INVESTIGATION OF END-TO-END SPEAKER-ATTRIBUTED ASR FOR CONTINUOUS MULTI-TALKER RECORDINGS

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ABSTRACT

Recently, an end-to-end (E2E) speaker-attributed automatic speech recognition (SA-ASR) model was proposed as a joint model of speaker counting, speech recognition and speaker identification for monaural overlapped speech. It showed promising results for simulated speech mixtures consisting of various numbers of speakers. However, the model required prior knowledge of speaker profiles to perform speaker identification, which significantly limited the application of the model. In this paper, we extend the prior work by addressing the case where no speaker profile is available. Specifically, we perform speaker counting and clustering by using the internal speaker representations of the E2E SA-ASR model to diarize the utterances of the speakers whose profiles are missing from the speaker inventory. We also propose a simple modification to the reference labels of the E2E SA-ASR training which helps handle continuous multi-talker recordings well. We conduct a comprehensive investigation of the original E2E SA-ASR and the proposed method on the monaural LibriCSS dataset. Compared to the original E2E SA-ASR with relevant speaker profiles, the proposed method achieves a close performance without any prior speaker knowledge. We also show that the source-target attention in the E2E SA-ASR model provides information about the start and end times of the hypotheses.

Index Terms— Rich transcription, speech recognition, speaker identification, speaker diarization, serialized output training

1. INTRODUCTION

Speaker-attributed automatic speech recognition (SA-ASR), which recognizes "who spoke what", is essential to meeting transcription. SA-ASR requires to count the number of speakers, transcribe the utterances, and identify or diarize the speaker of each utterance from conversational recordings where some utterances are usually overlapped. It has a long research history, from the projects in the early 2000's [1][2][3] to the recent international efforts such as the CHiME [4][5] and DIHARD [6][7] challenges. While significant progress has been made especially in multi-microphone settings (e.g., [8][9][10][11]), SA-ASR for monaural audio remains challenging due to the difficulty in handling overlapped speech for both ASR and speaker diarization/identification.

One dominant approach to SA-ASR is applying speech separation (e.g., [12][13][14]) before ASR and speaker diarization/identification. However, a speech separation module is often designed and trained with a signal-level criterion and therefore suboptimal for the downstream modules. To overcome this problem, joint modeling of multiple modules has been investigated from a variety of viewpoints. For example, a number of studies have investigated joint modeling of speech separation and ASR (e.g., [15][16][17][18][19][20]). Several methods were also proposed for integrating speaker identification and speech separation [21][22][23]. A few studies attempted to improve the speaker diarization by leveraging ASR results [24][25].

However, only a limited number of research works investigated the joint modeling of all necessary modules of SA-ASR. [26] proposed to generate transcriptions for different speakers interleaved by speaker role tags to recognize doctor-patient conversations based on a recurrent neural network transducer (RNN-T). Although promising results were shown, the method cannot deal with speech overlaps due to the monotonicity constraint of RNN-T. Furthermore, their method is difficult to extend to an arbitrary number of speakers because the target speaker roles need to be uniquely defined. In [27], the authors applied a similar technique to [26] by interleaving multiple utterances with speaker identity tags instead of speaker role tags. To handle speakers who were unseen in the training data, the authors used speaker identity tags from the training data even for the unseen test speakers, or they simply applied a separated speaker diarization module. However, their method showed severe degradation of ASR and diarization accuracy when the oracle utterance boundaries were not used. [28] proposed a joint decoding framework for overlapped speech recognition and speaker diarization, where speaker embedding estimation and target-speaker ASR were performed alternately. While their formulation is applicable to any number of speakers, the method was actually implemented and evaluated in a way that could be used only for the two-speaker case, as target-speaker ASR was performed with an auxiliary output branch representing a single interference speaker [29].

Recently, an end-to-end (E2E) SA-ASR model has been proposed as a joint model of speaker counting, speech recognition, and speaker identification for monaural (possibly) overlapped speech [29]. It was trained to maximize the joint probability for multi-talker speech recognition and speaker identification, and achieved a significantly lower speaker-attributed word error rate (SA-WER) than a system that separately performs overlapped speech recognition and speaker identification. However, the model only works with a speaker inventory that includes the profiles (i.e., embeddings) of all speakers involved in the input speech. This requirement strongly limited its application to real scenarios.

In this paper, we extend the previous E2E SA-ASR work to address the case where no speaker profile is available. Specifically, we propose to cluster the internal speaker representations of the E2E SA-ASR model to diarize the utterances of the speakers whose

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speaker inventory

\[ \text{The goal of this method is to estimate a multi-speaker transcription } Y = \{y_1, \ldots, y_N\} \text{ and the speaker identity of each token } S = \{s_1, \ldots, s_N\} \text{ given acoustic input } X = \{x_1, \ldots, x_T\} \text{ and a speaker inventory } D = \{d_1, \ldots, d_K\}. \]

Here, \( N \) is the number of the output tokens, \( T \) is the number of the input frames, and \( K \) is the number of the speaker profiles (e.g., d-vector) in the inventory \( D \). Following the idea of serialized output training (SOT) [32], the multi-speaker transcription \( Y \) is represented by concatenating individual speakers’ transcriptions interleaved by a special symbol (\( \langle \rangle \)) representing the speaker change.

