

RUN-AND-BACK STITCH SEARCH: NOVEL BLOCK SYNCHRONOUS DECODING FOR STREAMING ENCODER-DECODER ASR

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ABSTRACT

A streaming style inference of encoder–decoder automatic speech recognition (ASR) systems is important for reducing latency, which is essential for interactive use cases. To this end, we propose a novel blockwise synchronous decoding algorithm with a hybrid approach that combines endpoint prediction and endpoint post-determination. In the endpoint prediction, we compute the expectation of the number of tokens that are yet to be emitted in the encoder features of the current blocks using the CTC posterior. Based on the expectation value, the decoder predicts the endpoint to realize continuous block synchronization, as a *running stitch*. Meanwhile, endpoint post-determination probabilistically detects backward jump of the source–target attention, which is caused by the misprediction of endpoints. Then it resumes decoding by discarding those hypotheses, as *back stitch*. We combine these methods into a hybrid approach, namely *run-and-back stitch search*, which reduces the computational cost and latency. Evaluations of various ASR tasks show the efficiency of our proposed decoding algorithm, which achieves a latency reduction, for instance in the Librispeech test set from 1487 ms to 821 ms at the 90th percentile, while maintaining a high recognition accuracy.

Index Terms— Streaming automatic speech recognition (ASR), encoder–decoder, end-to-end, Transformer, CTC

1. INTRODUCTION

In recent years, end-to-end automatic speech recognition (ASR) has garnered significant attention. For interactive use cases in particular, streaming style inference is essential; thus, several approaches have been discovered for both the encoder–decoder (Enc–Dec) [1, 2, 3] and transducer models [4, 5]. Blockwise processing can be easily introduced to the encoders of both models [6, 7, 8, 9, 10]. Although transducers are efficient for streaming ASR owing to frame-synchronous decoding, they are less accurate than Enc–Dec [11] and Enc–Dec can be used additionally to achieve higher performance [12]. However, during blockwise Enc–Dec inference, it is still challenging for the decoder to know when to stop decoding, that is, endpoints with limited encoder features in the currently given blocks.

Several studies on streaming Enc–Dec ASR have introduced additional training or modules to predict endpoints. By predicting endpoints, the decoder realizes continuous block synchronization with the encoder, which we refer to as the *running stitch* approach. Monotonic chunkwise attention (MoChA) [13] is a popular approach for achieving online processing [6, 14, 15]. However, it makes training complicated and sometimes degrades accuracy [14, 15]. A triggered attention mechanism [7] and its modification with a scout network [16] are further methods for predicting the endpoints, but they also require additional modules in the network and training criteria.

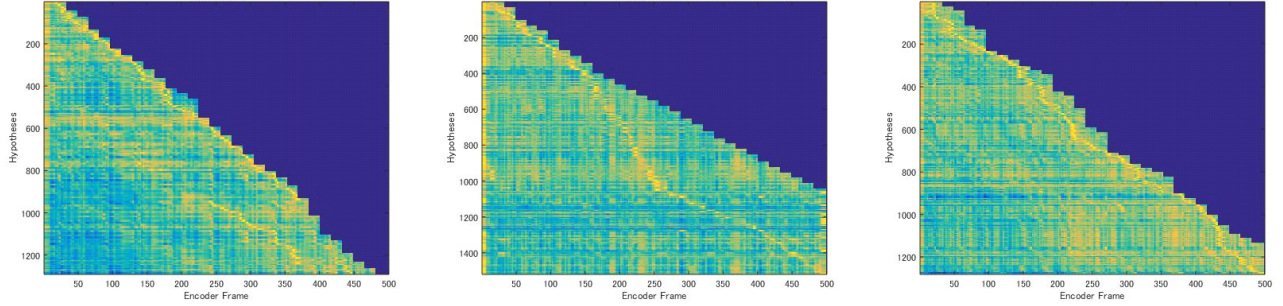
As an alternative approach, block synchronization with the encoder can also be established by examining the tendency of hypotheses that exceed the endpoint [17, 18]. If an exceeded hypothesis is detected, the decoder turns back to the previous hypotheses and restarts the beam search with the subsequent encoder features, which we refer to as a *back stitch* approach. Tian et. al. trained the model to emit $\langle \text{eos} \rangle$ tokens when the decoder exceeded endpoints [17]. In our previous work, we revealed that detecting only $\langle \text{eos} \rangle$ is insufficient for some ASR tasks, and showed that it is also necessary to detect repeated tokens during decoding [18]. This method achieved better performance than most *running-stitch* approaches, and it did not require any additional training. However, hypotheses might be discarded during decoding and latency can become large, particularly for long utterances because there are real token repetitions.

