CIF: CONTINUOUS INTEGRATE-AND-FIRE FOR END-TO-END SPEECH RECOGNITION

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ABSTRACT

In this paper, we propose a novel soft and monotonic alignment mechanism used for sequence transduction. It is inspired by the integrate-and-fire model in spiking neural networks and employed in the encoder-decoder framework consists of continuous functions, thus being named as: Continuous Integrate-and-Fire (CIF). Applied to the ASR task, CIF not only shows a concise calculation, but also supports online recognition and acoustic boundary positioning, thus suitable for various ASR scenarios. Several support strategies are also proposed to alleviate the unique problems of CIF-based model. With the joint action of these methods, the CIF-based model shows competitive performance. Notably, it achieves a word error rate (WER) of 2.86% on the test-clean of Librispeech and creates a new state-of-the-art result on Mandarin telephone ASR benchmark.

Index Terms— continuous integrate-and-fire, end-to-end model, soft and monotonic calculation, online speech recognition, acoustic boundary positioning

1. INTRODUCTION

Automatic speech recognition (ASR) system is undergoing an exciting pathway to be more simplified and accurate with the spring up of various end-to-end models. Among them, the attention-based model [1, 2], which builds a soft alignment between each decoder step and every encoder step, not only shows a performance advantage in comparison with other end-to-end models [3], but also successfully challenged the dominance of HMM-LSTM Hybrid system in ASR [4]. However, despite the superiority of accuracy, such attention-based model often encounters incompetent scenarios in real ASR application: 1) it cannot support online (or streaming) recognition since it need refer to the entire encoded sequence; 2) it cannot well time-stamp the recognition result since it’s not frame-synchronous. Besides, attending to every encoder step is bound to bring a mass of unnecessary computations on steps that are acoustically irrelevant to the decoding step. Focusing on solving above problems, we aim at seeking a soft alignment which not only forms an efficient monotonic calculation but also locates acoustic boundaries. And we find inspirations from the integrate-and-fire model [5, 6].

Integrate-and-fire is one of the earliest models in spiking neural networks (SNNs), which are more bio-plausible and known as the next generation of neural networks [7]. The integrate-and-fire neuron operates using spikes, which are discrete events that take place at points in time. Specifically, it forwardly integrates the stimulations in the input signal (e.g. spike train), and its membrane potential changes accordingly. When the potential reaches a specific threshold, it fires a spike that will stimulate other neurons, and its potential is reset. It’s not hard to find that: 1) such integrate-and-fire process is strictly monotonic; 2) the fired spikes could be used to represent the events that locate an acoustic boundary. By transferring the idea of integrate-and-fire to the end-to-end ASR, we could imagine such an alignment mechanism: it forwardly integrates the information in acoustic signals, once a boundary is located, it instantly fires the integrated acoustic information for further recognition. And the difficulty of achieving it lies in how to simulate the process of integrate-and-fire using continuous functions that support back-propagation.

In this paper, we propose Continuous Integrate-and-Fire (CIF), a novel soft and monotonic alignment employed in the encoder-decoder framework. At each encoder step, it receives the vector representation of current encoder step and a corresponding weight that scales the amount of information contained in the vector. Then, it forwardly accumulates the weights and integrates the vector information until the accumulated weight reaches a threshold, which means an acoustic boundary is located. At this point, the acoustic information of current encoder step is shared by two adjacent labels, thus CIF divides the information into two part: the one for completing the integration of current label and the other for the next integration, which mimics the processing of the integrate-and-fire model when it fires at some point during the period of a encoder step. Then, it fires the integrated acoustic information to the decoder to predict current label. Such process is sketched in Fig1(b) and is performed till to the end of the encoded sequence.

We also present several supporting strategies to refine the performance of CIF-based model, including: 1) a scaling strategy to solve the problem of unequal length between the predicted labels and the targeted labels in the cross-entropy training; 2) a quantity loss to supervise the model to predict the quantity of labels closer to the targets; 3) a tail handling method to process the residual information at the end of inference. With the joint action of these methods, our CIF-based model shows impressive performance on multiple ASR datasets covering different languages and speech types.