In the E2E SA-ASR modeling, it is assumed that the profiles of all the speakers involved in the input speech are included in \( D \). Note that, as long as this assumption holds, the speaker inventory may include irrelevant speakers’ profiles.

\subsection{Model architecture}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig1.png}
\caption{The architecture of the E2E SA-ASR model.}
\end{figure}

Figure 1 shows the architecture of the E2E SA-ASR model. It consists of ASR-related blocks (shown in green), and speaker identification-related blocks (shown in yellow). The computation consists of the following five steps.

\subsubsection{Step1: applying ASR- and speaker- encoders}

Given the acoustic input \( X \), an ASR encoder firstly converts \( X \) into a sequence, \( H^{\text{enc}} \), of embeddings for ASR, i.e.,

\[ H^{\text{enc}} = \{h_1^{\text{enc}}, \ldots, h_T^{\text{enc}}\} = \text{AsrEncoder}(X). \]

At the same time, a speaker encoder converts \( X \) into a sequence, \( H^{\text{spk}} \), of embeddings representing the speaker features of the input \( X \) as follows:

\[ H^{\text{spk}} = \{h_1^{\text{spk}}, \ldots, h_T^{\text{spk}}\} = \text{SpeakerEncoder}(X). \]

\subsubsection{Step2: attention weight estimation}

Secondly, at each decoder step \( n \), an attention module generates attention weight \( \alpha_n = \{\alpha_{n,1}, \ldots, \alpha_{n,T}\} \) as

\[ \alpha_n = \text{Attention}(u_n, \alpha_{n-1}, H^{\text{enc}}), \]

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

where \( u_n \) is a decoder state vector at the \( n \)-th step, and \( c_{n-1} \) is a context vector at the previous time step.

\subsubsection{Step3: calculating context vector for ASR}

Then, context vector \( c_n \) for the current decoder step \( n \) is generated as a weighted sum of the encoder embeddings as follows:

\[ c_n = \sum_{t=1}^{T} \alpha_{n,t} h_t^{\text{enc}}. \]

\subsubsection{Step4: speaker identification}

At every decoder step \( n \), the attention weight \( \alpha_n \) is also applied to \( H^{\text{spk}} \) to extract an attention-weighted average, \( p_n \), of the speaker embeddings as

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

Note that \( p_n \) could be contaminated by interfering speech because some time frames include two or more speakers.

The speaker query RNN in Fig. 1 then generates a speaker query \( q_n \) given the speaker embedding \( p_n \), the previous output \( y_{n-1} \), and the previous speaker query \( q_{n-1} \), i.e.,

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

With the speaker query \( q_n \), an attention module for speaker inventory (shown as InventoryAttention in the diagram) estimates attention weight \( \beta_{n,k} \) for each profile in \( D \):

\[ \beta_{n,k} = \frac{q_n \cdot d_k}{|q_n| |d_k|}, \]

\[ b_{n,k} = \exp(b_{n,k}) \sum_j \exp(b_{n,j}). \]

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 \( D \), i.e.,

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

Attention-weighted speaker profile \( \bar{d}_n \) is also calculated based on the attention weight \( \beta_{n,k} \) and input profile \( d_k \) as

\[ \bar{d}_n = \sum_{k=1}^{K} \beta_{n,k} d_k. \]

\subsection{Overview}

In this section, we review the E2E SA-ASR method proposed in [29]. The goal of this method is to estimate a multi-speaker transcription \( Y = \{y_1, \ldots, y_N\} \) and the speaker identity of each token \( S = \{s_1, \ldots, s_N\} \) given acoustic input \( X = \{x_1, \ldots, x_T\} \) and a speaker inventory \( D = \{d_1, \ldots, d_K\} \). Comprehensive experimental results using the monaural LibriCSS dataset [30], consisting of eight-speaker sessions, show the effectiveness of the proposed method.

2. REVIEW: E2E SA-ASR

2.2. Model architecture

Figure 1 shows the architecture of the E2E SA-ASR model. It consists of ASR-related blocks (shown in green), and speaker identification-related blocks (shown in yellow). The computation consists of the following five steps.

2.2.1. Step1: applying ASR- and speaker- encoders

Given the acoustic input \( X \), an ASR encoder firstly converts \( X \) into a sequence, \( H^{\text{enc}} \), of embeddings for ASR, i.e.,

\[ H^{\text{enc}} = \{h_1^{\text{enc}}, \ldots, h_T^{\text{enc}}\} = \text{AsrEncoder}(X). \]

At the same time, a speaker encoder converts \( X \) into a sequence, \( H^{\text{spk}} \), of embeddings representing the speaker features of the input \( X \) as follows:

\[ H^{\text{spk}} = \{h_1^{\text{spk}}, \ldots, h_T^{\text{spk}}\} = \text{SpeakerEncoder}(X). \]
2.2.5. Step5: ASR using context and speaker vectors

Finally, the output distribution for $y_n$ is estimated given the context vector $c_n$, the decoder state vector $u_n$, and the weighted speaker vector $d_n$ as follows:

$$Pr(y_n|y_{1:n-1}, s_{1:n}, X, D) \sim \text{DecoderOut}(c_n, u_n, d_n)$$

Here, it is assumed that $c_n$ and $u_n$ have the same dimensionality, and $W_d$ is a matrix to change the dimension of $d_n$ to that of $c_n$. Variable $W_{out}$ is the affine transformation matrix of the final layer. Typically, DecoderOut consists of a single affine transform with a softmax output layer. However, in this work, we insert one LSTM just before the affine transform as it improves the efficacy of the SOT model as shown in [32].

