

STREAMING AUTOMATIC SPEECH RECOGNITION WITH THE TRANSFORMER MODEL

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ABSTRACT

Encoder-decoder based sequence-to-sequence models have demonstrated state-of-the-art results in end-to-end automatic speech recognition (ASR). Recently, the transformer architecture, which uses self-attention to model temporal context information, has been shown to achieve significantly lower word error rates (WERs) compared to recurrent neural network (RNN) based system architectures. Despite its success, the practical usage is limited to offline ASR tasks, since encoder-decoder architectures typically require an entire speech utterance as input. In this work, we propose a transformer based end-to-end ASR system for streaming ASR, where an output must be generated shortly after each spoken word. To achieve this, we apply time-restricted self-attention for the encoder and triggered attention for the encoder-decoder attention mechanism. Our proposed streaming transformer architecture achieves 2.7% and 7.0% WER for the “clean” and “other” test data of LibriSpeech, which to our knowledge is the best published streaming end-to-end ASR result for this task.

Index Terms— automatic speech recognition, streaming, end-to-end, transformer, triggered attention

1. INTRODUCTION

Hybrid hidden Markov model (HMM) based automatic speech recognition (ASR) systems have provided state-of-the-art results for the last few decades [1, 2]. End-to-end ASR systems, which approach the speech-to-text conversion problem using a single sequence-to-sequence model, have recently demonstrated competitive performance [3]. The most popular and successful end-to-end ASR approaches are based on connectionist temporal classification (CTC) [4], recurrent neural network (RNN) transducer (RNN-T) [5], and attention-based encoder-decoder architectures [6]. RNN-T based ASR systems achieve state-of-the-art ASR performance for streaming/online applications and are successfully deployed in production systems [7, 8]. Attention-based encoder-decoder architectures, however, are the best performing end-to-end ASR systems [9], but they cannot be easily applied in a streaming fashion, which prevents them from being used more widely in practice. To overcome this limitation, different methods for streaming ASR with attention-based systems have been proposed such as the neural transducer (NT) [10], monotonic chunkwise attention (MoChA) [11], and triggered attention (TA) [12]. The NT relies on traditional block processing with fixed window size and stride to produce incremental attention model outputs. The MoChA approach uses an extra layer to compute a selection probability that defines the length of the output label sequence and provides an alignment to chunk the encoder state sequence prior to soft attention. The TA system requires that the attention-based encoder-decoder model is trained jointly with a CTC objective function, which has also been shown to improve attention-based systems [13], and the CTC output is

used to predict an alignment that triggers the attention decoding process [12]. A frame-synchronous one-pass decoding algorithm for joint CTC-attention scoring was proposed in [14] to further optimize and enhance ASR decoding using the TA concept.

Besides the end-to-end ASR modeling approach, the underlying neural network architecture is of paramount importance as well to achieve good ASR performance. RNN-based architectures, such as the long short-term memory (LSTM) neural network, are often applied for end-to-end ASR systems. Bidirectional LSTMs (BLSTMs) achieve state-of-the-art results among such RNN-based systems but are unsuitable for application in a streaming fashion, where unidirectional LSTMs or latency-controlled BLSTMs (LC-BLSTMs) must be applied instead [15]. The parallel time-delayed LSTM (PTDLSTM) architecture has been proposed to further reduce the word error rate (WER) gap between unidirectional and bidirectional architectures and to improve the computational complexity compared to the LC-BLSTM [15]. Recently, the transformer model, which is an encoder-decoder type of architecture based on self-attention originally proposed for machine translation [16], has been applied to ASR with promising results and improved WERs compared to RNN-based architectures [17].

In this work, we apply time-restricted self-attention to the encoder, and the TA concept to the encoder-decoder attention mechanism of the transformer model to enable the application of online/streaming ASR. The transformer model is jointly trained with a CTC objective to optimize training and decoding results as well as to enable the TA concept [3, 12]. For joint CTC-transformer decoding and scoring, we employ the frame-synchronous one-pass decoding algorithm proposed in [14].

