



End-to-End Speaker-Attributed ASR with Transformer

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Abstract

This paper presents our recent effort on end-to-end speaker-attributed automatic speech recognition, which jointly performs speaker counting, speech recognition and speaker identification for monaural multi-talker audio. Firstly, we thoroughly update the model architecture that was previously designed based on a long short-term memory (LSTM)-based attention encoder decoder by applying transformer architectures. Secondly, we propose a speaker deduplication mechanism to reduce speaker identification errors in highly overlapped regions. Experimental results on the LibriSpeechMix dataset shows that the transformer-based architecture is especially good at counting the speakers and that the proposed model reduces the speaker-attributed word error rate by 47% over the LSTM-based baseline. Furthermore, for the LibriCSS dataset, which consists of real recordings of overlapped speech, the proposed model achieves concatenated minimum-permutation word error rates of 11.9% and 16.3% with and without target speaker profiles, respectively, both of which are the state-of-the-art results for LibriCSS with the monaural setting.

Index Terms: multi-speaker speech recognition, speaker counting, speaker identification, serialized output training

1. Introduction

Speaker attributed automatic speech recognition (SA-ASR) for recognizing “who spoke what” from multi-talker recordings has long been studied to enable conversation analysis [1, 2, 3]. It requires counting the participating speakers, transcribing each speaker’s utterance, and assigning a speaker tag to each utterance from possibly overlapped speech. One approach for SA-ASR is to first perform speech separation and then apply ASR and speaker diarization/identification to the separated audio streams (e.g., [4, 5]). However, such combination could limit the overall accuracy since each module is separately trained with its own criterion. To overcome this suboptimality, a joint modeling approach has been studied widely, ranging from partially joint modeling methods (speech separation plus ASR [6, 7, 8, 9, 10, 11], speaker identification plus speech separation methods [12, 13], etc.) to fully joint modeling [14, 15, 16].

Recently, an end-to-end (E2E) SA-ASR model was proposed to jointly perform all the sub-tasks of SA-ASR regardless of the number of speakers in an input recording [17, 18]. The E2E SA-ASR consists of an ASR-block and a speaker-block. Both blocks were designed by using attention-based encoder decoders (AEDs) based on long short-term memory (LSTM), and the two blocks worked interdependently to perform ASR and speaker identification. The E2E SA-ASR model showed significant improvement in speaker-attributed word error rate (SA-WER) compared with a system combining multi-talker ASR and speaker identification. Furthermore, it was also shown that the E2E SA-ASR could be combined with speaker

clustering to perform speaker diarization when relevant speaker profiles were unavailable [19]. However, noticeable degradation of accuracy was still observed especially when the number of overlapping speakers became large.

In this paper, we present our recent progress on further improving the E2E SA-ASR. We first apply the recent advancement of transformer architecture [20, 21, 22, 23, 24, 25] to both the ASR- and speaker-blocks of the E2E SA-ASR. We also propose a simple modification to the joint inference procedure, named speaker deduplication, to prevent the system from predicting the same speaker in highly overlapped regions. Evaluation on two datasets shows that the proposed model is especially good at counting the number of speakers and it can significantly improve the accuracy over the LSTM-based baseline.

2. E2E SA-ASR: Review

2.1. Problem statement

Suppose we observe a sequence of acoustic feature $X \in \mathbb{R}^{f^a \times l^a}$, where f^a and l^a are the feature dimension and the length of the feature sequence, respectively. Also suppose that a set of speaker profiles $D = \{d_k \in \mathbb{R}^{f^d} | k = 1, \dots, K\}$ is available, where K is the total number of the profiles, d_k is a speaker embedding (e.g., d-vector [26]) of the k -th speaker, and f^d is the dimension of the speaker embedding. K can be greater than the actual number of speakers in the recording.