2.3. Training

All network parameters are optimized by maximizing the speaker-attributed maximum mutual information criterion as follows:

$$F_{SA-MMII} = \log Pr(Y, S|X, D)$$

$$= \log \prod_{n=1}^{N} \left\{ Pr(y_n|y_{1:n-1}, s_{1:n}, X, D) \cdot Pr(s_n|y_{1:n-1}, s_{1:n-1}, X, D)^{\gamma} \right\}.$$  

Here, $\gamma$ is a scaling parameter for the speaker estimation probability and is set to 0.1 per [29].

2.4. Decoding

An extended beam search algorithm is used for decoding for the E2E SA-ASR. With the conventional beam search, each hypothesis contains estimated tokens accompanied by the posterior probability of the hypothesis. In addition to these, a hypothesis for the E2E SA-ASR contains estimated tokens accompanied by the posterior probability of SA-ASR. With the conventional beam search, each hypothesis contains multiple utterances of different speakers with overlaps. Specifically, we first determine the number of clusters based on normalized maximum eigengap (NME) [33], and then perform spectral clustering with a normalized graph Laplacian matrix [34].

One may have multiple questions about this procedure. For example, how many example irrelevant speaker profiles are necessary in step 2? How does the silence-region detector in step 1 affect the final result? How about using the weighted profile $d_n$ for speaker counting and clustering in step 3 instead of the speaker query $q_n$? We will experimentally examine these questions in Section 4.

3. EXTENSIONS OF E2E SA-ASR

This section describes our proposed extensions of the E2E SA-ASR for recognizing continuous multi-talker recordings without prior speaker knowledge.

3.1. Combination of E2E SA-ASR and speaker clustering

The E2E SA-ASR requires the speaker inventory to include the profiles of all speakers involved in the input speech. However, it is often difficult to prepare such a speaker inventory for various reasons, including the participation of guest speakers who are not originally invited to a meeting and the privacy concern about voice enrollment.

1 We observed slight performance improvement by using the speaker estimation at the end of an utterance (i.e., the \langle sc \rangle or \langle eos \rangle position) instead of the original scheme proposed in [29] which uses the average $\beta_{n,k}$ values calculated over all tokens of the utterance.

2 In [33], spectral clustering was applied to a binarized and unnormalized graph Laplacian matrix after speaker counting. However, we applied the conventional spectral clustering with a normalized graph Laplacian as this yielded slightly better results in our preliminary experiments.
We generated 500,000 utterances when the utterances were mixed, randomly selected from training samples, each of which was a mixture of multiple utterances. We call this utterance-based modified version what an end of an utterance is in continuous speech. We call this scheme implicitly assumes that we can define token. Note that this scheme results in better performance.

4. EXPERIMENTS

4.1. Evaluation settings

4.1.1. Evaluation data

We evaluated the effectiveness of the proposed method by using the LibriCSS dataset [30], which comprises conversation-like recordings created based on the LibriSpeech corpus [35]. 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. While the recordings have seven channels, we used only the first channel data (i.e., monaural audio) for all our experiments.

The LibriCSS dataset consists of 10 sessions, each being one hour long and comprising eight speakers. Per [34], each session is decomposed to six 10-minute-long "mini-sessions" that have different overlap ratios ranging from 0% to 40%. The recordings of the first session (Session 0) was used to tune the decoding parameters, and those in the rest of 9 sessions (Session 1–9) were used for the evaluation. Note that there are two types of mini-sessions for the 0% overlap case: one has only 0.1-0.5 sec of silence between adjacent utterances (called "0S"); one has 2.9-3.0 sec of silence between the adjacent utterances (called "0L").

4.1.2. Training data

For the E2E SA-ASR training, we used multi-speaker signals that were generated by room simulation from the 960 hours of LibriSpeech training data (“train_960”) [35, 36]. We generated 500,000 training samples, each of which was a mixture of multiple utterances randomly selected from train_960. When the utterances were mixed, each utterance was shifted by a random delay to simulate partially overlapped conversational recordings. Each training sample was generated under the following conditions.

- The number of speakers was randomly chosen from 1 to 5.
- The number of utterances was randomly chosen from 1 to 5.
- The start times of different utterances were apart by 0.5 sec or longer.
- Every utterance in each mixed audio sample had at least one speaker-overlapped region with other utterances.
- Utterances of the same speakers do not overlap.

Before mixing the source utterances, a room impulse response generated by the image method was applied to each utterance [37]. In addition, random noise was generated by following [38], and added at a random SNR from 10 to 40 dB after mixing the utterances. Finally, the volume of the mixed audio was changed by a random scale between 0.125 and 2.0.

In addition to the multi-speaker signals, speaker profiles were generated for each training sample as follows. For a training sample consisting of S speakers, the number of the profiles was randomly selected from S to 8. Among those profiles, S profiles were for the speakers involved in the overlapped speech. The utterances for creating the profiles of these speakers were different from those constituting the input overlapped speech. The rest of the profiles were randomly extracted from different speakers in train_960. Each profile was extracted by using 10 utterances.

