Reducing the Latency of End-to-End Streaming Speech Recognition Models with a Scout Network

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Abstract

Attention-based Transformer model has achieved promising results in offline speech recognition (SR). Recently, Transformer based streaming SR attracts attention from both industry and academia, however, its latency increase linearly as the number of encoder layers when adopting a fixed-length look-ahead window. In order to both ensure the recognition quality and reduce the latency, we propose a novel streaming recognition method consisting of a scout network and a recognition network. The scout network detects a whole word boundary without seeing any future frames, and the recognition network predicts the next subword by considering all frames before the predicted boundary. Our model achieves the best performance (2.7/6.4 WER) with only 639 million seconds latency on the test-clean and test-other data sets of the Librispeech.

Index Terms: online speech recognition, adaptive look-ahead, streaming model

1. INTRODUCTION

Currently, a surge of end-to-end (E2E) automatic speech recognition (ASR) models, such as the connectionist temporal classification (CTC) [1, 2, 3], the RNN-Transducer [4, 5, 6], and the attention-based encoder-decoder (AED) models [7, 8, 9, 10] have gained popularity in the ASR community because of their simple training procedure, desirable decoding efficiency, and promising performance on large-scale speech benchmarks.

Recently, the Transformer model [11] has been successfully introduced into the E2E ASR, which enjoys faster training and better performance advantages in comparison with RNNs. To enable Transformer AED models to handle streaming ASR task, Transformer based monotonic chunkwise attention (MoChA) [12] and trigger attention mechanism [13] have been proposed to replace the global encoder-decoder attention. Regarding the streaming Transformer encoder, existing approaches can be categorized into look ahead based method [13] [14] and chunk-based method [15] [16] [17] [18], as shown in Figure 1(a) and Figure 1(b). The former sets a look-ahead window for each frame to take the necessary context information into consideration. However, the latency increases linearly with the number of stacked encoder layers. As shown in Figure 1(a), when the look-ahead window is 2, a 3-layer encoder requires 6 future frames to produce the current hidden states. The latter adopts a chunk-wise approach, where the entire utterance is segmented into several fixed-length chunks and the encoder processes the input chunk by chunk. To improve the performance, there are always overlaps between chunks to provide left and right context. However, the method hurts the training parallelism of self-attention layers, and its performance is not good when the chunk size is small.

To encode the current input, the most relevant context should be the frames of the whole word, and the length-fixed look ahead frames are sometimes not necessary. In the length-fixed look ahead method, the frames in the following words may not be able to bring much quality gain, but will increase the latency significantly, especially when the current frame approaches the word end. In order to not only leverage indispensable context to ensure the recognition quality but also reduce the latency as much as possible to generate the output promptly, we propose an adaptive looking ahead strategy, where a latency free scout network (SN) detects a whole word boundary and then a recognition network (RN) decodes subwords by looking ahead to the detected boundary. As the SN is latency free and always goes ahead of the RN, the averaged latency of our method depends only on the distance between two predicted word boundaries.

Specifically, we formulate the whole word segmentation as a sequence labeling problem, where each frame is either a boundary or not. In terms of training process, we regard force-alignment results as the ground-truth, and fit it with a sequence labeling network. The sequence labeling network is dubbed as the Scout Network, because it goes ahead of the recognition model like a scout sent out ahead of the main force (the recognition model) so as to gather information. We implement the scout network with the Transformer architecture to predict the boundary label of the current frame without seeing any future frame. The scout network is trained to prefer a high precision instead of recall segmentation result [19] which ensures the recognition quality. When the boundary is obtained, any end-to-end (E2E) model can be employed as the RN. In this paper, we use the trigger attention based Transformer model [13] as a recognition network (RN) to conduct frame-synchronous one-pass decoding by looking ahead to the detected word boundaries.

Our experiments are conducted on Librispeech benchmark [20]. The results show that our proposed SN can not only significantly reduce the latency, but also achieve the state-of-the-art recognition quality. Our base model with 78M parameters and large model with 138M parameters achieve 2.9/7.4 and 2.7/6.4 on test-clean and test-other datasets.

