Intermediate-layer output Regularization for Attention-based Speech Recognition with Shared Decoder

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Abstract

Intermediate layer output (ILO) regularization by means of multitask training on encoder side has been shown to be an effective approach to yielding improved results on a wide range of end-to-end ASR frameworks. In this paper, we propose a novel method to do ILO regularized training differently. Instead of using conventional multitask methods that entail more training overhead, we directly make the intermediate layer output as input to the decoder, that is, our decoder not only accepts the output of the final encoder layer as input, it also takes the output of the encoder ILO as input during training. With the proposed method, as both encoder and decoder are simultaneously “regularized”, the network is more sufficiently trained, consistently leading to improved results, over the ILO-based CTC method, as well as over the original attention-based modeling method without the proposed method employed.

Index Terms: speech recognition, intermediate layer output, end-to-end, attention-based, shared decoder

1. Introduction

End-to-end (E2E) ASR modeling framework, such as recurrent neural network transducer (RNN-T) \cite{1,3}, and attention-based encoder-decoder framework \cite{4,7}, say Listen, Attend and Spell (LAS) \cite{8,10}, Transformer \cite{11,13}, as well as Conformer \cite{14,16}, and etc., has de facto become predominant in both research and industrial areas of speech recognition \cite{17,18}, thanks to its simplicity, compactness, and more importantly effectiveness in yielding improved recognition results.

Despite much progress, E2E ASR modeling framework still faces a lot of challenges. For instance, data hungry issue is always inherent in the E2E modeling framework. This is particularly true when our models are getting deeper and deeper. To data, the most commonly used transformer encoder layer is 12 layers. As a result, to maximally exploit the potentiality of such a deeper model, more data is always desired. On the other hand, it would be very natural for one to ask a question: given a limited data set, how should we think of an approach to releasing the potentiality of existing E2E ASR framework? In this paper, we are meant to answer this question by means of employing an intermediate loss as a regularization term to the primary loss function. To achieve improved E2E ASR results, extra losses, including encoder intermediate loss, being employed has been practiced for long in ASR community. For instance, \cite{10} has introduced a series of auxiliary loss functions to boost RNN-T performance. To let the bottom layers of the encoder have more speech content-based classification capability, the intermediate layer output is employed as input to a shared decoder, and hence such a capability is intensified to learn. Furthermore, \cite{20} also attempted to enforce the intermediate layer to have more capabilities of learning grapheme-state classification. Likewise, \cite{21} proposed to use intermediate CTC loss to boost the performance of the Transformer and Conformer encoder-based CTC ASR models. Similar to \cite{21,22} proposed to take advantage of intermediate CTC losses to learn context dependence for CTC ASR model.

In this paper, we propose a novel intermediate loss to boost the performance of attention-based E2E ASR models. Different from the prior works, we let the output of the intermediate and final layers share the same decoder, as is shown in Figure 1. The advantage of the proposed method lies in though we have auxiliary loss from encoder intermediate layer, no extra tasks are introduced. This reduces necessity of learning extra parameters. More importantly, not only is the content-based knowl-
edge learning for the bottom layer of the encoder intensified, an extra input to the decoder also makes it more resilient to the change of encoder input, namely acoustic features.

The main contribution of this paper can be summarized as follows. 1) We introduce an extra connection between encoder intermediate layer and decoder. That is, except for taking normal input from the encoder final layer, the decoder also takes input from the encoder intermediate layer. By such a means, both encoder and decoder of our attention-based ASR system have been simultaneously regularized with such a extra back-propagation gradients, yielding consistent improved recognition results over ASR system with intermediate CTC loss as well as system without regularization at all. 2) We verified the efficacy of the proposed method over 3 public available data sets, one, an English accent data set [23], another, SEAME [24], a Southeast Asian English-Mandarin code-switching data set, and the third, 960-hour full Librispeech data set respectively. 3) As an ablation, we also analyze how the proposed method affects the ASR performance in detail.