4.1.3. Evaluation metric

The main evaluation metric used in this paper is the concatenated minimum-permutation word error rate (cpWER) [5]. The cpWER is computed as follows: (i) concatenate all reference transcriptions for each speaker; (ii) concatenate all hypothesis transcriptions for each detected speaker; (iii) compute the WER between the reference and hypothesis and repeat this for all possible speaker permutations; and (iv) pick the lowest WER among them. The cpWER is affected by both the speech recognition and speaker diarization results.

Besides cpWER, we evaluated the mean speaker counting error, which is the absolute difference between the estimated number of speakers and the actual number of speakers (= 8 in LibriCSS) averaged over all mini-sessions. We also analyzed the source-target attention of our system in terms of the diarization error rate (DER). It should be noted that the mean speaker counting error and the DER are not the performance metrics we care, and they were evaluated only for analysis purposes. The hyper-parameters of our systems were tuned on the development set to improve only the cpWER.

4.1.4. Model settings

In our experiments, an 80-dim log mel filterbank extracted every 10 msec was used for the input feature. 3 frames of features were stacked, and the model was applied on top of the stacked features. For the speaker profile, we used a 128-dim d-vector [31], whose extractor was separately trained on VoxCeleb Corpus [39, 40]. The d-vector extractor consisted of 17 convolution layers followed by an average pooling layer, which was a modified version of the one presented in [41].

The AsrEncoder consisted of 5 layers of 1024-dim bidirectional long short-term memory (BLSTM), interleaved with layer normalization [42]. The DecoderRNN consisted of 2 layers of 1024-dim unidirectional LSTM, and the DecoderOut consisted of 1 layer of 1024-dim unidirectional LSTM. We used a conventional location-aware content-based attention [43] with a single attention head. The SpeakerEncoder had the same architecture as the d-vector extractor except for not having the final average pooling layer. Our SpeakerQueryRNN consisted of 1 layer of 512-dim unidirectional LSTM. We used 16k subwords based on a unigram language model [44] as a recognition unit.

When we trained the E2E SA-ASR model, we initialized the parameters of AsrEncoder, Attention, DecoderRNN, and DecoderOut by the parameter values of a three-speaker SOT-ASR model trained on simulated LibriSpeech utterance mixtures. We followed the setting described in [32] for pre-training the SOT model, and used the parameter values obtained after 640k training iterations. We also initialized the SpeakerEncoder parameters by using those of the d-vector extractor. After the initialization, we updated the entire net-

| FIFO order | 0S | 0L | 10 | 20 | 30 | 40 | Avg. |
|------------|----|----|----|----|----|----|-----|
| Speaker    | 7.1 | 6.8 | 21.4 | 24.3 | 42.7 | 44.6 | 26.7 |
| Utterance  | 6.9 | 7.0 | 11.2 | 15.0 | 28.4 | 30.3 | 17.8 |
work based on $F^{SA-MM1}$ with $\gamma = 0.1$ by using an Adam optimizer with a learning rate of 0.00002. We used 8 GPUs, each of which worked on 6k frames of minibatch. We report the results of the dev_clean-based best models found after 120k training iterations.

In addition to the E2E SA-ASR model described above, we trained an external language model (LM) that consisted of 4 layers of 2,048-dim LSTM. As training data, we generated a text corpus of 8k frames of minibatch. We used 8 GPUs, each of which worked on 6k frames of minibatch. We report the results of the dev_clean-based best models found after 120k training iterations.

### Table 2. CpWERs (%) and speaker counting errors with different speaker profile settings

| # of relevant profiles | # of irrelevant profiles | Speaker clustering | Speaker counting | 0S 0L 10 20 30 40 Avg. Mean speaker counting error |
|------------------------|-------------------------|--------------------|-----------------|----------|------|
| E2E SA-ASR             |                         |                    |                 |          |      |
| 8                      | 0                       | automatic          | 6.1 5.7 9.3 15.3 26.7 30.3 16.9 0.00 |
| 8                      | 5                       | automatic          | 6.2 5.8 10.1 14.9 26.0 36.1 18.0 0.37 |
| 8                      | 10                      | automatic          | 6.2 6.2 9.9 15.4 27.1 36.7 18.5 0.91 |
| 8                      | 20                      | automatic          | 7.0 6.9 10.4 15.8 27.6 37.4 19.0 1.59 |
| 8                      | 100                     | automatic          | 10.2 10.2 12.1 17.3 31.5 41.9 22.1 3.91 |
| E2E SA-ASR + Speaker Clustering (proposed method) | | | 71.3 67.7 64.4 67.8 80.1 78.1 72.1 7.19 |
| 0                      | 100                     | oracle             | 5.6 6.8 9.3 14.2 26.4 30.3 16.7 0.00 |
| 0                      | 100                     | NME (max=8)        | 6.6 9.0 13.3 14.2 26.4 30.7 17.9 0.11 |
| 0                      | 100                     | NME (max=12)       | 6.6 13.7 14.9 15.9 28.1 30.7 19.3 0.30 |
| 0                      | 100                     | NME (max=16)       | 11.0 13.7 14.9 15.9 28.1 30.7 20.0 0.43 |
| Speaker embedding       | Overlap ratio in %      | 0S 0L 10 20 30 40 Avg. Mean speaker counting error |
| for clustering          |                        |                   |                 |          |      |
| Weighted profile $a_n$  | 10.1 10.4 17.2 23.6 34.3 34.7 16.7 |
| Speaker query $q_n$     | 5.6 6.8 9.3 14.2 26.4 30.3 16.7 |

