Exploring Continuous Integrate-and-Fire for Efficient and Adaptive Simultaneous Speech Translation

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Abstract

Simultaneous speech translation (SimulST) is a challenging task that aims to directly translate streaming speech before the complete input is observed. A SimulST system generally includes two important components: the pre-decision that aggregates the speech information, and the policy that decides read or write. While recent works had proposed a variety of strategies to improve the pre-decision, they mostly adopt the fixed wait-k policy. The adaptive policies are rarely explored. We propose to model the adaptive policy using the Continuous Integrate-and-Fire (CIF). In our proposed model, the CIF is not only responsible for aggregating speech information, but also deciding when to read or write. To adapt the CIF to SimulST task, we propose two modifications: a token-level quantity loss or an infinite lookback attention. We show that our model can learn an adaptive policy effectively, achieving comparable or superior performance to MMA at lower latency, while being more efficient to train.

Index Terms: simultaneous speech translation, streaming, continuous integrate-and-fire, online sequence-to-sequence model, end-to-end model

1. Introduction

Simultaneous translation is a task that performs translation in a streaming fashion. It requires producing translation of partial input before the complete input is observed. It is a challenging task because it needs to take reordering between languages into account. In order to achieve the best trade off between latency and quality, a simultaneous translation system needs to decide at each timestep whether to read more input or write a new token. This decision can follow either a fixed policy [1] or a flexible (adaptive) policy [2]. Typically, a simultaneous machine translation (SimulMT) system is cascaded with a streaming speech recognition (ASR) to form a system for practical applications such as international conferences.

End-to-end simultaneous speech translation (SimulST) aims to directly perform simultaneous translation on the speech input. Compared to cascaded SimulMT, end-to-end methods avoid error propagation [3] and are faster thanks to a unified model. However, it faces more challenge like acoustically ambiguous inputs or variable speech rate. Because speech input may be too fine-grained for policies to be learned, the pre-decision was introduced [5]. The pre-decision segments the speech based on fixed chunks (fixed) or word boundaries (flexible), before read-write policies are applied. Most research on SimulST improves the speech encoding or the pre-decision, while adopting the fixed policy [6, 7, 8, 9, 10, 11]. To our best knowledge, the only exceptions are the monotonic multthead attention (MMA) with pre-decision [12, 13], or the Cross Attention Augmented Transducer (CAAT) [14].

In this paper, we explore the Continuous Integrate-and-Fire (CIF) [14] for another adaptive policy (Figure 1). Similar to connectionist temporal classification (CTC) [15] or the MMA, the CIF is also a monotonic alignment method. During training, the MMA requires the cumulative product function, which is hard to maintain stability. Besides, it requires marginalizing out the alignment at each decoder layer, which is time consuming. In comparison, the CIF is realized by addition and weighted sum. These primitive operations are both faster and more stable to compute. In addition, while the MMA makes read-write decisions at every pre-decision, the CIF can make write decisions at a level finer than frames, thanks to its soft alignment mechanism. This means the CIF has potentially lower latency than the MMA.

We proposed two modification to the CIF to improve its performance on SimulST. First, we improve the the quantity loss [14] by extending it to a token-level objective. It leverages the forced alignment from an auxiliary CTC prediction head. Second, we explore having the decoder attend to past CIF integration states to allow explicit reordering. Experiments show that our models achieve competitive results to the MMA on lower latency, while being simpler to compute.

2. Related Works

2.1. Continuous Integrate-and-Fire

The CIF was proposed for ASR to learn the “soft” acoustic boundaries [16]. Compared against the standard Transformer [16], it exhibited several desirable traits: (1) It is faster due to its linear computation complexity. (2) It is more robust
to long or noisy utterances [17]. Due to its ability to integrate longer sequence into shorter one, the CIF can also be used to bridge the gap between pretrained acoustic and linguistic representations [18]. In UniST [11], the CIF is leveraged to integrate the speech features into the length of the source transcription, in order to feed into the semantic encoder. Our work differs from previous works in that we leverage CIF to learn the adaptive policy of SimulST. We do not use the transcription when training translation models.

