HYPOTHESIS STITCHER FOR END-TO-END SPEAKER-ATTRIBUTED ASR ON LONG-FORM MULTI-TALKER RECORDINGS

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ABSTRACT

An end-to-end (E2E) speaker-attributed automatic speech recognition (SA-ASR) model was recently proposed to jointly perform speaker counting, speech recognition, and speaker identification. The model achieves a low speaker-attributed word error rate (SA-WER) for monaural overlapped speech comprising an unknown number of speakers. However, the E2E modeling approach is susceptible to the mismatch between the training and testing conditions. It has yet to be investigated whether the E2E SA-ASR model works well for recordings that are much longer than those seen during training. In this work, we first apply a known decoding technique that was developed to perform single-speaker ASR for long-form audio to our E2E SA-ASR task. Then, we propose a novel method using a sequence-to-sequence model, called hypothesis stitcher. The model takes multiple hypotheses obtained from short audio segments that are extracted from the original long-form input, and it then outputs a fused single hypothesis. We propose several architectural variations of the hypothesis stitcher model and compare them with the conventional decoding methods. Experiments using LibriSpeech and LibriCSS corpora show that the proposed method significantly improves SA-WER especially for long-form multi-talker recordings.

Index Terms—Hypothesis stitcher, speech recognition, speaker identification, rich transcription

1. INTRODUCTION

Speaker-attributed automatic speech recognition (SA-ASR) for overlapped speech has long been studied to realize meeting transcription [1-3]. It requires counting the number of speakers, transcribing utterances, and diarizing or identifying the speaker of each utterance from multi-talker recordings that may contain overlapping utterances. Despite the significant progress that has been made especially for multi-microphone settings (e.g., [4-8]), SA-ASR remains very challenging when we can only access monaural audio. One typical approach is a modular approach combining individual modules, such as speech separation, speaker counting, ASR and speaker diarization/identification. However, since different modules are designed based on different criteria, the simple combination does not necessarily result in an optimal solution for the SA-ASR task.

An end-to-end (E2E) SA-ASR model was recently proposed in [9] for monaural multi-talker speech as a joint model of speaker counting, speech recognition, and speaker identification. Unlike prior studies in joint SA-ASR modeling [10-12], it unifies the key components of SA-ASR, i.e., speaker counting, speech recognition, and speaker identification, and thus can handle speech consisting of any number of speakers. The model greatly improved the speaker-attributed word error rate (SA-WER) over the modular system. [13] also showed that the E2E SA-ASR model could be used even without prior speaker knowledge by applying speaker counting and speaker clustering to model’s internal embeddings.

While promising results have been reported, it is still unclear whether the E2E SA-ASR model works well for audio recordings that are much longer than those seen during training. Our preliminary analysis using in-house real conversation data revealed that a considerable number of long segments existed even after applying voice activity detection to the original long-form recordings. Note that, for a conventional single-speaker E2E ASR, it is known that the long-form audio input causes significant accuracy degradation due to the mismatch of the training and testing conditions [14,15]. To mitigate this, [15] proposed an “overlapping inference” algorithm in which the long-form audio was segmented by sliding windows with a 50% shift and the hypotheses from each window were fused to generate one long hypothesis with an edit-distance-based heuristic. Although the overlapping inference could be applied to multi-talker recordings, the effectiveness of the method could be negatively impacted by the speaker recognition errors. In addition, the decoding cost in the overlapping inference is two times higher due to the overlap of the adjacent window positions.

With this as a background, in this paper, we propose a novel method using a sequence-to-sequence model, called hypothesis stitcher, which takes multiple hypotheses obtained from a sliding-window and outputs a fused single hypothesis. We propose several architectural variants of the hypothesis stitcher model and compare them with the conventional decoding methods. Note that, while we propose and evaluate the hypothesis stitcher in the context of SA-ASR, the idea is directly applicable to a standard ASR task. In our evaluation using the LibriSpeech [17] and LibriCSS [18] corpora, we show that the proposed method significantly improves SA-WER over the previous methods. We also show that the hypothesis stitcher can work with a sliding window with less than 50% overlap and thereby reduce the decoding cost.

2. REVIEW OF RELEVANT TECHNIQUES

In this section, we review relevant techniques to the proposed method. Due to the page limitation, we only describe the overview of each technique. Refer to the original papers for further details.