### Table 3. Average cpWER (%) with different numbers of irrelevant profiles (i.e., example profiles) for proposed method using oracle speaker numbers. Oracle boundary-based segmentation was used.

| # of irrelevant profiles | 1 5 10 100 |
|--------------------------|-----------|
| LM                       |           |
| 19.4                     | 18.9 18.9 |
| Oracle                   | 16.9 16.9 |

### Table 4. CpWERs (%) with different internal speaker embeddings for speaker clustering. Oracle boundary-based segmentation was used.

| Speaker embedding for clustering | Overlap ratio in % | 0S 0L 10 20 30 40 Avg. |
|---------------------------------|--------------------|------------------------|
| Weighted profile $a_n$          | 10.1 10.4 17.2 23.6 34.3 34.7 16.7 |
| Speaker query $q_n$             | 5.6 6.8 9.3 14.2 26.4 30.3 16.7 |

Next, we evaluated the accuracy of the E2E SA-ASR when the speaker inventory included irrelevant speaker profiles. In this experiment, irrelevant speakers were randomly chosen from train_960 of LibriSpeech, and a randomly selected one utterance was used to extract the speaker profile of each irrelevant speaker. The result is shown in the first five rows of Table 2. When no irrelevant profiles were included in the speaker inventory, the E2E SA-ASR achieved the best cpWER of 16.9%. The cpWER gradually deteriorated as the addition of irrelevant profiles, but the system still achieved 22.1% of cpWER even with 100 irrelevant profiles.

Finally, to analyze the impact of the speaker profiles, we also evaluated the E2E SA-ASR with no relevant speaker profiles. The results of this experiment are shown from the 6th to 8th rows of Table 2 where we provided 10, 20, or 100 irrelevant profiles as input while not using any profiles for the relevant speakers. Speaker diarization was conducted purely based on the speaker identification result for each utterance. As expected, we observed a very high cpWER of 72.1–81.3%. Note that, the mean speaker counting error for the 10 irrelevant profile case was relatively small ($= 1.19$) just because the given (10) and correct (8) numbers of speakers were close.

### 4.2. Evaluation with oracle silence boundary

We firstly evaluated the proposed method with an oracle silence-region detector. Namely, we divided each recording at every silence position obtained from the oracle utterance boundary information. Note that each segmented audio still consisted of multiple overlapped utterances of different speakers. The minimum and maximum numbers of utterances were found to be 1 and 24, respectively. In this subsection, we used the oracle silence detection. The performance using an automatic silence detector is reported in the next subsection.

#### 4.2.1. Baseline results of E2E SA-ASR

As a baseline, we evaluated the E2E SA-ASR with a speaker inventory consisting only of the eight relevant speakers. Each speaker’s profile was extracted by using 5 utterances that were not included in the recording used for the evaluation. We firstly compared the speaker-based and utterance-based FIFO training schemes that we described in Section 4.2. The result is shown in Table 2. We can see that the utterance-based FIFO training significantly outperformed the speaker-based FIFO training. Therefore, we always used the E2E SA-ASR model based on the utterance-based FIFO training in the remaining experiments.

We then evaluated the proposed procedure of the combination of the E2E SA-ASR and speaker clustering. The results are shown in the last two rows of Table 2. In this experiment, we used 100 irrelevant speaker profiles as a set of example profiles. When we applied the speaker clustering with the oracle number of speakers, the proposed method achieved 16.7% of cpWER, which was even better than the best number obtained by the E2E SA-ASR with the relevant speaker inventory. This is because spectral clustering can access to the speaker embeddings of all utterances while the speaker identification inside the E2E SA-ASR was done by accessing only the information of the single segment. When we estimated the number of speakers by using NME with a maximum possible number of speakers of {8, 12, 16}, the cpWER was slightly degraded to 17.9–20.0%. Nonetheless, it was still as good as the E2E SA-ASR with
In this paper, we proposed to apply speaker counting and clustering to the speaker query of an E2E SA-ASR model to diarize utterances of speakers whose speaker profiles are not included in the speaker inventory. We also proposed a simple yet effective modification to the reference label construction for E2E SA-ASR training, which helps cope with the continuous multi-talker recordings. In the evaluation, compared with the original E2E SA-ASR with a speaker inventory consisting only of relevant speaker profiles, the proposed method achieved a close cpWER even without any prior speaker knowledge.