2. Related Work

As above-mentioned, employing encoder Intermediate Layer Output (ILO) to learn an auxiliary task has been widely adopted for long. Generally, the prior work can be classified into two categories. One category belongs to multitask learning. For example, [25] employs ILO to learn an accent classification in addition to a normal ASR recognition task under a single E2E-based encoder-decoder framework. The other category is to employ the ILO-based auxiliary task to assist the primary speech recognition task. For example, [26] proposed to use the ILO to learn phoneme or senone classification, boosting the performance of the E2E model, which is particularly useful for deeper network. Similarly [22] proposed intermediate losses to strengthen the learning capability of CTC models. However, all these works have introduced an extra new task, resulting in more parameters to learn. In this paper, though we focus on ILO loss, no extra task is introduced, and hence it is much simpler.

To the best of our knowledge, the most related work is from [19]. In [19], an intermediate layer output is also taken as input to the shared decoder. However, the difference are remarkable. First, [19] thinks the intermediate layer output is more focused on feature learning and hence its directly connecting to the shared decoder is “suboptimal”. As a result, [19] introduces a lightweight MLP to transform the intermediate layer output first, and then let the output of the MLP as input to the shared decoder. In this paper, we let the intermediate output of our encoder directly connect with the decoder as a normal input instead. The proposed method is much simpler. More importantly, during back-propagation, the shared decoder for the intermediate layer is frozen for updating in [19], while we keep updating both encoder and decoder for the intermediate loss sequentially.

3. Proposed Method

The proposed method is verified with the Conformer [14] ASR framework. The encoder of Conformer is composed of blocks, which are denoted as layers in this paper. For each layer \(i\), suppose the input is \(x_i\), and the output is \(y_i\), then the operation of each layer can be described with following equations:

\[
\tilde{x}_i = x_i + \frac{1}{2} \text{FFN}(x_i) \tag{1}
\]

\[
x'_i = \tilde{x}_i + \text{MHSA}(\tilde{x}_i) \tag{2}
\]

\[
x''_i = x'_i + \text{Conv}(x'_i) \tag{3}
\]

\[
y_i = \text{LayerNorm}(x''_i) + \frac{1}{2} \text{FFN}(x''_i) \tag{4}
\]

where FFN, MHSA, Conv, and LayerNorm refer to feed-forward network, multi-head self-attention, convolution, and layer normalization [27] operations respectively. As a result, the so-called intermediate output refers to some \(y_i\), where \(1 \leq i < N\), and \(N\) is the total layers of Conformer encoder.

With the Conformer framework, the baseline ASR system is trained with multitask learning method, that is, our encoder is optimized with CTC loss \(L_{ctc}\), while the entire network is optimized with ASR negative log posterior, i.e., \(L_{asr}\). Combining the two losses, the overall training loss is

\[
L_{asr} = \alpha L_{ctc} + (1 - \alpha) L_{att} \tag{5}
\]

where \(\alpha\) is a weighing factor, and it is fixed with 0.3 in what follows. In [28][29], it is shown employing such a combined loss of Eqs. 5 can consistently yield improved recognition results.

For the proposed method as illustrated in Figure 1 we employ the encoder intermediate output as an extra input to the decoder. Consequently, we introduce another loss, denoted as \(L_{inter}\), into Eqn 5 yielding the new loss:

\[
L'_{asr} = \alpha L_{ctc} + \beta L_{att} + \gamma L_{inter} \tag{6}
\]

where we let \(\alpha + \beta + \gamma = 1\). As the proposed method is very close to an ILO-based multitask learning method, that is, we let the encoder ILO connect with another recognition or classification task, such as a CTC-based ASR task, and etc. it is necessary to compare the proposed method with such an ILO-based multitask method, particularly CTC method. For completeness, the loss of the ILO-based CTC method is rewritten as follows:

\[
L'_{asr} = \alpha L_{ctc} + \beta L_{att} + \gamma L_{inter} \tag{7}
\]

where we also restrict \(\alpha + \beta + \gamma = 1\).

From Equations 5[6] and [7] we can produce three ASR systems with three losses to train corresponding models. To check the efficacy of the proposed method simply, we can compare the accuracy on the validation data between the three ASR systems during training process. Figure 2 plots the validation accuracy versus training epochs for the three methods. For CTC-grapheme and CTC-WPM, it means that the middle layer sends grapheme based CTC and subword based CTC respectively.

From Figure 2 we notice that the proposed method obtains consistently best accuracy on the validation data during training. The CTC-grapheme and CTC-WPM method has not shown clear improvement over the baseline ASR system on the accented English data set. Further performance results on different test sets will be presented in Section 4.