2.1. E2E SA-ASR

The E2E SA-ASR was proposed as a joint model of speaker counting, speech recognition and speaker identification for monaural overlapped audio [9]. The inputs to the model are acoustic features $X = \{x_1, \ldots, x_T\}$ and speaker profiles $D = \{d_1, \ldots, d_K\}$,
where \( T \) is the length of the acoustic feature, and \( K \) is the number of the speaker profiles. The model outputs the multi-speaker transcription \( \mathbf{Y} = \{y_1, \ldots, y_N\} \) and the corresponding speaker labels \( \mathbf{S} = \{s_1, \ldots, s_N\} \) for each output token, where \( N \) is the output length. Following the idea of serialized output training (SOT) [19], the multi-speaker transcription \( \mathbf{Y} \) is represented by concatenating individual speakers’ transcriptions interleaved by a special symbol (\( \langle se \rangle \)) which represents the speaker change.

The E2E SA-ASR consists of two interdependent blocks: an ASR block and a speaker identification block. The ASR block is represented as follows.

\[
E_{\text{enc}} = \text{AsrEncoder}(\mathbf{X}),
\]

\[
e_{\alpha}, \alpha = \text{Attention}(u_n, \alpha_{n-1}, E_{\text{enc}}),
\]

\[
u_n = \text{DecoderRNN}(y_{n-1}, c_{n-1}, u_{n-1}),
\]

\[
o_n = \text{DecoderOut}(c_n, u_n, d_n).
\]

Firstly, AsrEncoder maps \( \mathbf{X} \) into a sequence of hidden representations, \( E_{\text{enc}} = \{h_{1}^{\text{enc}}, \ldots, h_{T}^{\text{enc}}\} \) (Eq. (1)). Then, an attention module computes attention weights \( \alpha_n = \{\alpha_1, \ldots, \alpha_T\} \) and context vector \( c_n \) as an attention weighted average of \( E_{\text{enc}} \) (Eq. (2)). The DecoderRNN then computes hidden state vector \( u_n \) (Eq. (3)). Finally, DecoderOut computes the distribution of output token \( o_n \) based on the context vector \( c_n \), the decoder state vector \( u_n \), and the weighted average of the speaker profiles \( d_n \) (Eq. (4)). Note that \( d_n \) is computed in the speaker identification block, which is explained in the next paragraph. The posterior probability of token \( i \) (i.e. i-th token in the dictionary) at the \( n \)-th decoder step is represented as

\[
P(y_n = i|y_{1:n-1}, s_{1:n}, \mathbf{X}, \mathbf{D}) \sim \alpha_{n,i},
\]

where \( o_{n,i} \) represents the \( i \)-th element of \( o_n \).

Meanwhile, the speaker identification block works as follows.

\[
E_{\text{spk}} = \text{SpeakerEncoder}(\mathbf{X}),
\]

\[
p_n = \sum_{t=1}^{T} \alpha_{n,t} h_{t}^{\text{spk}},
\]

\[
q_n = \text{SpeakerQueryRNN}(y_{n-1}, p_n, q_{n-1}),
\]

\[
\beta_n = \text{InventoryAttention}(q_n, \mathbf{D}),
\]

\[
d_n = \sum_{k=1}^{N} \beta_{n,k} d_k.
\]

Firstly, SpeakerEncoder converts the input \( \mathbf{X} \) to a sequence of hidden representations, \( E_{\text{spk}} = \{h_{1}^{\text{spk}}, \ldots, h_{T}^{\text{spk}}\} \), as speaker embeddings (Eq. (5)). Then, by using the attention weight \( \alpha_n \), a speaker context vector \( p_n \) is computed for each output token (Eq. (6)). The SpeakerQueryRNN module then generates a speaker query \( q_n \) by taking \( p_n \) as an input (Eq. (7)). After getting the speaker query \( q_n \), an InventoryAttention module estimates the attention weights \( \beta_n = \{\beta_{1:n}, \ldots, \beta_{n,k}\} \) for each speaker profile \( d_k \) in \( \mathbf{D} \) (Eq. (8)). Finally, \( d_n \) is obtained by calculating the weighted sum of the speaker profiles using \( \beta_n \) (Eq. (9)), which is input to the ASR block. In the formulation, the attention weight \( \beta_{n,k} \) can be seen as a posterior probability of person \( k \) speaking the \( n \)-th token given all the previous tokens and speakers as well as \( X \) and \( \mathbf{D} \), i.e.,

\[
P(s_n = k|y_{1:n-1}, s_{1:n-1}, X, D) \sim \beta_{n,k}.
\]

With these models combined, all the E2E SA-ASR parameters are trained by maximizing \( \log P(Y, S|X, D) \), which is defined as

\[
\log P(Y, S|X, D) = \log \prod_{n=1}^{N} \{P(y_n|y_{1:n-1}, s_{1:n}, X, D) \cdot P(s_n|y_{1:n-1}, s_{1:n-1}, X, D)\}.
\]

where \( \gamma \) is a scaling parameter. Decoding with the E2E SA-ASR model is conducted by an extended beam search. Refer to [9] for further details.