5. CONCLUSION

### Table 5.
CpWERs (%) with automatic silence-region detector to segment the audio recordings.

| System number | # of relevant profiles | # of irrelevant profiles | Speaker clustering | Speaker counting | 0S 0L 10 20 30 40 Avg. | Mean speaker counting error |
|---------------|------------------------|-------------------------|--------------------|-----------------|---------------------|-----------------------------|
| E2E SA-ASR    | 1 8 0                  | -                       | automatic          | automatic        | 15.7 8.0 12.5 17.5 24.3 27.6 18.6 | 0.00 |
|               | 2 8 5                  | -                       | automatic          | automatic        | 16.4 8.9 13.4 18.2 25.0 28.3 19.3 | 0.89 |
|               | 3 8 10                 | -                       | automatic          | automatic        | 16.6 9.0 13.9 19.0 25.8 28.8 19.9 | 1.78 |
|               | 4 8 20                 | -                       | automatic          | automatic        | 18.1 10.2 14.9 19.5 27.0 30.6 21.1 | 3.11 |
|               | 5 8 100                | -                       | automatic          | automatic        | 24.0 15.5 18.8 23.8 32.3 35.4 26.0 | 9.00 |
| E2E SA-ASR + Speaker Clustering (proposed method) | 6 0 100 | ✓ | oracle | 15.8 10.3 13.4 17.1 24.4 28.6 19.2 | 0.00 |
|               | 7 0 100                | ✓ | NME (max=16) | 24.4 12.2 15.0 17.1 28.6 28.6 21.8 | 0.31 |

We also evaluated the effect of the number of irrelevant profiles (= example profiles) for the combination of the E2E SA-ASR and speaker clustering. The result of this study is shown in Table 5. It can be seen that using too few irrelevant profiles resulted in the degradation of cpWER. It is because we cannot calculate an appropriate weighted profile when we have too few profiles, which ends up with degrading the overall accuracy. Note that the computational cost of the inventory attention (Eq. 8–11) was negligible even with 100 profiles. Thus, we used 100 irrelevant speaker profiles in the following experiments unless otherwise stated.

We also compared clustering using the weighted profile $d_{av}$ and that using speaker query $q_s$. The results are shown in Table 6. In this experiment, we applied the E2E SA-ASR with 100 irrelevant speaker profiles, and then applied speaker clustering given the oracle number of speakers. As seen in the table, the use of the speaker query $q_s$ resulted in significantly better speaker clustering performance.

### Table 6.
Analysis on the source-target attention of two systems in Table 5 based on DERs (%).

| System number | DER (%) for different overlap ratio | Avg. |
|---------------|-----------------------------------|------|
| 0S 0L 10 20 30 40 | 15.23† |
| System 1      | 15.72 11.15 12.64 14.50 18.04 17.33 | 15.23† |
| System 7      | 19.71 12.97 13.81 14.49 19.98 17.97 | 16.75 |

1 Miss = 4.72%, false alarm = 7.04%, speaker error = 3.47%
2 Miss = 4.75%, false alarm = 7.00%, speaker error = 5.00%

We finally evaluated the proposed method with an automatic silence-region detector. In this experiment, we applied the WebRTC Voice Activity Detector for each recording, and segmented the audio whenever silence regions were detected.

The result with the automatic silence-region detector is shown in Table 7. The original E2E SA-ASR with the relevant speaker inventory achieved 18.6% to 26.0% of cpWER depending on the number of the additional irrelevant profiles. On the other hand, the proposed combination of the E2E SA-ASR and speaker clustering achieved 19.2% of cpWER with oracle speaker counting, and 21.8% of cpWER with NME-based speaker counting, respectively.

Compared with the case using the oracle silence-region information, the cpWER was degraded by 3.1%. Especially, we noticed that “0S” setting showed a severe cpWER degradation even though the overlap ratio was 0%. With “0S”, there was very short silence (0.1-0.5 sec) between adjacent utterances of different speakers. As a result, segments in “0S” often consisted of consecutive speech of multiple speakers. We observed the E2E SA-ASR sometimes misrecognized the speaker change points for such speech, which resulted in the degradation of cpWER. Note that the speaker change detection for non-overlapped speech could be more difficult than that for overlapped speech because speech overlaps could be used as a clue of speaker change besides the difference of voice characteristics.

4.3.2. Analysis of the source-target attention with DER

We analyzed the source-target attention $\alpha_s$ of the E2E SA-ASR. We estimated the start and end times of each utterance based on $\alpha_s$ as follows and calculated the DER accordingly.

1. For each utterance hypothesis, the attention ($\alpha_s$)-weighted average of the frame indices was calculated for each token other than $(sc)$ or $(eos)$.
2. The minimum frame index $f_{min}$ and the maximum frame index $f_{max}$ were calculated.
3. The start time $T_s$ was defined as $T_s = \max(0, f_{min}, T_f - T_m)$. The end time $T_e$ was defined as $T_e = f_{max}$.

Here, $T_s$ is the frame shift in second, and it was 0.03 sec according to our model settings. The term $T_m$ is a heuristic margin tuned by the development set, and it was determined as 0.5 sec in our experiment.

The DER result is shown in Table 7. In this evaluation, we calculated the DER without a collar margin, and the overlapping regions were included in the DER calculation. As shown in the table, the E2E SA-ASR systems showed 15.23–16.75% of DER on average. In the high overlap test sets (with the overlap ratios of 20%–40%), the DERs were significantly better than the overlap ratios of the input audio, which indicates that the source-target attention scanned the encoder embeddings back and forth to recognize overlapped utterances one by one as originally designed by SOT [32]. On the other hand, the DER was as high as 11.15% even for the non overlapped speech (0L). This could be because the our model is optimized to achieve good SA-ASR accuracy, unlike other diarization methods, such as the end-to-end neural diarization [45, 46] or target-speaker voice activity detection [41, 47], that are optimized for DER. That being said, the result shows that the source-target attention in the E2E SA-ASR model provides information about the start and end times of the hypotheses and thus can be used for applications requiring both the time boundary and the recognition result.