The goal of E2E SA-ASR [17] is to estimate a multi-speaker transcription $Y = (y_n \in \{1, \dots, |\mathcal{V}|\} | n = 1, \dots, N)$ accompanied by the speaker identity of each token $S = (s_n \in \{1, \dots, K\} | n = 1, \dots, N)$ given input X and D . Here, $|\mathcal{V}|$ is the size of the vocabulary \mathcal{V} , and y_n and s_n are the word index and speaker index for the n -th token, respectively. Following the serialized output training (SOT) framework [27], we represent a multi-speaker transcription of overlapping speech as follows: word sequences of multiple speakers are joined by a special change symbol $\langle sc \rangle$ to form a single sequence Y . For example, for the three-speaker case, the reference token sequence to Y is given as $R = \{r_1^1, \dots, r_{N_1}^1, \langle sc \rangle, r_1^2, \dots, r_{N_2}^2, \langle sc \rangle, r_1^3, \dots, r_{N_3}^3, \langle eos \rangle\}$, where r_i^j represents the i -th token of the j -th utterance.

2.2. Model architecture

The E2E SA-ASR model consists of the ASR block and the speaker block, which jointly perform ASR and speaker identification (Fig. 1). The ASR block follows an encoder-decoder design and is represented as,

$$H^{\text{asr}} = \text{AsrEncoder}(X), \quad (1)$$

$$o_n = \text{AsrDecoder}(y_{[1:n-1]}, H^{\text{asr}}, \bar{d}_n). \quad (2)$$

Given the acoustic input X , an AsrEncoder module, which will be detailed in the next section, first converts X into a sequence

of hidden embeddings $H^{\text{asr}} \in \mathbb{R}^{f^h \times l^h}$ for ASR (Eq. (1)), where f^h and l^h are the embedding dimension and the length of the embedding sequence, respectively. At each decoder step n , AsrDecoder calculates the output distribution $o_n \in \mathbb{R}^{|\mathcal{V}|}$ given previous token estimates $y_{[1:n-1]}$, H^{asr} , and the weighted speaker profile \bar{d}_n (Eq. (2)). Note that \bar{d}_n is computed from the speaker profiles D in the speaker block, which will be explained later. The posterior probability of token i (i.e. the i -th token in \mathcal{V}) at the n -th decoder step is represented as

$$Pr(y_n = i | y_{[1:n-1]}, s_{[1:n]}, X, D) = o_{n,i}, \quad (3)$$

where $o_{n,i}$ represents the i -th element of o_n .

On the other hand, the speaker block is represented as

$$H^{\text{spk}} = \text{SpeakerEncoder}(X), \quad (4)$$

$$q_n = \text{SpeakerDecoder}(y_{[1:n-1]}, H^{\text{spk}}, H^{\text{asr}}), \quad (5)$$

$$\beta_{n,k} = \frac{\exp(\cos(q_n, d_k))}{\sum_{j=1}^K \exp(\cos(q_n, d_j))}, \quad (6)$$

$$\bar{d}_n = \sum_{k=1}^K \beta_{n,k} d_k. \quad (7)$$

The SpeakerEncoder module first converts X into a speaker embeddings $H^{\text{spk}} \in \mathbb{R}^{f^h \times l^h}$ that represents the speaker characteristic of X (Eq. (4)). At every decoder step n , SpeakerDecoder calculates a speaker query $q_n \in \mathbb{R}^{f^d}$ given $y_{[1:n-1]}$, H^{spk} and H^{asr} (Eq. (5)). Next, a cosine distance-based attention weight $\beta_{n,k} \in \mathbb{R}$ is calculated for all profiles d_k in D given the speaker query q_n (Eq. (6)). The $\beta_{n,k}$ can be seen as a posterior probability of person k speaking the n -th token given all the previous estimation as well as X and D , i.e.,

$$Pr(s_n = k | y_{[1:n-1]}, s_{[1:n-1]}, X, D) = \beta_{n,k}. \quad (8)$$

Finally, the weighted speaker profile $\bar{d}_n \in \mathbb{R}^{f^d}$ is calculated as the weighted average of the profiles in D (Eq. (7)), which is fed to the ASR block (Eq. (2)).