In this study, we propose a novel blockwise synchronous decoding algorithm that does not require any additional training, with a hybrid approach combining endpoint prediction and endpoint post-determination, namely the *run-and-back stitch* (RABS) search. To realize endpoint prediction, the CTC posterior and source–target (ST) attention of the decoder within the CTC/attention framework [3] are used. We compute the expectation of the number of tokens to be emitted in the current encoder output blocks to predict the endpoint. We recover a possible misprediction of this endpoint using the post-determination approach. To achieve this, we explicitly compute the probability of a backward jump in the ST attention to improve on our previous repeated phrase detection. By combining the *running stitch* and *backward stitch* in the hybrid RABS search, we can reduce the computational cost and latency. Experiments on the Librispeech English, AISHELL-1 Mandarin, and CSJ Japanese tasks demonstrate that the proposed RABS search achieves a reduction in latency without significant degradation in word error rates (WERs). We particularly reduce the 90th percentile latency, in the Librispeech test set for instance, from 1487 ms to 821 ms.

2. STREAMING ENCODER-DECODER ASR

To realize a streaming Enc–Dec ASR system, both the encoder and decoder must be processed online synchronously. A simple way to process the encoder online is through blockwise computation, as in [6, 7, 8]. However, the global channel, speaker, and linguistic context are also important for local phoneme classification. Therefore, a context inheritance mechanism for block processing was proposed in [9, 10] by introducing an additional context embedding vector in the encoder. Thus, the encoder sequentially computes encoded features $\mathbf{h}_{1:T_b}$ from the currently given b block input $\mathbf{x}_{1:T_b}$.

The synchronous decoding in this work bases on the Transformer architecture proposed in [18]. The decoder predicts the probability of the subsequent character from the previous output



(a) ST attention of *running stitch* search. The decoder repeats a sequence after approximately hypothesis 900.

(b) ST attention of block synchronous beam search. The decoder struggles after approximately hypothesis 400, whereas the encoder proceeds forward.

(c) ST attention of *run-and-back stitch* search. The attention is synchronously aligned to the blockwise encoder.

Fig. 1: Examples of ST attentions.

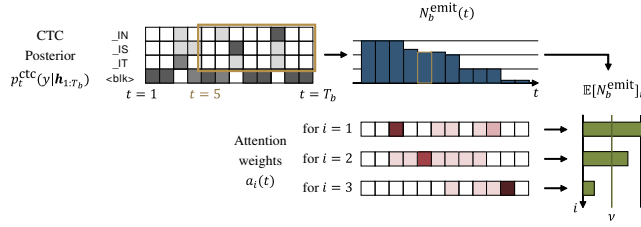


Fig. 2: Endpoint prediction by expecting the number of tokens in the encoded features using a CTC posterior and a ST attention.

characters $\mathbf{y}_{0:i-1}$ and the current encoder output blocks $\mathbf{h}_{1:T_b}$, as

$$p(y_i | \mathbf{y}_{0:i-1}, \mathbf{h}_{1:T_b}) = \text{Dec}(\mathbf{y}_{0:i-1}, \mathbf{h}_{1:T_b}). \quad (1)$$

Self-attention in the decoder attends to the output history, $\mathbf{y}_{0:i-1}$, and the subsequent ST attention is directed to the encoder output sequence, $\mathbf{h}_{1:T_b}$. In addition to the Enc-Dec Transformer, a linear layer is added to the encoder to project $\mathbf{h}_{1:T_b}$ onto the token probability for CTC, which is jointly trained as in [3].