2. STREAMING TRANSFORMER

The streaming architecture of the proposed transformer-based ASR system is shown in Fig. 1. The transformer is an encoder-decoder type of architecture which uses two different attention layers: encoder-decoder attention and self-attention. The encoder-decoder attention can produce variable output lengths by using one or multiple query vectors, the decoder states, to control attention to a sequence of input values, the encoder state sequence. In self-attention (SA), the queries and values are equal, which results in an output sequence of the same length as the input. Both attention types of the transformer model are based on the scaled dot-product attention mechanism,

$$\text{Attention}(Q, K, V) = \text{Softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V, \quad (1)$$

where $Q \in \mathbb{R}^{n_q \times d_q}$, $K \in \mathbb{R}^{n_k \times d_k}$, and $V \in \mathbb{R}^{n_v \times d_v}$ are the queries, keys, and values, where the d_* denote dimensions and the n_* denote sequence lengths, $d_q = d_k$, and typically $n_k = n_v$ [16]. Instead of using a single attention head, multiple attention heads are

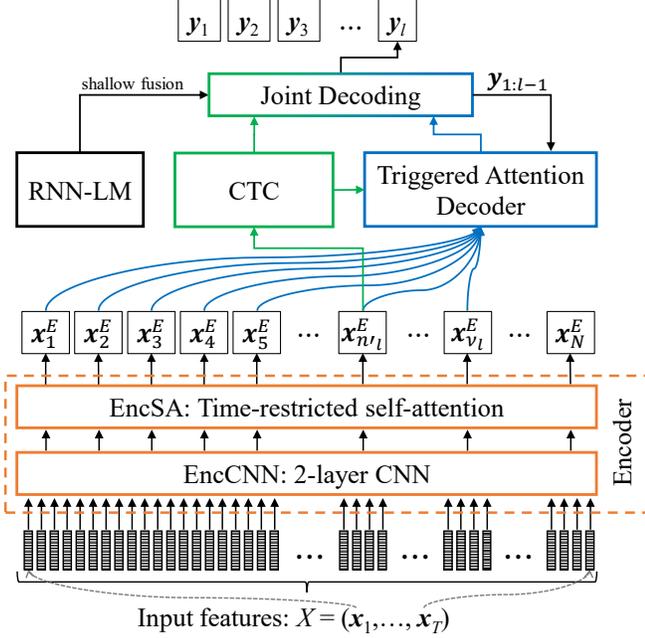


Fig. 1. Joint CTC-TA decoding scheme for streaming ASR with a transformer-based architecture.

used by each layer of the transformer model with

$$\text{MHA}(\hat{Q}, \hat{K}, \hat{V}) = \text{Concat}(\text{Head}_1, \dots, \text{Head}_{d_h})W^H \quad (2)$$

$$\text{and Head}_i = \text{Attention}(\hat{Q}W_i^Q, \hat{K}W_i^K, \hat{V}W_i^V), \quad (3)$$

where \hat{Q} , \hat{K} , and \hat{V} are inputs to the multi head attention (MHA) layer, Head_i represents the output of the i -th attention head for a total number of d_h heads, and $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_q}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ as well as $W^H \in \mathbb{R}^{d_h d_v \times d_{\text{model}}}$ are trainable weight matrices with $d_k = d_v = d_{\text{model}}/d_h$.

2.1. Encoder: Time-restricted self-attention

The encoder of our transformer architecture consists of a two-layer CNN module ENCCNN and a stack of E self-attention layers ENCSA:

$$X_0 = \text{ENCCNN}(X), \quad (4)$$

$$X_E = \text{ENCSA}(X_0), \quad (5)$$

where $X = (\mathbf{x}_1, \dots, \mathbf{x}_T)$ denotes a sequence of acoustic input features, which are 80-dimensional log-mel spectral energies plus 3 extra features for pitch information with its first and second-order derivatives [18]. Both CNN layers of ENCCNN use a stride of size 2, a kernel size of 3×3 , and a ReLU activation function. Thus, the striding reduces the frame rate of output sequence X_0 by a factor of 4 compared to the feature frame rate of X . The ENCSA module of (5) consists of E layers, where the e -th layer, for $e = 1, \dots, E$, is a composite of a multi-head self-attention layer

$$X'_e = X_{e-1} + \text{MHA}_e(X_{e-1}, X_{e-1}, X_{e-1}), \quad (6)$$

and two feed-forward neural networks of inner dimension d_{ff} and outer dimension d_{model} that are separated by a ReLU activation function as follows:

$$X_e = X'_e + \text{FF}_e(X'_e), \quad (7)$$

$$\text{with } \text{FF}_e(X'_e) = \text{ReLU}(X'_e W_{e,1}^{\text{ff}} + b_{e,1}^{\text{ff}}) W_{e,2}^{\text{ff}} + b_{e,2}^{\text{ff}}, \quad (8)$$

where $W_{e,1}^{\text{ff}} \in \mathbb{R}^{d_{\text{model}} \times d_{\text{ff}}}$, $W_{e,2}^{\text{ff}} \in \mathbb{R}^{d_{\text{ff}} \times d_{\text{model}}}$, $b_{e,1}^{\text{ff}} \in \mathbb{R}^{d_{\text{ff}}}$, and $b_{e,2}^{\text{ff}} \in \mathbb{R}^{d_{\text{model}}}$ are trainable weight matrices and bias vectors.

In order to control the latency of the encoder architecture, the future context of input sequence X_0 is limited to a fixed size, which is referred to as restricted or time-restricted self-attention [16] and was first applied to hybrid HMM-based ASR systems [19]. We can define a time-restricted self-attention encoder ENCSA^{tr} , with $n = 1, \dots, N$, as

$$\mathbf{x}_{1:n}^E = \text{ENCSA}^{\text{tr}}(\mathbf{x}_{1:n+\varepsilon^{\text{enc}}}^0), \quad (9)$$

where $\mathbf{x}_{1:n+\varepsilon^{\text{enc}}}^0 = X_0[1:n+\varepsilon^{\text{enc}}] = (\mathbf{x}_1^0, \dots, \mathbf{x}_{n+\varepsilon^{\text{enc}}}^0)$, and ε^{enc} denotes the number of look-ahead frames used by the time-restricted self-attention mechanism.

2.2. Decoder: Triggered attention

The encoder-decoder attention mechanism of the transformer model is using the TA concept [12, 14] to enable the decoder to operate in a streaming fashion. TA training requires an alignment between the encoder state sequence X_E and the label sequence $Y = (y_1, \dots, y_L)$ to condition the attention mechanism of the decoder only on past encoder frames plus a fixed number of look-ahead frames ε^{dec} . This information is generated by forced alignment using an auxiliary CTC objective $p_{\text{ctc}}(Y|X_E)$ [4], which is jointly trained with the decoder model, where the encoder neural network is shared [12, 13, 17].

The triggered attention objective function is defined as

$$p_{\text{ta}}(Y|X_E) = \prod_{l=1}^L p(y_l | \mathbf{y}_{1:l-1}, \mathbf{x}_{1:\nu_l}^E) \quad (10)$$

with $\nu_l = n'_l + \varepsilon^{\text{dec}}$, where n'_l denotes the position of the first occurrence of label y_l in the CTC forced alignment sequence [12, 14], $\mathbf{y}_{1:l-1} = (y_1, \dots, y_{l-1})$, and $\mathbf{x}_{1:\nu_l}^E = (\mathbf{x}_1^E, \dots, \mathbf{x}_{\nu_l}^E)$, which corresponds to the truncated encoder sequence $X_E[1:\nu_l]$. The term $p(y_l | \mathbf{y}_{1:l-1}, \mathbf{x}_{1:\nu_l}^E)$ represents the transformer decoder model, which can be written as

$$p(y_l | \mathbf{y}_{1:l-1}, \mathbf{x}_{1:\nu_l}^E) = \text{DECTA}(\mathbf{x}_{1:\nu_l}^E, \mathbf{y}_{1:l-1}), \quad (11)$$

with

$$Y'_{d,l} = \mathbf{y}_{1:l-1}^{d-1} + \text{MHA}_d^{\text{self}}(\mathbf{y}_{1:l-1}^{d-1}, \mathbf{y}_{1:l-1}^{d-1}, \mathbf{y}_{1:l-1}^{d-1}), \quad (12)$$

$$Y''_{d,l} = Y'_{d,l} + \text{MHA}_d^{\text{dec}}(Y'_{d,l}, \mathbf{x}_{1:\nu_l}^E, \mathbf{x}_{1:\nu_l}^E), \quad (13)$$

$$\mathbf{y}_{1:l-1}^d = Y''_{d,l} + \text{FF}_d(Y''_{d,l}), \quad (14)$$

for $d = 1, \dots, D$ and $Y_0 = Y$, where D denotes the number of transformer layers of the decoder model and $\mathbf{y}_{1:l-1}^0$ is a sequence of embedding vectors obtained from $\mathbf{y}_{1:l-1}$. DECTA finally predicts the posterior probability of label y_l by applying another feed-forward layer to $\mathbf{y}_{1:l-1}^D$ and a softmax distribution over that output.

