FluentSpeech with Conformer and CTS-Conformer on an Intel Xeon® Gold 6130 CPU @ 2.10GHz

| Decoding | Conf. | CTS-Conf. | Time savings |
|----------|-------|-----------|--------------|
| LibriSpeech |      |           |              |
| Beam 1    | 0.183 | 0.165     | 10%          |
| Beam 4    | 0.610 | 0.487     | 20%          |
| Beam 10   | 1.460 | 1.212     | 16%          |
| FluentSpeech |     |           |              |
| Beam 1    | 0.130 | 0.135     | -4%          |
| Beam 4    | 0.387 | 0.346     | 11%          |
| Beam 10   | 0.860 | 0.729     | 15%          |

All RTFs for LibriSpeech were reduced largely. A reduction of 20% was seen at a beamwidth of 4. It is important because we usually use this beamwidth in decoding of large vocabulary continuous ASR applications. A comparison of FluentSpeech decoding times between Conformer and CTS-Conformer reveals instabilities when the beamwidth is 1. An increase from 0.130 to 0.135 was found. Although CTS masking shortens the length of the encoding sequence, it does not always lead to reduced decoding times. When CTS-Conformer’s fine-tuning results in an encoder with higher CTC loss, it introduces increasing paths from CTC decoding to be rescored by attention decoding. Thus, it may cause longer computational consumption at some time. Especially, FluentSpeech is a small dataset with a limited vocabulary, there are many other words in the vocabulary could not be fine-tuned. Such an imbalance could cause problems like insertion errors in decoding, resulting in incorrectly increased decoding times. When decoding with a higher beamwidth than 1, such a phenomenon is smoothed out and disappears.

4. Conclusions

We add CTS masking to the Conformer model to construct CTS-Conformer models. This improves the Conformer decoder’s efficiency by simplifying the cross attention’s input acoustic sequence. We also propose several fine-tuning approaches. In our experiments, when using attention-rescoring decoding with beamwidth of four, CTS-Conformer reduces the overall computations on LibriSpeech and FluentSpeech by 20% or 10% respectively without harming ASR accuracy.

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