3. RABS DECODING SEARCH

3.1. Running stitch approach: endpoint prediction with CTC posterior

Endpoint prediction realizes continuous and efficient block synchronization. It would be a trivial problem to predict endpoints if the system knows the number of tokens to be emitted from the given limited partial encoder features; the decoder should only stop after a specific number of tokens are decoded. However, because the length of the input sequence and that of the output sequence differ and depend on token granularity, the number of tokens in the encoded features is unknown. Although most studies introduce an additional endpoint predictor into the ASR model [6, 7, 13], we predict endpoints without additional training or modules, within the standard CTC/attention architecture. We compute an expectation value of the number of tokens following the currently attending time frame in the currently given encoded blocks. The expectation value is calculated by combining a CTC posterior and an ST attention.

CTC computes a frame-wise token emission posterior, including a blank label. Let $p_t^{\text{ctc}}(y | \mathbf{h}_{1:T_b})$ be a CTC posterior of frame t given

encoded block $\mathbf{h}_{1:T_b}$, as shown in Fig. 2. In CTC, the same consecutive tokens are merged, and only the tokens transiting from the other tokens or the blank token are counted. Because the probability of the previous token not being y is $1 - p_{t-1}^{\text{ctc}}(y | \mathbf{h}_{1:T_b})$, the probability of emitting token y in frame t is described as follows:

$$e_y(t) = (1 - p_{t-1}^{\text{ctc}}(y | \mathbf{h}_{1:T_b})) \cdot p_t^{\text{ctc}}(y | \mathbf{h}_{1:T_b}) \quad (2)$$

Let $N_b^{\text{emit}}(t)$ be the remaining number of all the tokens except for the blank to be emitted from the encoded features $\mathbf{h}_{1:T_b}$ after frame t . The number can be expressed as an accumulation of the token emission probability (2) as follows:

$$N_b^{\text{emit}}(t) = \sum_{\tau=1}^{T_b-t} \sum_{y \neq \langle \text{blk} \rangle} e_y(t + \tau) \quad (3)$$

In the case of Fig. 2, to compute the number of tokens after $t = 5$, all the posterior except for the blank in the yellow box is accumulated for $N_b^{\text{emit}}(t = 5)$. $N_b^{\text{emit}}(t)$ is shown as the blue graph in Fig. 2.

We use ST attention to know the time frame currently attended to. An averaged attention weight for the current hypothesis can be computed from ST attention as follows:

$$a_i(t) = \sum_{m=1}^M \text{softmax} \left(\frac{q_{m,i-1} k_{m,t}}{\sqrt{d}} \right), \quad (4)$$

where $q_{m,i-1}$ denotes the query value of the last output in the hypothesis, y_{i-1} , $k_{m,t}$ is the key value of encoded frame t and of multi-head m of M heads, and d is the dimensionality of both vectors. In Transformer, the ST attention of each head is not always monotonic or aligned, because of the multi-head and residual connections. However, empirically, we found that the ST attention of the last decoder layer tends to be monotonic. Thus, we compute the expectation of the remaining number of tokens after currently attending time frame as follows:

$$\mathbb{E}[N_b^{\text{emit}}]_i = \sum_{t=1}^{T_b} a_i(t) N_b^{\text{emit}}(t) \quad (5)$$

As shown as the green graph in Fig. 2, the expectation values $\mathbb{E}[N_b^{\text{emit}}]_i$ decrease step by step. If $\mathbb{E}[N_b^{\text{emit}}]_i$ is less than the pre-defined threshold ν , we assume that current decoding step i reaches an endpoint of the current b blocks, and the decoder stops until the encoder outputs the next block $\mathbf{h}_{T_b+1:T_{b+1}}$.

3.2. Back stitch approach: endpoint post-determination

3.2.1. Block synchronous beam search

CTC and ST attention are not explicitly trained to be aligned; thus, the aforementioned endpoint prediction can cause some errors. Fig. 1a shows an example of ST attention of endpoint prediction search. The horizontal axis denotes the encoder frame and the vertical axis indicates the hypothesis number. In the earlier hypotheses, the decoder uses only the limited encoded features, e.g., $\mathbf{h}_{1:T_5} = \mathbf{h}_{1:96}$ for hypothesis 200. In this example, the ST attention jumps back and the decoder repeats a sequence after approximately hypothesis 900. The endpoint post-determination can recover such error. For this purpose, block synchronous (BS) beam search [18] can be applied, in which the repeated tokens are considered as well as $\langle \text{eos} \rangle$ to evaluate the excess of the endpoints. Detecting such tokens in the hypotheses is regarded as signs of exceeding the endpoint, and thus, we discard the hypotheses containing such tokens and resume decoding after the next block is encoded.