It is worth noting that once we use the ILO regularization to train the network, we disconnect the connection between ILO and decoder. That is, our decoding network is completely the same with the baseline without ILO employed at all. However, our decoder is still a multitask based one, i.e., the decoding output is a combination of CTC and attention output like what is proposed in [29].

4. Experiment
Figure 2: Validation accuracy versus training epoch for the three ASR systems trained with losses of Equations 5 and 7 respectively. The curve is drawn with the accented English data set, as detailed in Section 4.7.

### 4.1. Data

To verify the efficacy of the proposed method, we conduct experiments on three publicly available data corpora. They are Accented English data corpus [23], 960 hours of Librispeech data, as well as SEAME data [24], a Southeast Asia English-Mandarin code-switching data set. Table 1 summarizes the details of the overall data sets that are employed to evaluate the proposed method in what follows.

The Accented English data corpus is released by DataTang, in an Accented English Speech Recognition Challenge & Workshop of 2019. The purpose is targeted for both accent and speech recognition challenges. It’s a read speech and the total 8 accents are from American(U.S), British(UK), Chinese(CHN), Indian(IND), Japanese(JPN), Korean(KR), Portuguese(PT) and Russian(RU) accent respectvely. Each accent has roughly 20 hours. One can refers to [23] for more details.

For the SEAME code-switching data set, the total length of the data is about 110 hours. It is a spontaneous conversational speech corpus, recorded under clean environment. To evaluate the performance, two code-switching test sets are defined. One test set is denoted as Test\(_{train}\), of which the speech content is dominated with Mandarin, while another test set is named as Test\(_{tst}\), that is biased to Southeast Asian English speech, of which the speakers are mainly from Malaysia and Singapore. For more details, one can refer to [24].

### 4.2. Models

All experiments are performed using E2E-based Conformer modeling framework with Espnet toolkit [30]. We use the acoustic feature that is 83-dimensional with 80-d filter-bank plus 3-d pitch features [51]. In all experiments, we fix the Conformer with 12-layer encoder and 6-layer decoder. For the Accented English and SEAME experiments, both the encoder and decoder with 4 attention heads, the attention dimension is 256. But for Librispeech experiments, the attention heads are increased to 8 and corresponding attention dimension increased to 512 dimensions accordingly.

During training, we proceed with 0.1 dropout [32], and our Conformers are optimized with Noam optimizer [33]. For English data, we employ Byte Pair Encoding(BPE) [34] to train the scaling factors are 0.2 versus 0.8 respectively. We haven’t tweetted other parameters specifically.

### 5. Results

Table 2 presents the ASR performance of the proposed method on the accented English data set. From Table 2, we notice that the proposed method (M3) has achieved 8.2% relative WERR over the baseline Conformer model (M1) while it (M4) has gained 4.9% relative WERR over the model with SpecAugment-based data augmentation (M2) on test set respectively. After using SpecAug, we found that the effectiveness of the proposed method decreased, but the performance is still significantly improved. In other words, our proposed method can be effectively combined with SpecAug method to produce better results.

More interestingly, system M5 obtains the best WER once we combine the proposed method with the vanilla ILO-based CTC method using grapheme as output. Specifically, M5 obtains 8.6% relative WERR over M2 system. Finally, ILO-based CTC-grapheme and ILO-based CTC-WPM methods both obtain smaller WERR over baseline system compared with our proposed method. Table 3 reports the WER performance of the proposed method on Librispeech data set. We can see from Table 3, the proposed method is more effective when no SpecAug is employed, the proposed method(M3) can get \( \sim 8.2\% \) relative WERR over the baseline system (M1) on Test\(_{data}\). However, when using SpecAug, our method(M4) only gets 1.4% relative WERR over M2 on Test\(_{data}\). This again suggests the proposed method might be more beneficial for low-resource ASR modeling. Due to computing resource limitation, we omit the experiments for ILO-CTC-grapheme, as well as ILO-CTC-WPM.