To understand the effect of our proposed SN, we conduct experiments to analyze the relationship between the word error rate of the RN and the threshold in the SN. Experiments show that the higher threshold of the prediction precision (with lower recall of the boundaries, and higher latency), leads to better recognition quality. The latency and the quality of the recognition can be balanced with the precision threshold of the SN.

Our contributions are summarized as follows: 1) We propose a new strategy for streaming speech recognition which sig-

1 Some word boundaries may not be detected, but the detected boundaries are correct.
nificantly reduces the latency of the fixed look-ahead strategy. 
2) We design a simple but effective scout network which works 
well on the benchmark dataset. 3) We achieve state-of-the-art 
streaming recognition performance on the Librispeech dataset.

2. Background

2.1. Transformer ASR

Transformer achieves promising results in ASR [19]. Given a 
sequence $X$, the encoder transforms it to an intermediate representation $H$, then the decoder predicts the 
following word $y_i$ based on $H$ and previous outputs $Y_{i-1} = (y_1, \ldots, y_{i-1})$.

The Transformer encoder consists of a convolution block and $N_e$ encoder blocks, each of which has a 
self-attention layer and a feedforward layer. The decoder is com-
posed of $N_d$ decoder blocks, including a self-attention layer, 
an encoder-decoder attention layer and a feed-forward layer. In 
the attention layers, weights are formed from queries ($Q \in \mathbb{R}^{d}$) 
and keys ($K \in \mathbb{R}^{d}$) and then applied to values ($V \in \mathbb{R}^{d}$) as

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK}{\sqrt{d}})V,$$ \hspace{1cm} (1)

where $Q$, $K$ and $V$ have the same dimension $d$. To enable dealing 
with multiple attentions, multi-head attention is proposed, which 
is formulated as

$$\text{Multihead}(Q, K, V) = [H_1 \ldots H_m]W^{head}$$ \hspace{1cm} (2)

$$H_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$ \hspace{1cm} (3)

where $m$ is the number of attention heads. Residual connections 
and layer normalization are applied for each block.

2.2. Streaming ASR

To realize a streaming AED based ASR system, both the en-
coder and the decoder should be processed online. For the 
Transformer encoder, the self-attention mechanism provides a 
flexible way to control the range of context by masking the at-
tention score within a look-ahead window [13][14]. However, 
the receptive field and latency will increase linearly with the 
number of stacked encoder layers. As shown in Figure 1(a), 
suppose the right look-ahead window size is $w_r$, the latency 
is computed as $N_e \times w_r \times r$. Motivated by Transformer-XL 
[20], other work [12][15][16][17][21] use a chunk-wise approach, 
where the entire utterance is segmented into several fixed-length chunks as shown in Figure 1(b).

Regrading to the decoder, the key is to learn the online 
onmonotonic alignments. In [22][23], the range of the attention 
is restricted to a fixed-size window with position determined 
by previous attention distribution. Monotonic chunkwise attention 
(MoChA) [24] uses a trainable energy function to shift the 
window. [12] and [25] extend MoChA where the window end-
point or the window size is changed adaptively through a func-
tion of previous attention energy. [21] applies MoChA to multi-
head encoder-decoder attention. [26] proposes trigger attention 
where a CTC module triggers the computation of the attention.

In this work, we use a Scout Network to detect the bound-
ary of words, which enables both the encoder and the decoder 
to have an adaptive right context window in decoding. We be-
lieve the context window to the word boundary provides most 
of useful information for recognition and reduces the latency as 
much as possible.

3. Method

3.1. Overview

Our method consists of a scout network which detects the word 
boundary, and a recognition network consisting of a streaming 
Transformer model with an adaptive look-ahead encoder and an 
adaptive trigger-attention based decoder. As shown in Figure 1(c), 
given an input sequence $X$, the Scout Network reads the 
input from left to right and detects whether or not the current 
frame is a word boundary. Once a boundary is detected, the 
recognition network begins decoding by considering all frames 
before the detected boundary.