The CTC model and the triggered attention model of (10) are trained jointly using the multi-objective loss function

$$\mathcal{L} = -\gamma \log p_{\text{ctc}} - (1 - \gamma) \log p_{\text{ta}}, \quad (15)$$

where hyperparameter γ controls the weighting between the two objective functions p_{ctc} and p_{ta} .

2.3. Positional encoding

Positional encodings are added to the input sequences X_0 and Y_0 . The transformer model uses sinusoidal positional encodings of dimension d_{seq} , which is equal to the dimension of input sequences

Algorithm 1 Joint CTC-triggered attention decoding

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1: procedure DECODE( $X_E, p_{\text{ctc}}, \lambda, \alpha_0, \alpha, \beta, K, P, \theta_1, \theta_2$ )
2:    $\ell \leftarrow (\langle \text{sos} \rangle, )$ 
3:    $\Omega \leftarrow \{\ell\}, \Omega_{\text{ta}} \leftarrow \{\ell\}$ 
4:    $p_{\text{nb}}(\ell) \leftarrow 0, p_{\text{b}}(\ell) \leftarrow 1$ 
5:    $p_{\text{ta}}(\ell) \leftarrow 1$ 
6:   for  $n = 1, \dots, N$  do
7:      $\Omega_{\text{ctc}}, p_{\text{nb}}, p_{\text{b}} \leftarrow \text{CTCPREFIX}(p_{\text{ctc}}(n), \Omega, p_{\text{nb}}, p_{\text{b}})$ 
8:     for  $\ell$  in  $\Omega_{\text{ctc}}$  do
9:        $p_{\text{prfx}}(\ell) \leftarrow p_{\text{nb}}(\ell) + p_{\text{b}}(\ell)$ 
10:       $\hat{p}_{\text{prfx}}(\ell) \leftarrow \log p_{\text{prfx}}(\ell) + \alpha_0 \log p_{\text{LM}}(\ell) + \beta|\ell|$ 
11:       $\hat{\Omega} \leftarrow \text{PRUNE}(\Omega_{\text{ctc}}, \hat{p}_{\text{prfx}}, K, \theta_1)$ 
12:      for  $\ell$  in  $\hat{\Omega}$  do ▷ Delete old prefixes in  $\Omega_{\text{ta}}$ 
13:        if  $\ell$  in  $\Omega_{\text{ta}}$  and  $\text{DCOND}(\ell, \hat{\Omega}, p_{\text{ctc}})$  then
14:          delete  $\ell$  in  $\Omega_{\text{ta}}$ 
15:        for  $\ell$  in  $\hat{\Omega}$  do ▷ Compute transformer scores
16:          if  $\ell$  not in  $\Omega_{\text{ta}}$  and  $\text{ACOND}(\ell, \hat{\Omega}, p_{\text{ctc}})$  then
17:             $p_{\text{ta}}(\ell) \leftarrow \text{DECTA}(\mathbf{x}_{1:n+\varepsilon^{\text{dec}}}, \ell)$ 
18:            add  $\ell$  to  $\Omega_{\text{ta}}$ 
19:          for  $\ell$  in  $\hat{\Omega}$  do ▷ Compute joint scores
20:             $\hat{\ell} \leftarrow \ell$  if  $\ell$  in  $\Omega_{\text{ta}}$  else  $\ell_{:-1}$ 
21:             $p \leftarrow \lambda \log p_{\text{prfx}}(\ell) + (1 - \lambda) \log p_{\text{ta}}(\hat{\ell})$ 
22:             $p_{\text{joint}}(\ell) \leftarrow p + \alpha \log p_{\text{LM}}(\ell) + \beta|\ell|$ 
23:             $\Omega \leftarrow \text{MAX}(\hat{\Omega}, p_{\text{joint}}, P)$ 
24:             $\hat{\Omega} \leftarrow \text{PRUNE}(\hat{\Omega}, \hat{p}_{\text{prfx}}, P, \theta_2)$ 
25:             $\Omega \leftarrow \Omega + \hat{\Omega}$ 
26:            remove from  $\Omega_{\text{ta}}$  prefixes rejected due to pruning
27:   return  $\text{MAX}(\hat{\Omega}, p_{\text{joint}}, 1)$ 
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X_0 and Y_0 , and which can be written as

$$\text{PE}(\text{pos}, 2i) = \sin(\text{pos}/10000^{2i/d_{\text{seq}}}), \quad (16)$$

$$\text{PE}(\text{pos}, 2i + 1) = \cos(\text{pos}/10000^{2i/d_{\text{seq}}}), \quad (17)$$

where pos and i are the position and dimension indexes [16].