2.2. Overlapping Inference

Overlapping inference was proposed for conventional single-speaker ASR systems to deal with long-form speech [15]. With the overlapping inference, the input audio is first broken into fixed-length segments. There is 50% overlap between every two consecutive segments so that the information loss around the segment boundaries can be recovered from the overlapping counterpart. Given the word hypothesis \( \mathbf{Y}^m = \{y_1^m, \ldots, y_{N_m}^m\} \), where \( y_i^m \) represents the \( i \)-th recognized word in the \( j \)-th segment and \( N_m \) is the hypothesis length of segment \( m \), we can generate two hypothesis sequences by concatenating all the odd segments or even segments as follows:

\[
\mathbf{Y}^o = \ldots, y_{2m-1}^1, y_{2m-1}^2, \ldots, y_{2m-1}^m, \ldots,
\]

\[
\mathbf{Y}^e = \ldots, y_{2}^1, y_{2}^2, \ldots, y_{2}^m, \ldots,
\]

An edit-distance-based algorithm is then applied to align the odd and even sequences, \( \mathbf{Y}^o \) and \( \mathbf{Y}^e \).

To avoid aligning words from non-overlapped segments (e.g. segments \( m \) and \( m + 2 \)), the distance between two words from non-overlapped segments is set to infinity. As a result, a sequence of word pairs \( \langle a_1, e_1 \rangle, \langle a_2, e_2 \rangle, \ldots, \langle a_L, e_L \rangle \) is generated:

\[
\langle a_i, e_i \rangle = \begin{cases} 
(y_{p_i,q_i}^o, y_{p_i,q_i}^e) & \text{if } y_{p_i,q_i}^e \text{ aligned with } y_{p_i,q_i}^o, \\
(y_{p_i,q_i}^e, y_{p_i,q_i}^o) & \text{if } y_{p_i,q_i}^o \text{ has no alignment,} \\
(y_{p_i,q_i}^o, ) & \text{if } y_{p_i,q_i}^e \text{ has no alignment,}
\end{cases}
\]

where \( i \) is the pair index, \( L \) is the total number of matched pairs, \( y_{p_i,q_i}^o \) is the \( p_i \)-th word from \( q_i \)-th segment in \( \mathbf{Y}^o \), \( y_{p_i,q_i}^e \) is the \( p_i \)-th word from \( q_i \)-th segment in \( \mathbf{Y}^e \) and \( \phi \) denotes no predictions.

The final hypothesis is formed by selecting words from the alignment according to the confidence:

\[
\mathbf{Y}_i^* = \begin{cases} 
a_i & \text{if } f(a_i) \geq f(e_i), \\
e_i & \text{otherwise.}
\end{cases}
\]

Here, \( f(\cdot) \) denotes the function to compute the confidence value of the token. In [15], a simple heuristic of setting a lower confidence value to the word near the edges of each segment (and a higher confidence value to the word near the center of each segment) was proposed and shown to be effective. In this approach, the confidence score for word \( n \) from segment \( m \), \( y_{n}^m \), is defined as \( f(y_{n}^m) = -|n/C_m - 1/2| \), where \( C_m \) denotes the number of words in window \( m \).

2.3. Overlapping inference with E2E SA-ASR

As a baseline system, we consider applying the overlapping inference to the SA-ASR task. Because the E2E SA-ASR model generates multiple speakers’ transcriptions from each segment, we simply apply the overlapping inference for each speaker independently. Namely, we first group the hypotheses from each segment based on the speaker identities estimated by the E2E SA-ASR model. We then apply the overlapping inference for each speaker’s hypotheses.

There are two possible problems in this procedure. Firstly, speaker misrecognition made by the model could cause a confusion in the alignment process. Secondly, even when two hypotheses are observed from overlapping segments for the same speaker, there is
a case where we should not merge the two hypotheses. This case happens when speakers A and B speak in the order of A-B-A and the audio is broken into two overlapped segments such that the overlapped region contains only speaker B’s speech. In this case, we observe hypotheses of “A-B” for the first segment, and hypotheses of “B-A” for the second segment. We should not merge the two hypotheses for speaker A because they are not overlapped. However, avoiding these problems is not trivial.