3.2. Scout Network

In our work, the architecture of the Scout Network (SN) is simi-
lar to a Transformer encoder, including a CNN module with 
downsampling rate $r$, denoted as SnCNN, and a stack of $N_s$ self-
attention blocks, denoted as SnSA. In each self-attention layer, 
we mask the attention score to the right of the current frame to 
produce output conditioned only on the previous states. Thus, 
the SnSA is a latency-free module. Given the input sequence 
$X = (x_1, \ldots, x_T)$, the SN first converts it to hidden states

Figure 1: A comparison between three Transformer based streaming models.
\( \mathbf{H}^0 = (h^*_{i,1}, \ldots, h^*_{i,T'}) \), where \( T' = \lceil \frac{T}{r} \rceil \) denotes the downsampled length. Then a detector layer predicts the probability \( p_i \) that the \( i \)-th frame is a boundary:

\[
p_i = \text{Sigmoid}(W_i h^*_{i} + b)
\]

(4)

The network is trained toward a cross entropy loss as:

\[
\mathcal{L}_{SN} = \sum_{T} b_i \log(p_i)
\]

(5)

where \( b_i \in \{0, 1\} \) is the ground truth of the boundary decision. Here, we use the Montreal Forced Aligner\(^2\) to perform word-level force-alignment and obtain a sequence \( \mathbf{B} = (b_1, \ldots, b_{T'}) \) as the ground truth. During inference, we set a threshold to determine whether a frame is a boundary, formulated as

\[
b_i = \begin{cases} 1 & p_i \geq \sigma \\ 0 & p_i < \sigma \end{cases}
\]

where \( \sigma \) is tuned on the dev set and \( b_i = 1 \) denotes that the \( i \)-th position is a boundary.

### 3.3. Streaming ASR with the Scout Network

#### 3.3.1. Recognition Network Training

In this section, we introduce the training procedure of the streaming Transformer equipped with the Scout Network. Suppose the SN produces the sequence \( \mathbf{B} = (b_1, \ldots, b_{T'}) \), where \( b_i \in \{0, 1\} \) is sampled according to the probability \( p_i \) in Equation (4). We can further obtain \( \mathbf{E} = (e_1, \ldots, e_L) \), in which each element \( e_i \) denotes the index of the \( i \)-th boundary, that is \( e_i = k \) and \( b_k = 1 \). The window sizes of the ASR encoder and the decoder are decided by \( \mathbf{E} \).

The CNN block in ASR encoder EncCnn has the same architecture and downsample rate \( r \) as Sncnn. It extracts local features from input \( \mathbf{X} \) and generates \( \mathbf{H}^0 = (h^1_{1,1}, \ldots, h^1_{1,T'}). \) Then a stack of \( N_c \) look-ahead encoder blocks ENCSA generates high-level representations \( \mathbf{H} \). Suppose that the next word boundary is \( e_i \), then the hidden state of \( h_i \), \( \forall i \in (e_{i-1}, e_i] \), is determined by the whole left context and the right context \( \mathbf{H}_{1:e_i} = \{h_k | 1 \leq k \leq e_i \} \). The computation for the \( l \)-th self-attention layer is written as:

\[
\hat{h}^l_i = \text{Multihead}(h^{l-1}_{i,1}, \mathbf{H}^{l-1}_{[1:e_i]}, \mathbf{H}^{l-1}_{[e_i:]})
\]

(6)

The frames between boundary \( e_{j-1} \) and \( e_j \) can be seen as a speech segment and the latency for the frame \( i \) is controlled to \( (e_j - 1) \times r \). It is similar to the chunk-based encoder where a segment between two boundaries is regarded as a chunk but there is no overlap between chunks. We use the mask strategy to avoid the model seeing context later than the \( e_j \)-th frame.