Fig. 1b shows an example of ST attention in the BS search, which shows another problem caused by repeated token detection. The decoder struggles after hypothesis 400, whereas the encoder proceeds forward. After the encoder reaches the end of the utterance at approximately hypothesis 1000, the decoder consumes all the remaining encoded features, which adversely impacts the latency. This particularly occurs in long utterances because there are several real token repetitions, which make the decoder discard hypotheses falsely and be left behind by the encoder. In this study, we improve the BS search by explicitly evaluating ST attention to find the back-jump phenomenon in Fig. 1a.

3.2.2. Attention back jump detection

When the back-jump phenomenon occurs, the peak of the current ST attention focuses on encoder features prior to the last decoded hypothesis. Thus, the probability of the attention back jump, $p_{i,b}^{\text{jump}}$, is calculated by accumulating all the ST attention that is concentrated behind the previous attention, as follows.

$$p_{i,b}^{\text{jump}} = \sum_{t=1}^{T_b} a_i(t) \left(\sum_{\tau=1}^{T_b-t} a_{i-1}(t+\tau) \right) \quad (6)$$

If the back jump probability is greater than a threshold, that is, $p_{i,b}^{\text{jump}} > v$, the current hypotheses ending with y_i are regarded as a repeated sequence and discarded. The decoder stops until the next block $\mathbf{h}_{T_b+1:T_{b+1}}$ is encoded.

3.3. Hybrid RABS beam search

To realize efficient yet accurate ASR decoding, we propose to combine the endpoint predictor using CTC posterior and the endpoint post-determination with attention back jump detection. The proposed hybrid beam search algorithm, namely RABS search, is summarized in Algorithm 1. In every beam search step, first, $\langle \text{eos} \rangle$ and back jump probability of ST attention are evaluated in the current hypotheses (line 6). If $\langle \text{eos} \rangle$ is found in the hypotheses or $p_{i,b}^{\text{jump}} > v$, the decoder is considered to exceed the endpoint and stops decoding until the next block $\mathbf{h}_{T_b+1:T_{b+1}}$ to be encoded. Subsequently, endpoint prediction is performed by evaluating the expectation of the remaining number of tokens to be emitted, as in (5), with a CTC posterior and a ST attention (line 14). An example of ST attention in the proposed RABS search is shown in Fig. 1c in which the attention of the decoder proceeds synchronously with the encoder.

Algorithm 1 Hybrid run-and-back stitch beam search

Input: encoder feature blocks \mathbf{h} , total block number B , beam width K , max output length I_{\max}

Output: $\hat{\Omega}$: complete hypotheses

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1: Initialize:  $y_0 \leftarrow \langle \text{sos} \rangle$ ,  $\Omega_0 \leftarrow \{y_0\}$ ,  $b \leftarrow 1$ ,  $i \leftarrow 1$ 
2: while  $b < B$  do
3:    $\text{NextBlock} \leftarrow \text{false}$ 
4:    $\Omega_i \leftarrow \text{Search}_K(\Omega_{i-1}, \mathbf{h}_{1:T_b})$ 
5:   for  $y_{0:i} \in \Omega_i$  do
6:     if  $y_i = \langle \text{eos} \rangle$  or  $p_{i,b}^{\text{jump}} > v$  then ▷ back-stitch search
7:        $\text{NextBlock} \leftarrow \text{true}$ 
8:     end if
9:   end for
10:  if  $\text{NextBlock}$  then
11:     $b \leftarrow b + 1$  ▷ discard current hypotheses and wait for the next block
12:  else
13:    if  $\mathbb{E}[N_b^{\text{emit}}]_i < \nu$  then ▷ running-stitch search
14:       $b \leftarrow b + 1$  ▷ wait for the next block
15:    end if
16:     $i \leftarrow i + 1$ 
17:  end if
18: end while
19: while  $i < I_{\max}$  unless  $\text{EndingCriterion}(\Omega_{i-1})$  do ▷ ordinary
20:   decoding follows to obtain  $\hat{\Omega}$  after  $b = B$ 
21:    $\Omega_i \leftarrow \text{Search}_K(\Omega_{i-1}, \mathbf{h}_{1:T_B})$ 
22:   for  $y_{0:i} \in \Omega_i$  do
23:     if  $y_i = \langle \text{eos} \rangle$  then
24:        $\hat{\Omega} \leftarrow \hat{\Omega} \cup y_{0:i}$ 
25:     end if
26:   end for
27: end while
28: return  $\hat{\Omega}$ 