2. RELATION TO PRIOR WORK

Several prior works have also studied the soft and monotonic alignment in end-to-end ASR models. [8, 9, 10] assumes the alignment...
3. METHODOLOGY

3.1. Continuous Integrate-and-Fire

Continuous Integrate-and-Fire (CIF) is a soft and monotonic alignment model employed in the encoder-decoder framework. As shown in Fig. 2, CIF connects the encoder and decoder. At each encoder step \( i \), it receives two inputs: 1) current output (state) of encoder: \( h_i \); 2) current weight: \( \alpha_i \), which scales the amount of information contained in \( h_i \). Then, it forwardly accumulates the received weights and integrates the received states (using the form of 'weighted sum') until the accumulated weight reaches a given threshold \( \beta \), which means an acoustic boundary is located. At this point, the information of current encoder step is shared by current label \( y_i \) and the next label, thus CIF divides current weight \( \alpha_i \) into two parts: the one is used to fulfill the integration of current label \( y_i \) by building a complete distribution (whose sum of weights is 1.0) on relevant encoder steps, the other is used for the integration of next label. After that, it fires the integrated embedding \( c_i \) (as well as the context vector) to the decoder to predict the corresponding label \( y_i \). The above process is roughly presented in Fig. 3 and is performed till the end of encoded sequence. The complete algorithm is detailed in Algorithm 1, where the threshold \( \beta \) is recommended to be 1.0.

![Algorithm 1: Continuous Integrate-and-Fire (CIF)](image)

### Algorithm 1: Continuous Integrate-and-Fire (CIF)

**Input:** The outputs of encoder \( \mathbf{h} = (h_1, h_2, h_3, \ldots) \) and the corresponding weights

\[
\mathbf{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_U), \text{ the threshold } \beta;
\]

**Output:** The integrated embeddings (corresponding to the output labels): \( \mathbf{c} = (c_1, c_2, \ldots, c_S) \);

1. Initialize \( i = 1 \), initial accumulated weight \( \alpha_0 = 0 \), initial accumulated state \( h_0^a = 0 \);
2. for \( u = 1; u < U; u++ \) do
   3. // calculate current accumulated weight:
   4. \( \alpha_u^a = \alpha_{u-1}^a + \alpha_u h_u \);
   5. if \( \alpha_u^a < \beta \) then
   6. // no boundary is located;
   7. \( h_u^a = h_{u-1}^a + \alpha_u h_u \);
   8. else
   9. // a boundary is located;
   10. // \( \alpha_u \) is divided into two part, the first part \( \alpha_{u1} \) is used to fulfill the integration of current label \( y_i \):
   11. \( \alpha_{u1} = 1 - \alpha_{u-1}^a \);
   12. \( c_i = h_{u-1}^a + \alpha_{u1} h_u \);
   13. \( i++ \);
   14. // The other part \( \alpha_{u2} \) is used for the next integration:
   15. \( \alpha_{u2} = \alpha_{u2} = \alpha_u - \alpha_{u1} \);
   16. \( h_u^a = \alpha_{u2} h_u \);
17. return \( \mathbf{c} = (c_1, c_2, \ldots, c_S) \);

3.2. Supporting Strategies for CIF-based Model

We also present some support strategies for the CIF-based model to alleviate its unique problems during training and inference:

**Scaling Strategy:** In the training, the length \( S \) of the produced integrated embeddings \( \mathbf{c} \) may differ from the length \( S \) of targets \( \mathbf{y} \), thus bringing difficulties to the cross-entropy training that better to be 'one-to-one'. To solve it, we propose a scaling strategy, which multiplies the calculated weights \( \mathbf{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_U) \) by a scalar \( \frac{S}{\sum_{u=1}^{U} \alpha_u} \) to generate the scaled weights \( \mathbf{\alpha}' = (\alpha_1', \alpha_2', \ldots, \alpha_U') \) whose sum is equal to \( \hat{S} \), thus teacher-forcing CIF to produce \( \mathbf{c} \) with length \( \hat{S} \) and driving more effective training.

**Quantity Loss:** We also present an optional loss function to supervise the CIF-based model to predict the quantity of integrated...
embeddings closer to the quantity of targeted labels. We term it as quantity loss $L_{QUA}$, which is defined as $\sum_{n=1}^{N} \alpha_n - \tilde{S}_n$, where $\tilde{S}_n$ is the length of the targets $y_n$. By providing the quantity constraints, this loss not only promotes the learning of acoustic boundary positioning, but also alleviates the performance degradation after removing the scaling strategy in the inference.