3. HYPOTHESIS STITCHER

3.1. Overview

To handle the long-form multi-talker recordings more effectively, we propose a new method using a sequence-to-sequence model, called hypothesis stitcher. The hypothesis stitcher consolidates multiple hypotheses obtained from short audio segments into a single coherent hypothesis. In our proposed approach, the hypothesis stitcher takes the multiple hypotheses of the k-th speaker, $\hat{Y}^k = \{\hat{Y}^{1,k}, \ldots, \hat{Y}^{M,k}\}$, where $\hat{Y}^{m,k}$ represents the hypothesis of speaker k for audio segment m. Then, the hypothesis stitcher outputs a fused single hypotheses $\hat{H}^k$ given the input $\hat{Y}^k$. There are several possible architectures of the hypothesis stitcher, and we will explain them in the next subsections.

The entire procedure of applying the hypothesis stitcher is as follows. Firstly, as with the overlapping inference, a long multi-talker recording is broken up into M fixed-length segments with overlaps. Then, the SA-ASR model is applied to each segment m to estimate the hypotheses $\{\hat{Y}^{m,1}, \ldots, \hat{Y}^{m,K}\}$, where K is the number of the profiles in the speaker inventory D. After performing the E2E SA-ASR for all segments, the hypotheses are grouped by the speaker to form $\hat{Y}^k$. Here, if speaker k is not detected in segment m, $\hat{Y}^{m,k}$ is set to empty. Finally, the hypothesis stitcher works for each speaker to estimate a fused hypothesis $\hat{H}^k$.

In this procedure, the input $\hat{Y}^k$ could have the same problems that we discussed for the overlapping inference in Section 2.3. However, we expect that the sequence-to-sequence model can work more robustly if it is trained appropriately. In addition, as an important difference from the overlapping inference, which requires the adjacent segments to overlap by 50%, variants of the hypothesis stitcher can work on segments with less than 50% of overlap. It is important because the smaller the overlap is, the lower the decoding cost becomes. In the next sections, we will explain the variants of the hypothesis stitcher that we examined in our experiments.

3.2. Alignment-based stitcher

We propose an alignment-based stitcher as an extension of the overlapping inference. In this method, the input audio is segmented by a sliding window with 50% overlap as with the overlapping inference. Then, the hypotheses from the odd-numbered segments and even-numbered segments are each joined to yield two sequences as

$\hat{Y}^{m,k}_{wc} = \{\hat{Y}^{1,k}_{wc}, WC, \hat{Y}^{3,k}_{wc}, WC, \ldots, \hat{Y}^{2m-1,k}_{wc}, WC, \ldots\}$,
$\hat{Y}^{e,k}_{wc} = \{\hat{Y}^{2,k}_{wc}, WC, \hat{Y}^{4,k}_{wc}, WC, \ldots, \hat{Y}^{2m,k}_{wc}, WC, \ldots\}$.

Here, we introduce a special window change symbols, WC, to indicate the boundary of each segment in the concatenated hypotheses. Next, by using the same algorithm as the overlapping inference, we align $\hat{Y}^{m,k}_{wc}$ and $\hat{Y}^{e,k}_{wc}$ to generate a sequence of word pairs $\langle o_1, e_1 \rangle, \langle o_2, e_2 \rangle, \ldots, \langle o_L, e_L \rangle$, where $o_i$ and $e_i$ can be WC. Finally, this word pair sequence is input to the hypothesis stitcher model to estimate the fused single hypothesis $\hat{H}^k$. In this paper, we represent the hypothesis stitcher by the transformer-based attention encoder-decoder [21], and we simply concatenate the embeddings of $o_i$ and $e_i$ for each position $l$ to form the input to the encoder.

In the overlapping inference, the word-position-based confidence function $f(\cdot)$ is used to select the word from the aligned word pairs. On the other hand, in the alignment-based stitcher, we expect better word selection to be performed by the sequence-to-sequence model by training the model on an appropriate data.

3.3. Serialized stitcher

We also propose another architecture, called a serialized stitcher, which is found to be effective while being much simpler than the alignment-based stitcher. In the serialized stitcher, we simply join all hypotheses of the k-th speaker from every short segments as

$\hat{Y}^k_{wc} = \{\hat{Y}^{1,k}_{wc}, WC, \hat{Y}^{2,k}_{wc}, WC, \hat{Y}^{3,k}_{wc}, WC, \ldots, \hat{Y}^{M,k}_{wc}\}$.