The decoder adopts TA concept but with adaptive look-ahead window size, denoted as TADEC. However, our method can also be applied to other monotonic attention mechanisms, e.g. MoChA. Given the predicted sequence \( \mathbf{Y}_{[1:k-1]} = (y_1, \ldots, y_{k-1}) \), the computation of the next token \( y_k \) is triggered when \( y_k \) is generated by the CTC module for the first time. Suppose the CTC generates \( y_k \) at frame \( i \), the range of encoder states used by the decoder is the same with state \( h_i \) and constricted to \( \mathbf{H}_{[1:e_j]} \):

\[
P_{y_k} = \text{TADEC}(\mathbf{Y}_{[1:k-1]}, \mathbf{H}_{[1:e_j]})
\]

(7)

where \( e_{j-1} < i \leq e_j \).

We initialize the model with a pre-trained offline Transformer and fine-tune it in a streaming manner. During training, both the model decoder and a CTC module predict the frame-wise distribution of \( \mathbf{Y} \), denoted as \( P_{\text{ctc}}(\mathbf{Y}|\mathbf{X}) \) and \( P_{\text{dec}}(\mathbf{Y}|\mathbf{X}) \). We weighted averaged two negative log likelihoods to train our model

\[
\mathcal{L} = -\gamma \log P_{\text{ctc}}(\mathbf{Y}|\mathbf{X}) - (1 - \gamma) \log P_{\text{dec}}(\mathbf{Y}|\mathbf{X}).
\]

(8)

where \( \gamma \) is set to 0.7 in our experiment.

To train the TADEC, the alignment between CTC paths and the label sequence \( \mathbf{Y} \) is required. Different from [13] which performs Viterbi alignment during training, we select the path with the highest Viterbi alignment score generated by the pre-trained offline model and use this path as guidance to trigger the decoder.

#### 3.3.2. Decoding

**Algorithm 1 Streaming Transformer Decoding with Scout Network**

1. **procedure** \textsc{Scout-Then-Decode}(\( \mathbf{X}, K, \sigma, \sigma_0, \lambda, \alpha, \beta \))
2. \( k \leftarrow 0, e_k \leftarrow 0 \)
3. \( t \leftarrow \{\emptyset\}, \Omega \leftarrow \{\} \)
4. for \( i = 0 \) to \( T \) do
5. \( p_i \leftarrow \text{SN}(x_i), t' \leftarrow t \) \( \triangleright \) Scout Boundary
6. if \( p_i > \sigma \) then
7. \( k \leftarrow k + 1, e_k \leftarrow i' \)
8. \( \mathbf{H}_{e_{k-1}+1:e_k} \leftarrow \text{ENC}(\mathbf{X}_{[1:i]}) \)
9. \( \Omega, p_{\text{point}} \leftarrow \text{DECODE}(\Omega, \mathbf{H}_{e_k}, e_k - e_{k-1} K, \sigma_0, \lambda, \alpha, \beta, \) )
10. return \( \text{MAX}(\Omega, p_{\text{point}}, 1) \)
11. **procedure** \textsc{Decode}(\( \Omega, \mathbf{H}, n, K, \sigma_0, \lambda, \alpha, \beta \))
12. \( \Omega_{\text{dec}} \leftarrow \emptyset \)
13. for \( j = 1 \) to \( n \) do
14. \( \Omega_{\text{dec}}, p_{\text{dec}} \leftarrow \text{CTCPrefix}(\Omega, \sigma_0) \)
15. for \( \ell \) in \( \Omega_{\text{dec}} \) do
16. if \( \ell \) not in \( \Omega_{\text{dec}} \) then
17. \( p_{\text{local}}(\ell) \leftarrow \text{TADEC}(\mathbf{H}, \ell) \)
18. add \( \ell \) to \( \Omega_{\text{dec}} \)
19. \( p_{\text{local}}(\ell) \leftarrow \log p_{\text{dec}} + \alpha \log p_{\text{LM}} + \beta |\ell| \)
20. \( p_{\lambda}(\ell) \leftarrow -\log p_{\text{dec}} + (1 - \lambda) \log p_{\text{dec}} + \alpha \log p_{\text{LM}} + \beta |\ell| \)
21. \( \Omega_{\text{local}} \leftarrow \text{MAX}(\Omega_{\text{dec}}, p_{\text{local}}, K) \) \( \triangleright \) Beam Pruning
22. \( \Omega_{\text{dec}} \leftarrow \text{MAX}(\Omega_{\text{dec}}, p_{\text{dec}}, K) \)
23. \( \Omega_{\text{point}} \leftarrow \text{MAX}(\Omega_{\text{dec}}, p_{\text{point}}, K) \)
24. \( \Omega \leftarrow \Omega_{\text{local}} \cup \Omega_{\text{dec}} \cup \Omega_{\text{point}} \)
25. return \( \Omega, p_{\text{point}} \)