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4. EXPERIMENTS

4.1. Experimental Setup

We conducted experiments using the English LibriSpeech dataset [21], AISHELL-1 [22] Mandarin tasks, and the Japanese CSJ dataset [23]. The input acoustic features were 80-dimensional filter bank features and the pitch. Regular, small, and large models were trained using multitask learning with CTC loss as in [3] with a weight of 0.3. We used the Adam optimizer and Noam learning rate decay, and applied SpecAugment [24].

We adopted contextual block processing with a Transformer encoder, following [18]. For the regular and small models, we trained a 12-layer encoder with 2048 units, $d = 256$ of the hidden dimension size, and $M = 4$ multihead attention. The large model was trained with $d = 512$ and $M = 8$ and used HuBERT [25] features¹ pretrained on Libri-light [26].

The decoder had six layers with 2048 units for the regular and large models, and two layers for the small model. The parameters for the ordinary (batch) decoder were directly used in the proposed hybrid RABS algorithm of the decoder. We set the parameters for the RABS search as $\nu = 1.0$ and $v = 0.5$.

The real-time factor (RTF) and latency were measured with our implementation of the proposed search algorithm in C++, using a subset of each task with a beam size of 10. We only evaluated regular and small models because we did not implement the large model with HuBERT in C++. We adopted EP latency, following [20], which is the time required to emit $\langle \text{eos} \rangle$ token after the end of each utterance. The 50th and 90th percentile latencies are shown.

¹We used causal features for decoding.

Table 1: WERs and computation efficiency in the LibriSpeech task. (*: There is no description of the beam size in the literature. †: The EPs were evaluated on a different dataset and by simulation without considering computation time.)

	Beam 30		Beam 10		RTF	Latency		Avg. last steps
	test-clean	test-other	test-clean	test-other		EP50	EP90	
Triggered Attention [7]	2.8	7.3	—	—	—	—	—	—
HS-DACS [19]	2.7	6.6	—	—	—	—	—	—
Scout Network [16]	—	—	2.7	6.4	—	—	—	—
Emformer Transducer (pretrained in hybrid ASR) [10]	—	—	2.4*	6.1*	—	—	—	—
FastEmit Conformer Transducer [20]	—	—	3.5*	9.1*	—	290 [†] ms	660 [†] ms	—
Regular model (6-layer decoder with $d = 256$ and $M = 4$)								
BS-Dec [18]	2.7	7.1	3.0	7.7	0.25	552 ms	1487 ms	7.95
Running-stitch search (Sec. 3.1)	3.0	7.7	3.3	8.5	0.24	349 ms	508 ms	3.09
Back-stitch search (Sec. 3.2)	2.7	7.1	3.0	7.7	0.25	497 ms	919 ms	5.22
RABS search (proposed)	2.8	7.2	3.0	7.8	0.24	491 ms	821 ms	4.71
Small model (2-layer decoder with $d = 256$ and $M = 4$)								
BS-Dec [18]	2.9	7.5	3.4	8.4	0.15	341 ms	857 ms	8.29
RABS search (proposed)	3.0	7.6	3.4	8.3	0.14	246 ms	354 ms	3.25
Large model (6-layer decoder with $d = 512$ and $M = 8$)								
HuBERT BS-Dec + Transformer LM	2.2	4.3	2.2	4.4	—	—	—	12.28
HuBERT RABS search + Transformer LM (proposed)	2.2	4.3	2.3	4.5	—	—	—	1.52