By using Eqs. (3) and (8), the joint posterior probability of token Y and speaker S given input X and D is represented as,

$$Pr(Y, S | X, D) = \prod_{n=1}^N \{Pr(y_n | y_{[1:n-1]}, s_{[1:n]}, X, D) \times Pr(s_n | y_{[1:n-1]}, s_{[1:n-1]}, X, D)\}. \quad (9)$$

The model parameters are optimized by maximizing $Pr(Y, S | X, D)$ over training data.

3. Proposed method

3.1. Transformer-based SA-ASR architecture

In the prior work [17], AsrEncoder, AsrDecoder, SpeakerDecoder were represented by the stack of LSTM layers. In this paper, we thoroughly update the model architecture by applying the recent advancement of the transformer. Note that the AsrDecoder and SpeakerDecoder requires a special design to work jointly, so we use most of the space to explain them.

AsrEncoder is represented by a modified version of Conformer network [25]. We follow the architecture shown in [25] except that (i) we insert a squeeze and excitation module [28] before the dropout of the convolution module and (ii) we add one more point-wise convolution after depth-wise convolution. These changes were made based on our preliminary test.

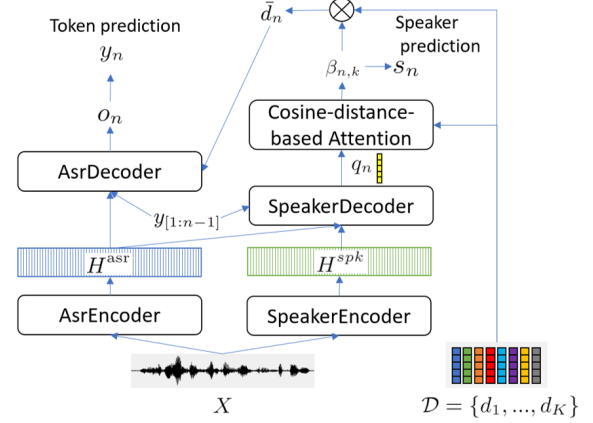


Figure 1: Overview of E2E SA-ASR

AsrDecoder is similar to a conventional transformer-based decoder except that the weighted speaker profile \bar{d}_n is added at the first layer. The AsrDecoder is represented as follows.

$$z_{[1:n-1],0}^{\text{asr}} = \text{PosEnc}(\text{Embed}(y_{[1:n-1]})), \quad (10)$$

$$\bar{z}_{n-1,l}^{\text{asr}} = z_{n-1,l-1}^{\text{asr}} + \text{MHA}_l^{\text{asr-self}}(z_{n-1,l-1}^{\text{asr}}, z_{[1:n-1],l-1}^{\text{asr}}, z_{[1:n-1],l-1}^{\text{asr}}), \quad (11)$$

$$\bar{z}_{n-1,l}^{\text{asr}} = \bar{z}_{n-1,l}^{\text{asr}} + \text{MHA}_l^{\text{asr-src}}(\bar{z}_{n-1,l}^{\text{asr}}, H^{\text{asr}}, H^{\text{asr}}), \quad (12)$$

$$z_{n-1,l+1}^{\text{asr}} = \begin{cases} \bar{z}_{n-1,l}^{\text{asr}} + \text{FF}_l^{\text{asr}}(\bar{z}_{n-1,l}^{\text{asr}} + W^{\text{spk}} \cdot \bar{d}_n) & (l = 1) \\ \bar{z}_{n-1,l}^{\text{asr}} + \text{FF}_l^{\text{asr}}(\bar{z}_{n-1,l}^{\text{asr}}) & (l > 1) \end{cases} \quad (13)$$