Algorithm 1 gives the decoding procedure for streaming Transformer with the Scout Network. The hyper-parameters used by the function include beam width \( K \), boundary decision threshold \( \sigma \), CTC decoding threshold \( \sigma_0 \), CTC decoding weight \( \lambda \), language model weight \( \alpha \) and length penalty \( \beta \). In line 2, we first initialize the index of speech segment \( k = 0 \) and the position of the \( k \)-th boundary \( e_k = 0 \). The hypothesis set

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2https://github.com/MontrealCorpusTools/Montreal-Forced-Aligner
\Omega \) is initialized in line 3 with the prefix sequence \( f \) containing only the start of the sequence label (sos). In line 4-6, the speech signals are fed into the Scout Network frame by frame and an instantaneous decision is made by threshold \( \sigma \). Once a boundary is detected, the computation for the ASR encoder and joint beam search scoring \( \text{DECODE} \) is triggered at line 8 and 9.

The process of \( \text{DECODE} \) is shown from line 11 to 25, which is similar to the decoding scheme in [13] with a small modification in beam pruning. In line 14, we perform the CTC prefix beam search [27] based on the current prefix set \( \Omega \) and generate candidates set \( \Omega_{\text{t}} \). Then the trigger attention decoder score every candidate. To avoid repeated computation and reduce the cost, we store all the scored candidates in \( \Omega_{\text{t}} \). In line 19 to 20, a local score and a joint score are assigned to each candidate. Then we select the top-\( K \) candidates based on local score, attention score and joint score respectively, and combine them as the hypothesis set for the next step. When the process finishes, we select the prefix with the highest joint score as the best result.

4. Experiments

4.1. Setup

We conduct our experiments on the LibriSpeech dataset [18], which contains 960 hours of training data. The “dev clean” is used as our validation set, which contains 2703 utterances. And the results are reported on “test clean” and “test other”, which contain 2620 and 2939 utterances respectively.

Our method is implemented based on ESPNet [19]. We extract 80-dim log Mel-filter bank features with 3-dim pitch features [28] every 10ms and normalize them with global mean computed from the training set. The text is tokenized using SentencePiece [29] and we set the vocabulary size as 5000. We evaluate our method in two settings, base setting and large setting. For the base setting, to setup a faire comparison, we use the same architecture as [13] with \( d_{\text{model}} = 512, d_{\text{ff}} = 2048, d_{\text{a}} = 4, N_e = 12, \) and \( N_d = 6 \). We use the released Transformer model provided by ESPNet [19] as the pretrained offline model. For the large setting, we use the architecture described in our previous work [30] with \( N_e = 24 \) and \( N_d = 12 \). We use a different CNN module which is composed of two 1D-CNN layers with layer normalization and max pooling layer. And we use 1D-CNN to extract local features to replace the pre-defined CNN layers. Correspondingly, we use two Scout Networks with different CNN modules for base and large setting. All the models have a downsample rate \( r = 4 \) so that each consumed frame of the self-attention layers corresponds to 40ms of input. The Scout Network is updated using Adam optimizer with a learning rate of 0.001. The ASR model is updated using a warmup step of 2500 and a learning rate coefficient of 1.0 following the similar schedule in [11]. SpecAugment [31] is used following the recipe in ESPNet. The fine-tune stage takes 20 epochs on 4 P40 GPUs, which approximately costs 1.5 days. For decoding, we average the last 5 checkpoints as the final model. The RNN language model uses the released LSTM language model provided by ESPNet. For decoding, we set \( K = 10, \sigma_0 = 0.0005, \lambda = 0.5, \alpha = 0.5, \beta = 2.0 \).