Then, $\hat{Y}^k_{wc}$ is fed into the hypothesis stitcher to estimate the fused single hypothesis. We again used the transformer-based attention encoder-decoder to represent the hypothesis stitcher.

We also examine a variant of the serialized stitcher where we insert two different symbols (WC) and (WCE) to explicitly indicate the odd-numbered segment and even-numbered segment.

$\hat{Y}^{wc}_{scale} = \{\hat{Y}^{1,k}_{wc}, WC, \hat{Y}^{2,k}_{wc}, WCE, \hat{Y}^{3,k}_{wc}, WC, \ldots, \hat{Y}^{M,k}_{wc}\}$.

Note that the serialized stitcher no longer requires the short segments to be 50% overlapped because there is no alignment procedure. In Section 4, we examine how the overlap ratio between the adjacent segments affects the accuracy of the serialized stitcher.

4. EXPERIMENTS

We conduct a basic evaluation of the hypothesis stitcher by using simulated mixtures of the LibriSpeech utterances [17] in Section 4.1. The best model is then evaluated on the LibriCSS [18], a noisy multi-talker audio recorded in a real meeting room, in Section 4.2.

4.1. Evaluation with clean simulated mixture of LibriSpeech

4.1.1. Evaluation settings

Our experiments used the E2E SA-ASR model of [13], which was trained using LibriSpeech. The training data were generated by randomly mixing multiple utterances in “train_960”. Up to 5 utterances were mixed for each sample, and the average duration was 29.4 sec. Refer to [13] for further details of the model and training configurations.

On top of the E2E SA-ASR model, we trained hypothesis stitcher models by using a 16-second-long sliding window. We first simulated monaural multi-talker data from LibriSpeech (see Table 1). There were 50,083 long-form audio training samples, each of which was a mixture of multiple utterances randomly selected from “train_960”. Each sample consisted of up to 12 utterances spoken by 6 or fewer speakers. When the utterances were mixed, each utterance was shifted by a random delay to simulate partially overlapped conversational speech so that an average overlap time.
ratio became 10%. All training samples were then broken into 16-second overlapped segments in a similar way to the settings of the overlapping inference paper [15], and they were decoded by the E2E SA-ASR model with relevant speaker profiles. The generated hypotheses and the original reference label were used for the input and output, respectively, to train the hypothesis stitcher.

For all variants of the hypothesis stitchers, we used the transformer-based attention encoder-decoder with 6-layers of encoder (1,024-dim, 8-heads) and 6-layers of decoder (1,024-dim, 8-heads) by following [21]. The model was trained by using an Adam optimizer with a learning rate of 0.0005 until no improvement was observed for 3 consecutive epochs on the development set. We applied the label smoothing and dropout with parameters of 0.1 and 0.3, respectively.

For evaluation, we generated two types of development and test sets: a short set with roughly 30-second-long samples and a long set with roughly 60-second-long samples (Table 1). We used the SA-WER, which was calculated by comparing the ASR hypothesis and the reference transcription of each speaker, as an evaluation metric.

4.2. Evaluation with LibriCSS corpus

Finally, we evaluated the proposed method on the LibriCSS dataset [18]. The dataset consists of 10 hours of recordings of concatenated LibriSpeech utterances that were played back by multiple loudspeakers in a meeting room and captured by a seven-channel microphone array. We used only the first channel data (i.e. monaural audio) for our experiments. Before applying the decoding procedure, we split the recordings at every silence regions by an oracle voice activity detector (VAD) that uses the reference time information. Note that the audio set after VAD still contains considerable amount of long-form multi-talker audio. Each recording consists of utterances of 8 speakers. When we applied the E2E SA-ASR, we fed the speaker profiles corresponding to the 8 speakers for each recording.

We used the serialized stitcher trained in the previous experiments on the segments obtained by a 50% overlapping sliding window. The evaluation result is shown in Table 4. According to the convention in [13], we report the results for different overlap speech ratios ranging from 0% to 40%. As shown in the table, we observed a large improvement when the overlap speech ratio was large (30–40%). This is because these test sets contained much more long-form audio due to the frequent utterance overlaps.

5. CONCLUSION

In this paper, we proposed the hypothesis stitcher to help improve the accuracy of the E2E SA-ASR model on the long-form audio. We proposed several variants of the model architectures for the hypothesis stitcher. The experimental results showed that one of the model called serialized stitcher worked the best. We also showed that the hypothesis stitcher yielded good performance even with sliding windows with less than 50% overlaps, which is desirable to reduce the computational cost of the decoding.

6. REFERENCES

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