$$o_n = \text{SoftMax}(W^o \cdot z_{n-1,L}^{\text{asr}} + b^o) \quad (14)$$

Here, Embed() and PosEnc() are the embedding function and absolute positional encoding function [20], respectively. $\text{MHA}_l^*(Q, K, V)$ represents the multi-head attention of the l -th layer [20] with query Q , key K , and value V matrices. $\text{FF}_l^*(\cdot)$ represents a position-wise feed forward network of l -th layer. In the AsrDecoder, token sequence $y_{[1:n-1]}$ is first converted into a sequence of embedding $z_{[1:n-1],0}^{\text{asr}} \in \mathbb{R}^{f^h \times (n-1)}$ (Eq. (10)). For each layer l in the AsrDecoder, the self-attention operation (Eq. (11)) and source-target attention operation (Eq. (12)) are applied. Finally, the position-wise feed forward layer is applied to calculate the input to the next layer $z_{n,l+1}^{\text{asr}}$ (Eq. (13)). Here, unlike the conventional transformer-based decoder, \bar{d}_n is added after being multiplied by the weight $W^{\text{spk}} \in \mathbb{R}^{f^h \times f^d}$ in the first layer. Finally, o_n is calculated by applying SoftMax function on the final L^{asr} -th layer's output with weight $W^o \in \mathbb{R}^{|\mathcal{V}| \times f^h}$ and bias $b^o \in \mathbb{R}^{|\mathcal{V}|}$ application (Eq. (14)).

SpeakerEncoder is almost identical to the speaker profile extractor (in our case, a d-vector extractor based on a convolutional neural network [29]) except that the final average pooling layer in the speaker profile extractor is replaced by a linear layer without pooling. The last linear layer maps f^d -dim output of the d-vector extractor into f^h -dim embeddings.

SpeakerDecoder is represented by a similar architecture to the transformer-based decoder, but it is designed to share the source-target attention information with that of the AsrDecoder. The first layer of the SpeakerDecoder is represented as

$$\bar{z}_{n-1,1}^{\text{spk}} = z_{n-1,1}^{\text{asr}} + \text{MHA}_{n-1,1}^{\text{spk-src}}(z_{n-1,1}^{\text{asr}}, H^{\text{asr}}, H^{\text{spk}}), \quad (15)$$

$$z_{n-1,2}^{\text{spk}} = \bar{z}_{n-1,1}^{\text{spk}} + \text{FF}_1^{\text{spk}}(\bar{z}_{n-1,1}^{\text{spk}}). \quad (16)$$

Here, we reuse $z_{n-1,1}^{\text{asr}}$, derived from $y_{[1:n-1]}$ in the ASR block, as the query to the key of H^{asr} (Eq. (15)). The value is cal-

Table 2: SER (%), WER (%), and SA-WER (%) for LibriSpeechMix with baseline and proposed models. LM was not used.

Setting ID	Model	Eval Set			1-speaker			2-speaker-mixed			3-speaker-mixed			Total		
		SER	WER	SA-WER	SER	WER	SA-WER	SER	WER	SA-WER	SER	WER	SA-WER	SER	WER	SA-WER
	LSTM SA-ASR [17]	0.2	4.2	4.5	2.5	8.7	9.9	10.2	20.2	23.1	6.0	13.7	15.6			
(a)	Transformer SA-ASR	0.5	3.3	3.8	2.1	5.3	6.5	4.9	8.9	10.7	3.2	6.8	8.2			
(b)	+ SpecAugment	0.5	3.2	3.8	2.3	5.3	6.8	4.6	7.7	9.4	3.1	6.2	7.6			
(c)	+ Speaker Deduplication	0.6	3.3	3.9	2.0	4.3	6.4	3.3	6.0	8.5	2.4	5.0	7.0			

Table 1: WER (%) comparison of ASR-block for LibriSpeechMix. LM was not used.