2.4. Joint CTC-triggered attention decoding

Algorithm 1 shows the frame-synchronous one-pass decoding procedure for joint scoring of the CTC and transformer model outputs, which is similar to the decoding scheme described in [14]. The decoding algorithm is based on the frame-synchronous prefix beam search algorithm of [20], extending it by integrating the triggered attention decoder. The joint hypothesis set Ω and the TA hypothesis set Ω_{ta} are initialized in line 3 with the prefix sequence $\ell = (\langle \text{sos} \rangle,)$, where the symbol $\langle \text{sos} \rangle$ denotes the start of sentence label. The CTC prefix beam search algorithm of [20] maintains two separate probabilities for a prefix ending in blank p_{b} and not ending in blank p_{nb} , which are initialized in line 4. The initial TA scores p_{ta} are defined in line 5.

The frame-by-frame processing of the CTC posterior probability sequence p_{ctc} and the encoder state sequence X_E is shown from line 5 to 26, where $p_{\text{ctc}}(n)$ denotes the CTC posterior probability distribution at frame n . The function CTCPREFIX follows the CTC prefix beam search algorithm described in [20], which extends the set of prefixes Ω using the CTC posterior probabilities p_{ctc} of the current time step n and returns the separate CTC prefix scores p_{b} and p_{nb} as well as the newly proposed set of prefixes Ω_{ctc} . A local pruning threshold of 0.0001 is used by CTCPREFIX to ignore labels of lower CTC probability. Note that no language model or any pruning technique is used by CTCPREFIX, they will be incorporated in the

following steps.

The prefix probabilities p_{prfx} and scores \hat{p}_{prfx} are computed in lines 9 and 10, where p_{LM} represents the language model (LM) probability and $|\ell|$ denotes the length of prefix sequence ℓ without counting the start of sentence label $\langle \text{sos} \rangle$. The function PRUNE prunes the set of CTC prefixes Ω_{ctc} in line 11 in two ways: first, the K most probable prefixes are selected based on \hat{p}_{prfx} , then every prefix of score smaller than $\max(\hat{p}_{\text{prfx}}) - \theta_1$ is discarded, with θ_1 being the beam width. The remaining set of prefixes is stored in $\hat{\Omega}$. From line 12 to 14, prefixes are removed from the set Ω_{ta} if they satisfy a delete condition DCOND, and from line 15 to 18, TA scores are computed by function DECTA if an add condition ACOND returns “true”. The delete and add conditions are used to delete “old” TA scores computed at a non-optimal frame position and to delay the computation of TA scores, if a new CTC prefix appeared at a supposedly too early time frame. The interested reader is referred to [14] for more details on both conditions. Note that our ASR experiments indicated that both conditions could be skipped without any WER degradation for the LibriSpeech task, which uses word-piece output labels, whereas their usage improves WERs for tasks like WSJ [21] with character-level label outputs. Joint CTC-TA scores, computed from line 19 to 22, are used to select the P most probable prefixes for further processing, which are stored in set Ω as shown in line 23. In line 24, the set of CTC prefixes $\hat{\Omega}$ is further pruned to a maximum number of P prefixes with prefix scores within the beam width θ_2 . Line 25 adds the CTC prefix set $\hat{\Omega}$ to the best jointly scored prefix set Ω , and line 26 removes prefixes from Ω_{ta} that are no longer in Ω for the current and last time steps. Finally, DECODE returns the prefix sequence of highest joint probability p_{joint} as shown in line 27.

3. EXPERIMENTS

3.1. Dataset

The LibriSpeech data set, which is a speech corpus of read English audio books [22], is used to benchmark ASR systems presented in this work. LibriSpeech is based on the open-source project LibriVox and provides about 960 hours of training data, 10.7 hours of development data, and 10.5 hours of test data, whereby the development and test data sets are both split into approximately two halves named “clean” and “other”. The separation into clean and other is based on the quality of the recorded utterance, which was assessed using an ASR system [22].