**Tail Handling:** In the inference, the tail leaves some useful information that is not enough to trigger one firing. Directly discarding this information causes the incomplete results (e.g. incomplete words in ASR) at the tail. To alleviate such problem, we utilize a rounding method which makes an additional firing if the residual weight is greater than 0.5 during inference. Besides, we also introduce a label <EOS> to the tail of target sequence to teach the model to predict the end of sentence and more importantly, provide cache.

### 3.3. Model Structure

Fig.2 shows the architecture of our CIF-based model used for ASR but lacks some details of the model structure. Here, we give these details and introduce some new characteristics of the CIF-based model:

**Encoder:** Our encoder follows the encoder structure in [15], which uses a two-layer convolutional front-end followed by a pyramid self-attention networks (SANs) and reduces the time resolution to 1/8. Forward encoding for online recognition is achieved by applying the chunk-hopping mechanism in [15]. As an aside, adjusting the encoding resolution enables CIF suitable for various tasks, e.g. we could use up-sampling to generate longer encoded sequence than outputs to make CIF apply to text-to-speech (TTS), etc.

To calculate the weight $\alpha_n$ corresponding to each encoded output $h_n$, we pass a window centered at $h_n$ (e.g. $[h_{n-1}, h_n, h_{n+1}]$) to a 1-dimensional convolutional layer and then a fully connected layer with one output unit and a sigmoid activation, where the convolutions can be replaced by other neural networks.

**Decoder:** Two versions of decoder are introduced in this work: the one is an autoregressive decoder, which follows the decoder structure in [15]. Specifically, it first projects the concatenation of $(e_{i-1})$ of the previous label and the previously integrated embedding $(c_{i-1})$ as the input of SANs. Then, it concatenates the output of SANs ($a_i$) and currently integrated embedding ($c_i$) and then projects the concatenation to obtain the logit.

The other is a non-autoregressive decoder, which directly passes the currently integrated embedding ($c_i$) to the SANs to get the output ($a_i$) that is then projected to get the logit. Compared with the autoregressive decoder, it has higher computational parallelization and could provide inference speedups for the offline ASR where the integrated embeddings can be calculated by CIF at once.

**Loss Functions:** In the training, the SAN-based encoder and decoder provide high parallelization to the teacher-forcing learning of CIF-based model, where the encoding, the CIF calculation (which is lightweight since it just performs the weighted calculation and has no trainable parameters) and the decoding are performed in order.

To further boost the model learning, in addition to the cross-entropy loss $L_{CE}$, two optional auxiliary loss functions are applied: one of them is the quantity loss $L_{QUA}$ in section 3.2, the other is the CTC loss $L_{CTC}$, which is applied on the encoder (similar to [16]) and addresses the left-to-right acoustic encoding. When using these two optional losses, our model is trained under the loss $L$ as follows:

$$L = L_{CE} + \lambda_1 L_{CTC} + \lambda_2 L_{QUA}$$

(1)

where $\lambda_1$ and $\lambda_2$ are tunable hyper-parameters. The importance of the two optional loss functions are explored in section 5.2

**LM Incorporation:** In the inference, we first perform beam search on the output distributions predicted by the decoder, then use a SAN-based language model (LM) to perform second-pass rescoring as [4], which determines the final transcript $y^*$ as follows:

$$y^* = \arg \max_{y \in \text{NBest}(x, N)} \left( \log P(y|x) + \gamma \log P_{LM}(y) \right)$$

(2)

where $\gamma$ is a tunable hyper-parameter. $\text{NBest}(x, N)$ is the hypothesis produced by the CIF-based model via beam search with size $N$.

### 4. EXPERIMENTAL SETUP

We experiment on three public ASR datasets including the popular English read-speech corpus (Librispeech [17]), current largest Mandarin read-speech corpus (AISHELL-2 [18]) and the Mandarin telephone ASR benchmark (HKUST [19]). For Librispeech, we use all the train data (960 hours) for training, mix the two development sets for validation, use the two test sets for evaluation, and use the separately prepared language model (LM) data for the training of LM. For AISHELL-2, we use all the train data (1000 hours) for training, mix the three development sets for validation and use the three test sets for evaluation. For HKUST, we use the same training (~168 hours), validation and evaluation set as [15]. The training of LM on AISHELL-2 and HKUST uses the text from respective training set.