Model	# of Params.	# of Speakers in Test Data			Total
		1	2	3	
SOT LSTM-AED [17]	135.6M	4.5	10.3	19.5	13.9
SOT Transformer-AED	128.6M	4.1	5.3	7.5	6.2
+ SpecAugment	128.6M	3.6	4.9	6.2	5.3

culated based on H^{spk} so that the speaker representation is obtained as $\bar{z}_{n-1,1}^{\text{spk}} \in \mathbb{R}^{f^h}$. Point-wise feed forward layer is then applied to obtain $z_{n-1,2}^{\text{spk}} \in \mathbb{R}^{f^h}$ (Eq. 16). The architecture after the first layer is represented as follows.

$$\bar{z}_{n-1,l}^{\text{spk}} = z_{n-1,l-1}^{\text{spk}} + \text{MHA}_1^{\text{spk-self}}(z_{n-1,l-1}^{\text{spk}}, z_{[1:n-1],l-1}^{\text{spk}}, z_{[1:n-1],l-1}^{\text{spk}}), \quad (17)$$

$$\bar{z}_{n-1,l-1}^{\text{spk}} = z_{n-1,l}^{\text{spk}} + \text{MHA}_1^{\text{spk-src}}(z_{n-1,l}^{\text{spk}}, H^{\text{spk}}, H^{\text{spk}}), \quad (18)$$

$$z_{n-1,l+1}^{\text{spk}} = \bar{z}_{n-1,l}^{\text{spk}} + \text{FF}_l^{\text{spk}}(\bar{z}_{n-1,l}^{\text{spk}}) \quad (19)$$

$$q_n = W^q \cdot z_{n-1,L}^{\text{spk}} \quad (20)$$

Here, the self attention, source-target attention, and point-wise feed forward layer are applied as with the conventional transformer decoder (Eqs. (17)–(19)). Finally, the speaker query q_n is obtained by multiplying a weight $W^q \in \mathbb{R}^{f^d \times f^h}$ to the final L^{spk} -th layer’s output (Eq. (20)).

3.2. Inference with speaker deduplication

At inference time, the extended beam search algorithm [17] is used to generate transcriptions with speaker labels. In the prior work, the speaker with the highest average $\beta_{n,k}$ score for each utterance is simply selected as the predicted speaker of that utterance. However, it was found that the same speaker was sometimes predicted for heavily overlapped utterances of different speakers. To avoid this kind of errors, we set a simple constraint that the same speaker cannot be assigned for the consecutive utterances joined by $\langle sc \rangle$. Given that constraint, a sequence of speakers that has the highest speaker probability (multiplication of $\beta_{n,k}$) among all possible speaker sequence is selected. We call this method as “speaker deduplication” in this paper.

4. Experiments

We first conducted experiments based on LibriSpeechMix [17], which is a clean mixed-audio test set, to assess the basic capability of the proposed model. We then conducted experiments based on LibriCSS [30], which is a set of multi-talker long-form audio recorded in a real meeting room.

4.1. Evaluation with LibriSpeechMix

4.1.1. Evaluation data and evaluation metric

LibriSpeechMix includes single-speaker data, two-speaker-mixed data, and three-speaker mixed data, all of which were

Table 3: Speaker counting accuracy (%) for LibriSpeechMix.

Model	Actual # of Speakers in Test Data	Estimated # of Speakers (%)			
		1	2	3	>4
LSTM	1	99.96	0.04	0.00	0.00
SA-ASR [17]	2	2.56	97.44	0.00	0.00
	3	0.31	25.34	74.35	0.00
Transformer	1	100.00	0.00	0.00	0.00
SA-ASR (setting (a))	2	2.21	97.79	0.00	0.00
	3	0.31	10.15	89.54	0.00
Transformer	1	99.92	0.08	0.00	0.00
SA-ASR (setting (c))	2	0.53	99.39	0.08	0.00
	3	0.00	3.74	96.26	0.00

made by mixing utterances of “test_clean” of LibriSpeech [31] without changing the signal level of each utterance. Each utterance was randomly delayed to simulate partially overlapped speech as seen in natural conversations. For each test sample, 8 speaker profiles, or 128-dim d-vectors [29], are extracted for the speaker identification task. The utterances to be used for speaker profile extraction are determined in the dataset. Speaker error rate (SER), WER, and SA-WER as defined in [17] were used for the evaluation.

4.1.2. Model and training settings

We used a 80-dim log mel filterbank extracted every 10 msec as the input feature. For the speaker profile, we used a 128-dim d-vector [26], whose extractor was separately trained on Vox-Celeb Corpus [32, 33]. Our d-vector extractor consisted of 17 convolution layers followed by an average pooling layer, which was a modified version of the one presented in [29].