3.2. Settings

Two transformer model sizes are used in this work: *small* and *large*. Parameter settings of the small transformer model are $d_{\text{model}} = 256$, $d_{\text{ff}} = 2048$, $d_h = 4$, $E = 12$, and $D = 6$, whereas the large transformer model uses $d_{\text{model}} = 512$ and $d_h = 8$ instead. The Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$, $\epsilon = 10^{-9}$ and learning rate scheduling similar to [16] is applied for training using 25000 warmup steps. The initial learning rate and the number of training epochs is set to 5.0 and 100 for the small model setup and to 1.0 and 120 for the large model setup [3, 23]. The set of label outputs consists of 5000 subwords obtained by the SentencePiece method [24]. Weight factor γ , which is used to balance the CTC and transformer model objectives during training, is set to 0.3. Layer normalization is applied before and dropout with a rate of 10% after each MHA and FF layer. In addition, label smoothing with a penalty of 0.1 is used [25]. An RNN-based language model (LM) is employed via shallow fusion. The RNN-LM consists of 4 LSTM layers with 2048

Table 1. Word error rates [%] of the full-sequence based CTC-transformer model. Results are shown for joint CTC-attention decoding [13], CTC prefix beam search decoding only [20], and attention beam search decoding only [3]. In addition, results for including the RNN-LM, for using data augmentation [25] as well as for the large transformer setup are shown.

System	CTC-attention dec.				CTC beam search				Att. beam search			
	clean		other		clean		other		clean		other	
	dev	test	dev	test	dev	test	dev	test	dev	test	dev	test
baseline	4.7	4.9	13.0	12.9	6.1	6.1	15.7	15.9	6.0	7.8	14.5	14.9
+RNN-LM	2.9	3.1	8.0	8.4	3.1	3.4	9.3	9.6	4.7	7.2	10.7	11.5
+SpecAug.	2.4	2.8	6.4	6.7	2.9	3.2	7.6	7.9	4.2	5.2	8.3	8.6
+large	2.4	2.7	6.0	6.1	2.5	2.8	6.9	7.0	4.1	5.0	7.9	8.0

units each trained using stochastic gradient descent and the official LM training text data of LibriSpeech [22].

The LM weight, CTC weight, and beam size of the full-sequence based joint CTC-attention decoding method are set to 0.7, 0.5, and 20 for the small transformer model and to 0.6, 0.4, and 30 for the large model setup. The parameter settings for CTC prefix beam search decoding [20] are LM weight $\alpha_0 = 0.7$, pruning beam width $\theta_1 = 14.0$, insertion bonus $\beta = 2.0$, and pruning size $K = 30$. Parameters for joint CTC-TA decoding are CTC weight $\lambda = 0.5$, CTC LM weight $\alpha_0 = 0.7$, LM weight $\alpha = 0.5$, pruning beam width $\theta_1 = 16.0$, pruning beam width $\theta_2 = 6.0$, insertion bonus $\beta = 2.0$, pruning size $K = 200$, and pruning size $P = 40$. All decoding hyperparameter settings are optimized using the development data sets of LibriSpeech.

3.3. Results

Table 1 presents ASR results of the baseline transformer system, which is jointly trained with CTC to optimize training convergence and ASR accuracy [3, 13]. Results of different decoding methods are shown with and without using the RNN-LM and the multi-condition training method SpecAugment [25]. In addition, results of the *large* transformer model are shown. Table 1 demonstrates that joint CTC-attention decoding provides the best ASR results among all three decoding methods. CTC prefix beam search decoding attains lower WERs compared to attention beam search decoding alone, except for the dev-clean, dev-other, and test-other conditions when no LM is used. For attention beam search decoding only when an RNN-LM is used, log posterior probabilities are normalized by the output hypothesis length in order to compensate for a different log probability scaling of the transformer and the LM model [17]. Still it seems to be more difficult to combine LM and transformer scores if the CTC output is not used, which may explain why our attention beam search decoding results are worse compared to the CTC prefix beam search results.