2.2. End-to-End Simultaneous Speech Translation

In recent years, several works had focused on improving the speech encoding and the pre-decision process. [6] mitigated the boundary effect of streaming speech on the VGG pre-net for ULSTM encoder. SimulSpeech [7] used CTC for pre-decision, and used multi-task learning and knowledge distillation to improve the performance. [5] introduced fixed pre-decision and flexible pre-decision via oracle word boundary. [8] adopted the Augmented Memory Transformer (AM-TRF) as the streaming encoder. [9] proposed to use a streaming ASR as a flexible pre-decision. RealTranS [10] used CTC to shrink the speech, followed by a semantic encoder to improve encoding. UnitST [11] used self-supervised representation for speech encoder, and used CIF to shrink the speech into source words, also followed by a semantic encoder. All these works adopted the wait-k or similar fixed policies.

On the other hand, adaptive policies has rarely been explored for speech. [5] explored MMA for its decoder. CAAT [13] augmented the RNN-T [19] with cross-attention to have a more complex joiner capable of reordering. Our work introduce a new adaptive policy learned using the CIF. We compare our results with that of the MMA.

3. Method

Figure 2 demonstrates the overall architecture of our CIF-based SimulST model. We describe each components here.

3.1. Streaming Speech Encoder

The speech encoder consists of a feature extractor, a positional encoding and a stack of Emformer [20] layers. We use the feature extractor from fairseq-S2T toolkit [21]. For positional encoding, we use a temporal convolution to capture relative positional information [22]. The Emformer is a block processing Transformer suitable for streaming. Each block has access to its main context, left context, right context and a memory bank. During training, the effect of block processing is achieved by using an attention mask and right-context hard copy trick. During inference, the input will be processed block by block with overlapping context, and the computational complexity of each block is constant.

3.2. Monotonic Alignment via CIF

In SimulST, monotonic attention is used to model the boundaries of read-write decisions. In this work, we use the CIF mechanism to find the position of the write actions.

Suppose the target sequence is \( y_1, y_2, \ldots, y_T \). The speech encoder produces a sequence of hidden states \( h_1, h_2, \ldots, h_T \). At each encoder step \( i \in [1, T] \), we first use a weight prediction network to predict \( \alpha_i \). Then, the CIF pushes the current encoder state \( h_i \) and its weight \( \alpha_i \) into a accumulation buffer. At this point, two possible things can occur. If the accumulated weight has yet to reach the threshold \( \beta \), the CIF simply proceed to the next encoder step \( i+1 \). Otherwise, it means a boundary is located. Thus, the CIF will divide the current weight into two parts (see Figure 2): (1) the left one will fulfill the integration of the current embedding \( c_j \), (2) the other is carried over to the next integration. The \( j \)-th integration \( (c_j) \) is fulfilled by taking the weighted sum of all \( h_i \)'s currently in the accumulation buffer, using their corresponding weight in the buffer. Then \( c_j \) is passed to the decoder to be fused with target features and predict the token \( y_j \).

During training, the accumulation of all predicted weights generally does not equal the target length \( T \). This creates a problem when fusing features in the decoder. To make sure the sequences \( \langle c_j \rangle, \langle y_j \rangle \) match in length, two strategies are employed. First, the scaling strategy normalizes the weight of each timestep by:

\[
\alpha'_i = \alpha_i \cdot \frac{T}{\sum_{i=1}^{T} \alpha_i} \quad (1)
\]

Using \( \alpha'_i \) for the calculation of the CIF ensures the number of integrated embeddings is exactly \( T \). Next, a sequence-level L2 quantity loss encourages the weights to sum to \( T \):

\[
\mathcal{L}_{\text{quan}} = \left\| T - \sum_{i=1}^{T} \alpha_i \right\|_2^2 \quad (2)
\]

The weight prediction network is composed of a temporal convolution, followed by layer normalization [23], a non-linear activation, dropout, a fully connected layer with one output and a sigmoid activation. We found that it generalizes better if we stop gradient flowing from the weight prediction network back into the encoder.

3.3. Monotonic Decoder

Our decoder follows the original autoregressive Transformer decoder, except for the cross-attention. We design two variant, one with position-wise fusion, and another with infinite look-back attention [2].
3.3.1. Position-wise Fusion

Because the number of integrated embeddings \( c_j \) is the same as decoder length \( T \), we replace the cross-attention in each layer with a position-wise fusion described below:

\[
\text{Fusion}(c_j, s_j) = W_s f_{\text{act}}(W_s c_j + W_i s_j + b),
\]

where \( s_j \) is the decoder hidden state after self-attention. \( W_s, W_i, b \) are trainable weight vectors and \( b \) is a bias vector. \( f_{\text{act}} \) is any non-linear activation. While fusion operations are the same across different positions, they use different parameters from layer to layer. We refer to this model as CIF-F.