The AsrEncoder consisted of 2 layers of convolution layers that subsamples the time frame by a factor of 4, followed by 18 conformer layers. Each conformer layer consisted of two 1024-dim feed forward layers in a sandwich structure, a multi-head attention with 8 heads, a depthwise convolution with kernel size 3, and a squeeze-and-excitation network with reduction factor 8 [28]. Embedding dimension f^h was set to 512. The AsrDecoder consisted of 6 layers, each of which had the multi-head attention with 8 heads, and 2048-dim feed forward layer. 16k subwords [34] were used as a recognition unit. The SpeakerEncoder was the same as the d-vector extractor except the final layer as explained in Section 3.1, and initialized by the parameter of the d-vector extractor. Finally, SpeakerDecoder consisted of 2 layers, each of which had a multi-head attention with 8 heads and a 2048-dim feed forward layer.

Following the previous work [17], we first optimized only the ASR block as a speaker-agnostic multi-speaker ASR model by setting $\bar{d}_n = 0$. The training data was the same as the one used in [27]. Namely, we generated multi-speaker audio segments by randomly mixing 1 to 3 utterances of LibriSpeech “train_960” with a random delay for each utterance, where the minimum difference of the starting time of each utterance was set to 0.5 sec. We used a mini-batch of 12,000 frames and trained the model for 160k iterations with 32 GPUs, with Noam learning rate schedule with a peak learning rate of 0.0002 after 25k iterations. After the 160k iterations, we reset the optimizer and conducted the additional 320k iterations of train-

Table 4: Comparison of cpWER (%) for LibriCSS with various methods.

System	# of channel	Speaker Profile	Speaker Counting	cpWER (%) for different overlap ratio						Avg.
				0S	0L	10	20	30	40	
7ch-CSS + SC + Transformer-ASR [5]	7	-	automatic	12.5	9.6	12.7	12.9	14.4	13.5	12.7
TS-VAD + Transformer-ASR [5]	1	-	oracle	11.0	9.5	16.1	23.1	33.8	40.9	23.9
LSTM SA-ASR [19]	1	✓	automatic	15.7	8.0	12.5	17.5	24.3	27.6	18.6
LSTM-SA-ASR + SC [19]	1	-	oracle	15.8	10.3	13.4	17.1	24.4	28.6	19.2
LSTM SA-ASR + SC [19]	1	-	automatic	24.4	12.2	15.0	17.1	28.6	28.6	21.8
Transformer SA-ASR	1	✓	automatic	12.1	7.9	9.6	10.8	13.4	15.7	11.9
Transformer SA-ASR + SC	1	-	oracle	12.7	8.6	11.2	11.3	16.1	17.5	13.3
Transformer SA-ASR + SC	1	-	automatic	14.7	10.4	16.3	14.7	21.3	17.5	16.3

CSS: Continuous Speech Separation, SC: Spectral Clustering, TS-VAD: Target-speaker Voice Activity Detection

ing with SpecAugment [35]. Table 1 shows the comparison of the WER by the transformer-based model (at the first 160k iteration w/o SpecAugment, and after additional 320k iteration with SpecAugment) and the LSTM-based model [17]. We can observe a significant WER improvement especially for the 2-speaker and 3-speaker mixed test data.

Given the well-trained ASR-block as the initial parameters, we further trained the entire model parameters (i.e. including the speaker block) by the training data used in [17]. The training data were again generated from LibriSpeech by randomly mixing 1 to 3 utterances with a minimum delay of 0.5 sec. We used a mini-batch of 6,000 frames and trained 160k iterations with 8 GPUs, with Noam learning rate schedule with a peak learning rate of 0.0001 after 10k iterations. We did not use SpecAugment at this stage since it degraded the accuracy.