Table 2 shows WERs of full-sequence and time-restricted self-attention encoder architectures combined with the offline (full-sequence) joint CTC-attention decoding method of [13, 17], the frame-synchronous CTC prefix beam search decoding method of [20], and our joint one-pass CTC-TA decoding method of Section 2.4. Results of the full-sequence based self-attention encoder demonstrate that our streaming CTC-TA decoder with 6 look-ahead encoder frames (corresponding to $6 \cdot 40 \text{ ms} = 240 \text{ ms}$), which was optimized using the development data sets of LibriSpeech, only increases WERs on average by 0.125% compared to the full-sequence CTC-attention decoder. In addition, joint CTC-TA decod-

Table 2. Word error rates [%] of the full-sequence and time-restricted encoder architectures coupled with the offline (full-sequence) CTC-attention decoding method of [13], the CTC prefix beam search decoding method of [20], and the streaming CTC-TA decoding method of Section 2.4. The TA-based decoder is using $\varepsilon^{\text{dec}} = 6$ look-ahead frames. SpecAugment [25] and the RNN-LM are applied for all systems as well as the large transformer setup.

Encoder	CTC-attention dec.				CTC beam search				CTC-TA dec.			
	clean		other		clean		other		clean		other	
	dev	test	dev	test	dev	test	dev	test	dev	test	dev	test
Full-seq.	2.4	2.7	6.0	6.1	2.5	2.8	6.9	7.0	2.4	2.7	6.2	6.4
$\varepsilon^{\text{enc}} = 4$	2.3	2.6	6.4	6.6	2.8	2.9	7.8	7.9	2.7	2.9	7.2	7.3
$\varepsilon^{\text{enc}} = 8$	2.3	2.5	6.4	6.3	2.6	2.8	7.5	7.5	2.6	2.7	7.0	7.0
$\varepsilon^{\text{enc}} = 12$	2.3	2.5	6.2	6.3	2.8	2.9	7.4	7.4	2.6	2.8	7.0	7.1
$\varepsilon^{\text{enc}} = 16$	2.3	2.5	6.2	6.3	2.7	2.8	7.3	7.4	2.6	2.7	6.7	6.9

ing outperforms CTC prefix beam search decoding, which are both frame-synchronous decoding methods suitable for streaming ASR.

Different settings of the time-restricted self-attention encoder architecture are compared in Table 2 using $\varepsilon^{\text{enc}} = 4, 8, 12$, and 16 look-ahead frames, which refers to input sequence X_0 whose frame rate is 40 ms. Thus, the output latency of the time-restricted self-attention encoder is limited to 160 ms, 320 ms, 480 ms, and 640 ms, respectively. It can be noticed that restricting the future context of the self-attention encoder mainly increases WERs for the dev-other and test-other conditions, whereby such WER increase seems to be larger for streaming decoding than for offline decoding, i.e., full-sequence based encoder-decoder attention can compensate to some extent the limited future context of the encoder. However, WERs only keep improving slowly for encoder look-ahead values larger than 8, and thus $\varepsilon^{\text{enc}} = 8$ provides the best trade-off between latency and ASR accuracy. This context size also correlates well with findings on amplitude modulation analysis for ASR [26]. The best fully streaming ASR system of Table 2 for $\varepsilon^{\text{enc}} = 8$ achieves 2.7% and 7.0% WER for the test-clean and test-other conditions of LibriSpeech, while the overall processing delay is limited to 30 ms (ENCCNN) + $8 \cdot 40 \text{ ms}$ (ENCSSA) + $6 \cdot 40 \text{ ms}$ (TA decoder) = 590 ms.

4. CONCLUSIONS

In this paper, a fully streaming end-to-end ASR system based on the transformer architecture is proposed. Time-restricted self-attention is applied to control the latency of the transformer encoder and the triggered attention (TA) concept to control the output latency of the encoder-decoder attention mechanism. For streaming recognition and joint CTC-transformer model scoring, a frame-synchronous one-pass decoding algorithm is applied, which demonstrated similar LibriSpeech ASR results compared to full-sequence based CTC-attention decoding for the test-clean condition and a small WER increase of 0.3% for the test-other condition. Combined with the time-restricted self-attention encoder architecture, our proposed triggered attention based streaming ASR system achieved WERs of 2.7% and 7.0% for the test-clean and test-other data sets of LibriSpeech, which to our knowledge is the best published LibriSpeech result of a fully streaming end-to-end ASR system. The total processing latency of the proposed system architecture is limited to 590 ms, whereby 350 ms delay are caused by the time-restricted self-attention encoder and 240 ms by the triggered attention based decoder.

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