3.3.2. Infinite Lookback (IL)

The infinite lookback attention improves monotonic models for SimulST thanks to its ability to explicitly reorder \([2, 13]\). Thus, we also explore having the decoder attend to past integrated embeddings. In this variant, the cross attention is retained, but the \( j \)-th decoder state can only attend to integrated embedding \( c_k \) if \( k \leq j \). We refer to this model as CIF-IL.

3.4. Token-level Quantity Loss

Preliminary experiments show that directly applying the CIF-F to SimulST has limitations. In particular, the prediction of \( \alpha_i \) tends to overfit after a while. We suspect this is because optimizing \( L_{\text{qua}} \) at the sequence-level provides a weak training signal for alignment. Since the CTC loss often accompanies the CIF \([13, 17, 18]\), this inspired us to leverage its alignment property. The sequence \( y_j \) aligns to \( y_i \), where the expected delay is

\[
\text{expected delay} = \text{delay of } y_i \text{ to } y_j.
\]

3.5. Latency Loss

The CIF-F achieves medium latency (AL<2000ms) \([24]\) without latency training. To achieve lower latency, we optimize the Differentiable Average Lagging (DAL) \([2]\). Define the expected delay \( d(y_j) \) of a target as the expected source position that \( y_j \) aligns to. Suppose the \( j \)-th integration \( c_j \) is fulfilled by weighted sum with weights \( \alpha'_i, \ldots, \alpha'_l \), then

\[
d(y_j) = \sum_{k=1}^{l} \alpha'_k \cdot k.
\]

The latency loss \( L_{\text{lat}} \) is calculated using DAL with the expected delays. Due to space constraint, we refer the reader to \([2]\) for details.

3.6. Final objective

The final objective is described by:

\[
L = L_{\text{ce}} + \lambda_{\text{ctc}} L_{\text{ctc}} + \lambda_{\text{qua}} L_{\text{qua}} + \lambda_{\text{lat}} L_{\text{lat}},
\]

where \( \lambda_{\text{ctc}} = 0.3, \lambda_{\text{qua}} = 1.0 \) for all experiments, and \( \lambda_{\text{lat}} \in \{0, 0.5, 1.0, 1.5, 2.0\} \).

4. Experimental Setup

We conduct experiments on the English-German (En-De) portion of MuST-C V2 \([25]\). The V2 released by IWSLT 2021 \([24]\) contains 435 hours of speech and 249k sentence pairs. We use the pre-processing pipeline from fairseq-S2T \([21]\). Input is transformed to 80 dimensional log-mel filter bank features using 25ms window and 10ms shift. We keep training examples within 5 to 3000 frames. SpecAugment \([26]\) with the LB policy is applied. SentencePiece \([27]\) is used to generate sub-word vocabulary with 4096 tokens for each language pairs. We tune the performance using the dev set, and report results the tst-COMMON set.

The feature extractor has 2 convolution layers with kernel size 5, stride 2, and hidden dimension 256. The positional encoding has kernel size 64 and group size 16. The Emformer has 12 layers and the decoder has 6 layers. The models have 4 attention heads, \( d_{\text{head}} = 256 \) and \( d_{\text{FFN}} = 2048 \). Dropout is set to 0.1 for activations and attentions, and 0.3 for others. We follow \([8]\) and set the Emformer main context to 640 ms, right context to 320 ms, memory bank to 5. We increase the left context to 1280 ms following \([20]\). The convolution in the CIF weight prediction has kernel size 3 and stride 1. The CIF threshold \( \beta = 1 \) during training, and is individually tuned for each model on the dev set during inference. Tail handling \([14]\) uses \( \beta/2 \). To enable streaming, all the convolution layers are causal. The 320 ms right context of the Emformer is the only look-ahead. The MMA models use fixed pre-decision ratio 8 (i.e. 320 ms). Latency weight is \( \lambda_{\text{lat}} \in \{0.02, 0.04, 0.06, 0.1, 0.2, 0.4\} \), and \( \lambda_{\text{max}} = 0 \) for MMA-H and \( \lambda_{\text{max}} = \lambda_{\text{lat}} \) for MMA-IL. Label smoothing \([28]\) of 0.1 is applied. We use inverse square root schedule and 4000 warm-up steps for the optimizer. The maximum learning rate is 1e-4 for MMA-H\([1]\) and 1e-3 for others. We use 2xV100 GPUs, a maximum batch size of 40000 frames per GPU, and gradient accumulation of 2 steps. Gradient norm are clipped at 10, and weight decay is set to 1e-6. We follow \([5]\) to first train without latency loss for 150K steps, then finetune with various latency weights for another 50k steps. We average the 5 checkpoints with best latency for evaluation. To ease optimization, all models use pre-trained encoder and sequence-level knowledge distillation (Seq-KD) \([29]\). Specifically, the encoders are initialized from an ASR model pre-trained under the joint CTC and cross-entropy loss for 300k steps. For Seq-KD we first train a NMT model on the sentence pairs, then we use beam search with width 5 to decode the Seq-KD set, which is used as the new training data for ST.