4.1.3. Evaluation results

Table 2 shows the comparison of the LSTM-based SA-ASR and the proposed transformer-based SA-ASR. Note that the setting (a) is the SA-ASR model initialized by the ASR-block w/o SpecAugment (middle row of Table 1) while the setting (b) is the SA-ASR model initialized by the ASR-block with SpecAugment (last row of Table 1). The setting (a) can be fairly compared with the LSTM-based SA-ASR model reported in [17], which was trained with the same data and used neither SpecAugment nor language models. The transformer-based SA-ASR achieved an SA-WER of 8.2%, outperforming the LSTM-based baseline by 47% relative. We observed a significant error reduction especially for the 2-speaker-mixed and 3-speaker-mixed test cases. Then, the application of SpecAugment significantly improved the SA-WER from 8.2% to 7.6% (setting (b)). Finally, the proposed speaker deduplication further improved the SA-WER to 7.0%, with notable SER improvement for the 3-speaker-mixed test case (setting (c)).

We also evaluated the speaker counting accuracy as shown in Table 3. The transformer SA-ASR showed significantly better speaker counting accuracy than the LSTM-based counterpart. By combining all techniques, the speaker counting accuracy finally reached 96–99% for all test conditions. Note that the improvement from setting (a) to setting (c) was mostly attributed to the speaker deduplication.

4.2. Evaluation with LibriCSS

4.2.1. Experimental settings

LibriCSS is 10 hours of audio recording made by playing back “test.clean” of LibriSpeech in a real meeting room. Each recording consists of utterances from 8 speakers. While the recording was conducted by a 7-ch microphone array, we used only the first channel in this experiment.

We used the same training data set as the one used in [19].

The training data were generated by mixing 1 to 5 utterances of 1 to 5 speakers from LibriSpeech, where randomly generated room impulse responses and noise were added to simulate the reverberant recordings. We initialized the ASR block by the model trained with SpecAugment, and performed 160k iterations of training with a mini-batch of 6,000 frames with 8 GPUs. Noam learning rate schedule with peak learning rate of 0.0001 after 10k iterations was used. In addition to the SA-ASR model, we trained a transformer-based language model (LM) (24-layers, 512-dim embedding, 8-heads MHA, 2048-dim feed forward) by using the same method in [19], and used it based on shallow fusion.

In the evaluation, each long-form recording was first segmented at silence points detected by WebRTC Voice Activity Detector¹ with the least aggressive setting. Then, we ran the E2E SA-ASR with two different conditions. In the first condition, we ran the E2E SA-ASR model with relevant speaker profiles of 8 speakers in the meeting. In the second condition, we ran the combination of the E2E SA-ASR model and speaker clustering proposed in [19]. Specifically, the E2E SA-ASR model was executed with 100 dummy profiles, and spectral clustering (SC) was applied on the speaker query of each utterance to assign a speaker cluster tag. The number of speakers was given or estimated by the normalized maximum eigengap (NME) method [36]. The concatenated minimum-permutation word error rate (cpWER) [37] was used for the evaluation to capture both the ASR and speaker diarization errors.

4.2.2. Evaluation results

The evaluation results are presented in Table 4. The proposed transformer-based E2E SA-ASR achieved a cpWER of 11.9%. This result was even better than that of the combination of 7-ch speech separation, spectral clustering-based speaker diarization and the transformer-based ASR (12.7% cpWER) reported in [5] while the E2E SA-ASR used only a 1-ch signal.

The combination of the transformer SA-ASR and speaker clustering achieved 13.3% or 16.3% of cpWER with the oracle number of speakers or the estimated number of speakers, respectively. These numbers are significantly better than the result of the combination of the target-speaker voice activity detection (TS-VAD) and the transformer-based ASR (23.9% of cpWER) reported in [5] as well as LSTM-based SA-ASR [19].

5. Conclusions

In this paper, we proposed the transformer-based E2E SA-ASR with the speaker deduplication mechanism. The proposed model was demonstrated to be especially good at counting speakers and showed significant accuracy improvement for both the LibriSpeechMix and LibriCSS datasets.

¹<https://github.com/wiseman/py-webrtcvad>

6. References

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