We extract input features using the same setup as [15] for all datasets. Speed perturbation [20] with fixed ±10% is applied for all training datasets. The frequency masking and time masking in [21] with $F = 8, m_F = 2, T = 70, m_T = 2, p = 0.2$ are applied to all models except the base model on Librispeech. We use the BPE [22] toolkit generating 3722 word pieces for Librispeech by merging 7500 times on its training text, plus three special labels: the blank <BLK>, the end of sentence <EOS> and the pad <PAD>, the number of output labels is 3725 for Librispeech. We collect the characters and markers from the training text of AISHELL-2 and HKUST, respectively. Plus the three special labels, we generate 5230 output labels for AISHELL-2 and 3674 output labels for HKUST.

We implement our model on TensorFlow [23]. For the self-attention networks (SANs) in our model, we use the structure in [15] and set $h = 4, d_{model} = 640, d_{ff} = 2560$ for the two Mandarin datasets, and change ($d_{model}, d_{ff}$) to $(512, 2048)$, $(1024, 4096)$ for the base, big model on Librispeech, respectively. For the encoder, we use the same configures as [15], where $n$ in the pyramid structure is all set to 5. The chunk-hopping [15] for forward encoding uses the chunk size of 256 (frames) and the hop size of 128 (frames). For the 1-dimensional convolutional layer that predicts weights, the number of filters is set to $d_{model}$, and the window width is all set to 3 except the base model on Librispeech is set to 5. Besides, layer normalization [24] and a ReLU activation are applied after this convolution. For CIF, we set the threshold $\beta$ to 0.9 for all models to allow the possible firing after a single step. But it may produce few negative weight after dividing weight, which is non-intuitive in weighted sum calculation. Here, we recommend $\beta = 1.0$, which calculates intuitively and performs slightly better than $\beta = 0.9$ in our later experiments. For the decoder, the number of SANs is all set to 2 except the base model on Librispeech is set to 3. The loss hyper-parameter $\lambda_1$ is set to 0.5 for two Mandarin datasets and to 0.25 for Librispeech, $\lambda_2$ is all set to 1.0. The LM uses SANs with $h = 4, d_{model} = 512, d_{ff} = 2048$, and the number of SAN layers is set to 3, 6, 20 for HKUST, AISHELL-2 and Librispeech, respectively.

In the training, we only apply dropout to the SANs, whose attention dropout and residual dropout are all set to 0.2 except the base model on Librispeech that is set to 0.1. We use the uniform label smoothing in [25] and set it to 0.2 for both of the CIF-based model and the LM. Scheduled Sampling [26] with a constant sampling rate of 0.5 is applied on two Mandarin datasets. In the inference, we use beam search with size 10. The hyper-parameter $\gamma$ for LM rescoring is set to 0.1, 0.2, 0.9 for HKUST, AISHELL-2 and Librispeech, respectively. All experimental results are averaged over 3 runs.

We display the aligned results (the located boundaries) of CIF on [https://linhodong.github.io/cif_alignment/](https://linhodong.github.io/cif_alignment/).
5. RESULTS

5.1. Results on Librispeech

On the Librispeech dataset, we use the word pieces as the output labels. Since the word pieces are obtained without referring to any acoustic knowledge, the acoustic boundary between adjacent labels may be blurred. Even so, our big CIF-based model still achieves a word error rate (WER) of 2.86% on test-clean and 8.08% on test-other (as shown in Table 1), which not only shows a clear performance advantage over other soft and monotonic models (e.g. triggered attention), but also matches or surpasses most of the published results of end-to-end models.