4.2. Scout Network Evaluation

We first evaluate the accuracy and efficiency of the Scout Network. As the SnNSA is latency free, an interesting question is whether such network can achieve a relatively high accuracy without considering any future frame. Given a predicted boundary \( E \) and a real boundary \( E' \) (by force-alignment), we compute the edit distance and count the ratio of substitution(sub), deletion(del), insertion(ins) between them. Table 1 gives an example of the accuracy evaluation for the Scout Network. \( E' \) and \( E \) are downsampled positions.

| \( \gamma \) | it gave an imposing appearance to |
|---|---|
| \( \epsilon' \) | most of the wholesale houses |
| \( \epsilon \) | evaluate |
| sub | del | ins |
| 7 | 12 | 14 | 28 | 42 | 45 | 52 | 56 | ** | 68 |
| 7 | 12 | 15 | 28 | 42 | 45 | 52 | 56 | 61 | 68 |

Table 1: An example of the accuracy evaluation for the Scout Network. \( E' \) and \( E \) are downsampled positions.

| \( N_e \) | GPU | CPU | \( \sigma \) | sub | del | ins |
|---|---|---|---|---|---|---|
| 12 | 11.1ms | 29.8ms | 0.5 | 13.0 | 7.2 | 1.9 |
| 8 | 7.4ms | 19.7ms | 0.6 | 10.7 | 13.4 | 1.7 |
| 4 | 3.7ms | 10.6ms | 0.7 | 8.0 | 21.0 | 0.6 |
| 0.8 | 5.2 | 30.1 | 0.3 |
| 0.9 | 2.6 | 42.6 | 0.1 |

Table 2: Segmentation Evaluation on the dev clean dataset. The first two columns are averaged per frame time cost.

| \( N_e \) | 12 | 24 |
|---|---|---|
| GPU | 11.1ms | 29.8ms |
| CPU | 13.0 | 7.2 |

4.3. Results

We compare our model with typical streaming models by copying their numbers in the literature or re-implementing by ourselves. The results are shown in Table 3. Contextual Block baseline [21] use a chunk-based encoder with a contextual embedding to incorporate global information and a decoder with global attention. TA baseline [13] adopts a look ahead based encoder and a trigger-attention based decoder. They use different look-ahead windows (1,2,4) for encoder layers while the decoder uses a window size of 6. [32] propose Transformer Trans-
Figure 2: The distribution of segment length for different thresholds. The blue area shows the density. The deep blue lines represent the mean values. The white markers represent the median values and the black vertical lines represent the interquartile ranges.

ducer with VGG-like CNN layers, look-ahead based encoder and self-attention predictor. For our re-implemented baselines, we re-implement the TA baselines with encoder window 1 and 2 using pretrain-then-finetune procedure and our decoding algorithm.

Suppose that our computation resource is powerful enough, we define two metrics to compute the latency: the frame-level latency and the word-level latency. The frame-level latency is the same as the latency metric used in previous paper [13] by computing how many future frames are considered in decoding current position $i$. Regarding our model, it is $(e_k - i) \times 40ms + 30ms$ (EncCNN), where $e_{k-1} < i \leq e_k$. Word-level latency is defined as the distance between the predicted boundaries and real boundaries (word ending point). For words with correct predicted boundary, the word-level latency is $30ms$(EncCNN). For words whose boundary is incorrect or missed, we compute the distance between the next boundary and the real boundary as word-level latency. An example is shown in Table 1. Since the frame-level or word-level latency is different for each frame or word, we report the average value on the combination of test sets. For look-ahead based encoder with a fixed window size, the word-level latency is the same as the frame-level latency.