Table 4 presents the WER performance of the proposed

| Corpus       | Set   | Len (Hrs) | Word/Utt. | Sec./Utt. |
|--------------|-------|-----------|-----------|-----------|
| Accented     | Train | 148.5     | 9.72      | 4.29      |
|               | Dev   | 14.5      | 9.66      | 4.35      |
|               | Test  | 20.95     | 9         | 4.15      |
| Librispeech  | Train | 961       | 33.43     | 12.3      |
|               | Test\(_{clean}\) | 5.4       | 20.0      | 7.4       |
|               | Test\(_{tst}\)  | 5.3       | 17.8      | 6.5       |
| SEAME        | Train | 93.6      | 14.14     | 3.9       |
|               | Test\(_{train}\) | 7.5       | 14.76     | 4.1       |
|               | Test\(_{tst}\)  | 3.9       | 10.12     | 2.7       |
Table 2: WERs(%) for the Accented English data, where ILO-CTC-g refers to ILO-based CTC with grapheme as output units while ILO-CTC-WPM stands for ILO-based CTC with WPM as output.

| ID | Model           | (Layer, γ) | WER(%) | Dev | Test |
|----|-----------------|------------|--------|-----|------|
| M1 | Conformer       | -          | 9.5    | 11  |
| M2 | M1 + SpecAug    | (9,0.2)    | 6.9    | 8.1 |
| M3 | Proposed        | (9,0.2)    | 8.8    | 10.1|
| M4 | M4 + SpecAug    | (9,0.2)    | 6.7    | 7.7 |
| M5 | M5 + ILO-CTC-g  | (9,0.2)    | 6.4    | 7.4 |
| M6 | ILO-CTC-g       | (9,0.15)   | 9.3    | 10.7|
| M7 | M6 + SpecAug    | (9,0.15)   | 6.8    | 8   |
| M8 | ILO-CTC-WPM     | (9,0.1)    | 9.4    | 10.7|
| M9 | M8 + SpecAug    | (9,0.1)    | 6.9    | 8   |

Table 3: WERs (%) for Librispeech data.

| ID | Model           | (Layer, γ) | WER(%) | Dev | Test  |
|----|-----------------|------------|--------|-----|-------|
| M1 | Conformer       | -          | 3.4    | 9.8 |
| M2 | M1 + SpecAug    | -          | 2.9    | 6.9 |
| M3 | Proposed        | (9,0.2)    | 3.2    | 9.0 |
| M4 | M4 + SpecAug    | (9,0.2)    | 2.8    | 6.8 |

6.2. Effect of the proposed ILO regularization

From Tables 2 to 4, we can see the proposed ILO regularization method has achieved consistent performance improvement over the baseline and other ILO-based multitask methods. Naturally, we are curious about how the proposed method affects both encoder and decoder. To this end, we let the Conformer that is trained with the proposed method decode with different mode. Specifically, we let the encoder final layer CTC decode, and see how the encoder is affected. Though we cannot easily infer how the decoder alone is affected, we can see how pure attention-based decoder results are affected. Table 5 reports the “decomposed” WERs in each case. We can see from Table 5, the most affected part is the encoder as the CTC system gets better performance improvement, i.e., 6.8% versus 3.66% relative WERR when M4 is compared with M2 in “CTC” versus “Attention” case respectively.

Table 5: WERs(%) of using the proposed ILO regularization method, where “CTC” refers to using pure CTC output to infer, “Attention” refers to using pure attention-based decoder output to infer, and while “Hybrid” is the interpolated inference method, of which the CTC and attention-based decoder output factors are 0.2 and 0.8 respectively.

| ID   | Model    | Test set(WER%) |
|------|----------|----------------|
| CTC  | Attention| Hybrid         |
| M1   | Conformer| 13.4           | 11.3           | 11  |
| M2   | M1 + SpecAug | 11.7           | 8.2            | 8.1 |
| M3   | Proposed | 12.5           | 10.4           | 10.1|
| M4   | M3 + SpecAug | 10.9           | 7.9            | 7.7 |

7. Conclusions

In this paper, we proposed an intermediate layer output regularization method to train state-of-the-art Conformer model for speech recognition. Different from the prior works, the regularization is realized with an extra connection between the intermediate layer of encoder and the decoder. Consequently, the proposed method is much cheaper to train. We verified the efficacy of the proposed method on three different publicly available data sets. It has achieved consistent WER reductions, when it is compared with the baseline Conformer, as well as various intermediate layer output CTC-loss-based Conformer.
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