In the degradation of cpWER. Note that the speaker change detection for non-overlapped speech could be more difficult than that for overlapped speech because speech overlaps could be used as a clue of speaker change besides the difference of voice characteristics.

5. CONCLUSION

In this paper, we proposed to apply speaker counting and clustering to the speaker query of an E2E SA-ASR model to diarize utterances of speakers whose speaker profiles are not included in the speaker inventory. We also proposed a simple yet effective modification to the reference label construction for E2E SA-ASR training, which helps cope with the continuous multi-talker recordings. In the evaluation, compared with the original E2E SA-ASR with a speaker inventory consisting only of relevant speaker profiles, the proposed method achieved a close cpWER even without any prior speaker knowledge.
6. REFERENCES

[1] Jonathan G Fiscus, Jerome Ajot, and John S Garofolo, “The rich transcription 2007 meeting recognition evaluation,” in *Multimodal Technologies for Perception of Humans*, pp. 373–389. Springer, 2007.

[2] Adam Janin, Don Baron, Jane Edwards, Dan Ellis, David Gelbart, Nelson Morgan, Barbara Peskin, Thilo Pfau, Elizabeth Shriberg, Andreas Stolcke, et al., “The ICSI meeting corpus,” in *Proc. ICASSP*, 2003, vol. 1, pp. I–I.

[3] Jean Carletta, Simone Ashby, Sebastien Bourban, Mike Flynn, Maël Guillemot, Thomas Hain, Jaroslav Kadlec, Vasiliis Karaïkos, Wessel Kraaij, Melissa Kronenthal, et al., “The AMI meeting corpus: A pre-announcement,” in *International workshop on machine learning for multimodal interaction*. Springer, 2005, pp. 28–39.

[4] Jon Barker, Shinji Watanabe, Emmanuel Vincent, and Jan Trmal, “The fifth ‘CHiME’ speech separation and recognition challenge: Dataset, task and baselines,” *Proc. Interspeech*, pp. 1561–1565, 2018.

[5] Shinji Watanabe, Michael Mandel, Jon Barker, Emmanuel Vincent, Ashish Arora, Xuankai Chang, Sanjeev Khudanpur, Vimal Manohar, Daniel Povey, Desh Raj, et al., “CHiME-6 challenge: Tackling multispeaker speech recognition for unsegmented recordings,” in *Proc. CHiME 2020*, 2020.

[6] Neville Ryant, Kenneth Churchb, Christopher Cieri, Alejandra Cristiаc, Jun Dud, Sriram Ganapathy, and Mark Liberman, “First DIHARD challenge evaluation plan,” 2018.

[7] Neville Ryant, Kenneth Church, Christopher Cieri, Alejandra Cristia, Jun Du, Sriram Ganapathy, and Mark Liberman, “The second DIHARD diarization challenge: Dataset, task, and baselines,” *Proc. Interspeech*, pp. 978–982, 2019.

[8] Naoyuki Kanda, Rintaro Ikeshita, Shota Horiguchi, Yusuke Fujita, Kenji Nagamatsu, and Shinji Watanabe, “Auxiliary interference speaker loss for target-speaker speech recognition,” in *Proc. Interspeech*, 2019, pp. 236–240.

[9] Takuya Yoshioka, Igor Abramovski, Cem Aksoyar, Zhuo Chen, Moshe David, Dimitrios Dimitriadis, Yifan Gong, Ilya Gurvich, Xuedong Huang, Yan Huang, et al., “Advances in online audio-visual meeting transcription,” in *Proc. ASRU*, 2019, pp. 276–283.

[10] Naoyuki Kanda, Christoph Boeddeker, Jens Heitkaemper, Yusuke Fujita, Shota Horiguchi, Kenji Nagamatsu, and Reinhold Haeb-Umbach, “Guided source separation meets a strong ASR backend: Hitachi/Paderborn University joint investigation for dinner party ASR,” in *Proc. Interspeech*, 2019, pp. 1248–1252.

[11] Ivan Medennikov, Maxim Korenevsky, Tatiana Prisyach, Yuri Khokhlov, Mariya Korenevskaya, Ivan Sorokin, Tatiana Timofeeva, Anton Mitrofano, Andrei Andrusenko, Ivan Podluzhny, et al., “The STC system for the CHiME-6 challenge,” in *CHiME 2020 Workshop on Speech Processing in Everyday Environments*, 2020.

[12] John R Hershey, Zhuo Chen, Jonathan Le Roux, and Shinji Watanabe, “Deep clustering: Discriminative embeddings for segmentation and separation,” in *Proc. ICASSP*, 2016, pp. 31–35.

[13] Zhuo Chen, Yi Luo, and Nima Mesgarani, “Deep attractor network for single-microphone speaker separation,” in *Proc. ICASSP*, 2017, pp. 246–250.

[14] Dong Yu, Morten Kolbæk, Zheng-Hua Tan, and Jesper Jensen, “Permutation invariant training of deep models for speaker-independent multi-talker speech separation,” in *Proc. ICASSP*. IEEE, 2017, pp. 241–245.