By fine-tuning the trained big model via the chunk-hopping mechanism, we enable our big model that uses a SAN encoder to support online recognition. As shown in Table 1, the online model obtains a WER of 3.25% on test-clean and 9.63% on test-other. Besides, the above CIF-based models all apply a very low encoded frame rate (12.5 Hz) for reducing the computational burden. Switching to a higher frame rate may further improve their performance.

| Model | WER (%) |
|-------|---------|
| LAS + SpecAugment | 2.8 | 2.5 | 6.8 | 5.8 |
| Attention + Tsf LM | 4.4 | 2.8 | 13.5 | 9.3 |
| Jasper | 3.86 | 2.95 | 11.95 | 8.79 |
| wav2letter++ | - | 3.44 | - | 11.24 |
| Cnv Cxt Tsf | 4.7 | - | 12.9 | - |
| CTC + SAN | - | 4.8 | - | 13.1 |
| CTC + Policy | - | 5.42 | - | 14.7 |
| Triggered Attention | 7.4 | 5.7 | 19.2 | 16.1 |
| CIF + SAN (base) | 4.48 | 3.68 | 12.62 | 10.89 |
| CIF + SAN (big) | 3.41 | 2.86 | 9.28 | 8.08 |
| + Chunk-hopping (online) | 3.96 | 3.25 | 11.19 | 9.63 |

5.2. Ablation Study on Librispeech

In this section, we use ablation study to evaluate the importance of different methods applied to the CIF-based model.

| Model | WER (%) |
|-------|---------|
| without scaling strategy | 6.03 | 14.98 |
| without quantity loss | 8.84 | 15.49 |
| without tail handling | 6.04 | 14.11 |
| without CTC loss | 4.96 | 13.27 |
| without autoregressive | 9.27 | 21.56 |
| Full Model | 4.48 | 12.62 |

As shown in Table 1, ablating the auto-regression in the decoder causes the largest performance degradation. To further verify this phenomenon, we compare the models with/without auto-regression on the Mandarin dataset of AISHELL-2 but find they achieve comparable performance. Since the acoustic boundaries between Mandarin characters are much more clear, we suspect the importance of auto-regression is related to the clearness of acoustic boundary between output labels. Besides, the proposed support strategies (scaling strategy, quantity loss and tail handling) for the CIF-based model all provide clear improvements. Among them, the quantity loss is the most important since ablating it causes the largest performance loss and brings large learning instability. The introduced CTC loss also benefits to the CIF-based model but not as important as others.

5.3. Results on AISHELL-2

On the AISHELL-2 dataset, we use the characters of Mandarin as the output labels. Since every character of Mandarin is single syllable and AISHELL-2 is a read-speech dataset, the acoustic boundary between labels are clear. Consistent with our expectations, the CIF-based model performs very competitive on all test sets and significantly improves the results achieved by the Chain model.

| Model | WER (%) |
|-------|---------|
| Chain-TDNN | 9.59 | 8.81 | 10.87 |
| CIF + SAN | 6.17 | 5.78 | 6.34 |
| + Chunk-hopping (online) | 6.52 | 6.04 | 6.68 |

5.4. Results on HKUST

On the HKUST dataset, the speech are all Mandarin telephone conversations, which are more challenging to recognize than read-speech due to the spontaneous and informal speaking style. Besides, the amount of training data on HKUST is smaller. Nevertheless, the CIF-based model still shows good generalization and creates new state-of-the-art result on this benchmark dataset.

| Model | CER (%) |
|-------|---------|
| Chain-TDNN | 23.7 |
| Self-attention Aligner | 24.1 |
| Transformer | 26.6 |
| Extended-RNA | 26.8 |
| Joint CTC-attention model / ESPNet | 27.4 |
| Triggered Attention | 30.5 |
| CIF + SAN | 23.09 |
| + Chunk-hopping (online) | 23.60 |

6. DISCUSSION AND CONCLUSION

At the theoretical level, CIF simulates the dynamic characteristics of the integrate-and-fire (IF) model on artificial neural networks. The IF model has the dynamics of $I = C * \left(\frac{dU_m}{dt}\right)$, where the membrane potential $U_m$ is constantly simulated by the input spikes $I$ in the period of $dt$, $C$ is a constant. Similarly, the dynamics of CIF can be described as $f(h) = \frac{dx}{dt}$, which follows the basic dynamic form of the IF model but differs at one aspect: CIF regards the information when it produces a firing in the period of a encoder step ($dt$). In the future, mimicking the dynamics of other models in spiking neural networks may be a way to improve CIF.

At the application level, CIF not only shows competitive performance on popular ASR benchmarks, but also could extract acoustic embeddings (which may be useful in multimodal tasks, etc.) in a concise way. In addition, CIF could support various sequence transduction tasks (e.g. TTS) by using a suitable encoding resolution. In the future, we will further verify the performance of CIF-based model on larger-scale ASR datasets and other tasks.
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