We use SimulEval \([10]\) to compute speech versions of widely adopted latency metrics: Average Proportion (AP) \([31]\), Average Latting (AL) \([1]\) and Differentiable Average Latting (DAL) \([22]\). We report case-sensitive detokenized BLEU using SacreBLEU \([15]\).

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\( \lambda_{\text{qua}} = 0.3, \lambda_{\text{lat}} \in \{0, 0.5, 1.0, 1.5, 2.0\} \)

\( \text{https://ict.fbk.eu/must-c/} \)

\( ^{1} \text{training diverges with 1e-3} \)

\( ^{2} \text{BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.5.1} \)
Figure 3: Latency-quality trade off on the MuST-C V2 tst-COMMON.

5. Results

5.1. Latency-quality trade off

Figure 3 shows the result on the MuST-C V2 tst-COMMON set. First, the performance of MMA-IL at low latency appear better with AL. It is shown by examples that AL may be exploited by adaptive policy models [32]. Therefore, we prefer DAL over AL for our analysis. Interestingly, the MMA-H and the MMA-IL have drastically different performance in SimulST, despite being comparable in SimulMT [12]. This may be due to the variable speech rate that is better handled by the IL attention. Compared with MMA-H, CIF-F/IL has lower latency at the same quality, and CIF-IL can achieve better quality. Compared with MMA-IL, CIF-based models has superior quality at lower latency regions (DAL<2000 or AP≤0.75), but falls short in higher latency. This shows that the CIF is a better choice in medium to low latency, while the MMA-IL is the best choice if high latency is tolerable. The effect of the IL-attention on CIF is quite limited compared to the improvement from MMA-H to MMA-IL. There are two possible reasons for this. The first is that the CIF-IL only computes the IL-attention using a single alignment, whereas the MMA-IL computes the expectation of IL-attention over all possible alignments. Besides, the CIF-F only attends to previous integrated embeddings, whereas the MMA-IL attends to previous encoder states, which is longer and have more information. These may help MMA-IL handle variable speech rate and reordering more effectively.

Figure 3 is an example from tst-COMMON that demonstrates the read-write policy from the CIF-F. We observe that the policy is close to ideal as it is near the diagonal. Notably, the model learns to speed up easier predictions like the punctuation “,” or the subword “en” right after “Lass” to complete the word “Lassen”, the translation of “show”. On the other hand, it slows down so as to reorder “show you” into “Ihnen zeigen”.

5.2. Robustness

In ASR, CIF-based model exhibits good robustness against noise and long utterances [17]. We isolate out utterances longer than 20 seconds from tst-COMMON, and evaluate them on each model. We compute the average BLEU score across all latency. From Table 1 we see that MMA models, particularly MMA-IL, have less robustness against long utterance. It has O(U) soft attention window compared with CIF-IL’s O(T), which means it is more prone to noise. In addition, MMA models tends to have a drop in the trade off curve (Figure 3), which may also mean weaker generalization ability.

5.3. Training speed and stability

Table 2 shows the comparison of the training time. Evidently, CIF-based models take less time to train compared to MMA-based models. The is because MMA marginalizes out the alignments at each decoder layer. Besides, the MMA requires cumulative product, which is numerically unstable. For example, in our experiments, MMA-based models are sensitive to the learning rate, and using 1e-3 leads to divergence on MMA-H. The CIF only computes accumulation once, and uses addition and weighted sum operations, which make it fast and numerically stable.

6. Conclusion

We applied the CIF mechanism to the problem of adaptive policy learning in SimulST. We show that despite its simplicity, the CIF-based models achieved decent latency and quality trade off. Compared with MMA-based models, our method has the advantage of faster training, more stability, and better quality in low latency. We verified that the CIF learns useful adaptive policy by speeding up easier predictions while slowing down harder ones.
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