Table 2: CERs and latency in the AISHELL-1 task

	Dev	Test	EP50	EP90
RNN-T [27]	10.1	11.8	—	—
Sync-Transformer (6-layer) [17]	7.9	8.9	—	—
HS-DACS [19]	6.2	6.8	—	—
BS-Dec [18]	5.8	6.4	439 ms	570 ms
RABS search (proposed)	5.8	6.4	326 ms	471 ms

Table 3: CERs and latency in the CSJ task

	eval 1	eval 2	eval 3	EP50	EP90
BS-Dec [18]	5.5	4.2	4.7	978 ms	2616 ms
RABS search (proposed)	5.6	4.2	4.7	582 ms	1079 ms

The RTF and latency were measured with an 8 core 3.60 GHz Intel i9-9900K processor.

4.2. Librispeech English results

For LibriSpeech, we adopted the byte-pair encoding subword tokenization [28], which has 5000 token classes. A language model (LM) of a four-layer LSTM with 2048 units was fused with a weight of 0.6 for the regular and small models. For the large model, a 16-layer Transformer LM was fused as in [18]. CTC weight was set as 0.4. We compare WERs with a beam size of 30 and that of 10. The running-stitch approach described in Sec. 3.1, the back-stitch approach described in Sec. 3.2, and their combination, that is, RABS search (Sec. 3.3), were compared with our previous BS search [18].

We also evaluated the average number of last decoding steps after the encoder reached the utterance end, that is, the number of steps after line 19 in Algorithm 1. We desire as few decoding steps as possible, but if the encoder and decoder are not sufficiently synchronous, as shown in Fig. 1b, the value increases.

The results are listed in Table 1 along with other streaming approaches with a larger number of parameters [7, 10, 16, 19, 20]. The results of the regular models show that the running-stitch search is efficient as RTF and latency decreased, particularly at EP90. However, WERs increased owing to the CTC posterior and ST attention misalignment. Back-stitch search successfully decreased the average number of last steps, by replacing repeated token detection with the proposed attention back jump probability while maintaining the WERs of BS search. With the RABS search, we observed a WER re-

duction compared with the running-stitch search because it successfully recovered the error by the back-stitch approach. In addition, the latency of RABS search improved over the back-stitch search, and the EP90 latency decreased compared with BS search, from 1487 ms to 821 ms. The same tendency can be found in the small model. In particular, the 10-beam RABS search with the small model was faster and more accurate than the FastEmit transducer [20]. We also confirmed that our proposed approach can be applied to the large model with HuBERT features, which drastically reduced the number of last steps without significant WER degradation.

4.3. AISHELL-1 Mandarin and CSJ Japanese results

We used the regular model architectures for AISHELL-1 Mandarin and CSJ Japanese tasks to confirm the effectiveness of our proposed method in other languages, i.e., in various token granularity. For the Mandarin task, 4231 character classes were used with parameters {CTC weight, beam width, LM weight} = {0.5, 10, 0.7}. For CSJ, the dataset had 3260 Japanese character classes, and parameters were set as {CTC weight, beam width, LM weight} = {0.3, 10, 0.3}. We used an external two-layer LSTM LM with 650 units for each tasks.

The results for AISHELL-1 are summarized in Table 2 and for CSJ are in Table 3. We observed a similar tendency as on LibriSpeech; the proposed RABS search reduced latency while WERs were maintained. In the Mandarin task, we achieved better performance compared to other streaming methods, such as head-synchronous decoding (HS-DACS) [19]. We confirmed that our proposed method is consistently effective in various languages.

5. CONCLUSION

We have proposed a novel blockwise synchronous decoding algorithm for Enc-Dec ASR, called RABS search, which is a hybrid approach combining endpoint prediction and endpoint post-determination. In the endpoint prediction, the expectation of the number of tokens that are yet to be emitted in the encoder features of currently given blocks is calculated. The endpoint post-determination recovers errors from endpoint misprediction, by computing backward jump probability of the ST attention. The RABS search successfully combined the advantages of both, reducing the computational cost and latency, and maintaining accuracy at the same time.

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