In the 78M setting, our base model outperforms Contextual baseline and TA baselines. Compared with TA-4, our model achieves a similar accuracy while reducing the latency from 2190ms to 619ms, which is attributed to the SN that is able to preserve the most necessary audio information. Model with Scout-4 achieves better WER but sacrificing latency since there are more boundary deletion phenomenons in Scout-4 segmentation. Compared with Transformer Transducer [14], our 140M big model also has lower WER and lower latency, which to our knowledge is the state-of-the-art results for streaming E2E ASR system on LibriSpeech benchmark.

Table 3: The comparison with literature baselines and re-implemented baselines. The offline AED models adopt hybrid CTC/Attention decoding algorithm. $\infty$ denotes the whole utterance.

| Models                  | WER | latency |
|-------------------------|-----|---------|
| clean                  | other | frame | word |
| literature baselines    |     |         |      |
| Contextual Block[21]   | 4.6 | 13.1   | $\infty$ |
| TA (78M)[13]           | 2.7 | 6.1    | $\infty$ |
| TA-1                   | 3.2 | 8.2    | 750ms |
| TA-2                   | 2.9 | 7.8    | 1230ms |
| TA-4                   | 2.8 | 7.3    | 2190ms |
| Transducer (139M)[14]  | 2.4 | 5.6    | $\infty$ |
| Transducer-2           | 3.0 | 7.7    | 1080ms |
| Transducer-6           | 2.8 | 6.9    | 3240ms |
| reimplemented baselines|     |         |      |
| TA-1                   | 3.4 | 9.5    | 750ms |
| TA-2                   | 3.0 | 8.5    | 1230ms |
| our results            |     |         |      |
| Base (78M)             | 2.7 | 5.9    | $\infty$ |
| Base & Scout-12        | 2.9 | 7.4    | 619ms  |
| Base & Scout-4         | 2.8 | 7.1    | 844ms  |
| Large (138M)           | 2.2 | 5.2    | $\infty$ |
| Large & Scout-12       | 2.7 | 6.4    | 639ms  |

5. Conclusion

In this paper, we propose a new strategy for E2E speech recognition model where a scout network detects the current whole word boundary and then a recognition network conducts frame-synchronous one-pass decoding by looking ahead to the predicted boundary. Our big model achieves WERs of 2.7% and 6.4% for test-clean and test other sets, which to our knowledge is the best published results for E2E streaming ASR model on LibriSpeech benchmark. We also perform exhaustive experiments to investigate the performance and accuracy of the scout network as well as the relationship between the recognition performance and different scout network settings.

Table 4: Performance and latency of different threshold for Base-Transformer with Scout-12. The latency is computed on the combination of two test sets.

| threshold | WER | latency |
|-----------|-----|---------|
| clean     | other | frame | word |
| 0.9       | 2.9 | 7.4    | 619ms |
| 0.8       | 3.1 | 8.0    | 478ms |
| 0.7       | 3.3 | 8.5    | 404ms |
| 0.6       | 3.4 | 8.9    | 352ms |
| 0.5       | 3.5 | 9.4    | 317ms |
| golden    | 2.1 | 5.6    | 299ms |

For words with correct predicted boundary, the word-level latency is 30ms(ECCNN). For words whose boundary is incorrect or missed, we compute the distance between the next boundary and the real boundary as word-level latency. An example is shown in Table 1. Since the frame-level or word-level latency is different for each frame or word, we report the average value on the combination of test sets. For look-ahead based encoder with a fixed window size, the word-level latency is the same as the frame-level latency.

Table 4: The comparison with literature baselines and re-implemented baselines. The offline AED models adopt hybrid CTC/Attention decoding algorithm. $\infty$ denotes the whole utterance.

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|-------------------------|-----|---------|
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| Transducer (139M)[14]  | 2.4 | 5.6    | $\infty$ |
| Transducer-2           | 3.0 | 7.7    | 1080ms |
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| 0.6       | 3.4 | 8.9    | 352ms |
| 0.5       | 3.5 | 9.4    | 317ms |
| golden    | 2.1 | 5.6    | 299ms |
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