[15] Dong Yu, Xuankai Chang, and Yanmin Qian, “Recognizing multi-talker speech with permutation invariant training,” *Proc. Interspeech 2017*, pp. 2456–2460, 2017.

[16] Hiroshi Seki, Takaaki Hori, Shinji Watanabe, Jonathan Le Roux, and John R Hershey, “A purely end-to-end system for multi-speaker speech recognition,” in *Proc. ACL*, 2018, pp. 2620–2630.

[17] Xuankai Chang, Yanmin Qian, Kai Yu, and Shinji Watanabe, “End-to-end monaural multi-speaker ASR system without pre-training,” in *Proc. ICASSP*, 2019, pp. 6256–6260.

[18] Xuankai Chang, Wangyou Zhang, Yanmin Qian, Jonathan Le Roux, and Shinji Watanabe, “MIMO-SPEECH: End-to-end multi-channel multi-speaker speech recognition,” in *Proc. ASRU*, 2019, pp. 237–244.

[19] Naoyuki Kanda, Yusuke Fujita, Shota Horiguchi, Rintaro Ikeshita, Kenji Nagamatsu, and Shinji Watanabe, “Acoustic modeling for distant multi-talker speech recognition with single-and multi-channel branches,” in *Proc. ICASSP*, 2019, pp. 6630–6634.

[20] Naoyuki Kanda, Shota Horiguchi, Ryoichi Takashima, Yusuke Fujita, Kenji Nagamatsu, and Shinji Watanabe, “Auxiliary interference speaker loss for target-speaker speech recognition,” in *Proc. Interspeech*, 2019, pp. 236–240.

[21] Peidong Wang, Zhuo Chen, Xiong Xiao, Zhong Meng, Takuya Yoshioka, Tianyan Zhou, Liang Lu, and Jinyu Li, “Speech separation using speaker inventory,” in *Proc. ASRU*, 2019, pp. 230–236.

[22] Thilo von Neumann, Keisuke Kinoshita, Marc Delcroix, Shoko Araki, Tomohiro Nakatani, and Reinhold Haeb-Umbach, “All-neural online source separation, counting, and diarization for meeting analysis,” in *Proc. ICASSP*, 2019, pp. 91–95.

[23] Keisuke Kinoshita, Marc Delcroix, Shoko Araki, and Tomohiro Nakatani, “Tackling real noisy reverberant meetings with all-neural source separation, counting, and diarization system,” arXiv preprint arXiv:2003.03987, 2020.

[24] Tae Jin Park and Panayiotis Georgiou, “Multimodal speaker segmentation and diarization using lexical and acoustic cues via sequence to sequence neural networks,” in *Proc. Interspeech*, 2018, pp. 1373–1377.

[25] Tae Jin Park, Kyu J Han, Jing Huang, Xiaodong He, Bowen Zhou, Panayiotis Georgiou, and Shrikanth Narayanan, “Speaker diarization with lexical information,” in *Proc. Interspeech*, 2019, pp. 391–395.

[26] Laurent El Shafey, Hagen Soltuа, and Izhak Shafран, “Joint speech recognition and speaker diarization via sequence transduction,” in *Proc. Interspeech*, 2019, pp. 396–400.
[27] Huanru Henry Mao, Shuyang Li, Julian McAuley, and Garrison Cottrell, “Speech recognition and multi-speaker diarization of long conversations,” arXiv preprint arXiv:2005.08072, 2020.
[28] Naoyuki Kanda, Shota Horiguchi, Yusuke Fujita, Yawen Xue, Kenji Nagamatsu, and Shinji Watanabe, “Simultaneous speech recognition and speaker diarization for monaural dialogue recordings with target-speaker acoustic models,” in Proc. ASRU, 2019.
[29] Naoyuki Kanda, Yashesh Gaur, Xiaofei Wang, Zhong Meng, Zhuo Chen, Tianyan Zhou, and Takuya Yoshioka, “Joint speaker counting, speech recognition, and speaker identification for overlapped speech of any number of speakers,” arXiv preprint arXiv:2006.10930, 2020.
[30] Zhuo Chen, Takuya Yoshioka, Liang Lu, Tianyan Zhou, Zhong Meng, Yi Luo, Jian Wu, and Jinyu Li, “Continuous speech separation: dataset and analysis,” in Proc. ICASSP, 2020 (to appear).
[31] Ehsan Variani, Xin Lei, Erik McDermott, Ignacio Lopez Moreno, and Javier Gonzalez-Dominguez, “Deep neural networks for small footprint text-dependent speaker verification,” in Proc. ICASSP, 2014, pp. 4052–4056.
[32] Naoyuki Kanda, Yashesh Gaur, Xiaofei Wang, Zhong Meng, and Takuya Yoshioka, “Serialized output training for end-to-end overlapped speech recognition,” arXiv preprint arXiv:2003.12687, 2020.
[33] Tae Jin Park, Kyu J Han, Manoj Kumar, and Shrikanth Narayanan, “Auto-tuning spectral clustering for speaker diarization using normalized maximum eigengap,” IEEE Signal Processing Letters, vol. 27, pp. 381–385, 2019.
[34] Ulrike Von Luxburg, “A tutorial on spectral clustering,” Statistics and computing, vol. 17, no. 4, pp. 395–416, 2007.
[35] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, “Librispeech: an ASR corpus based on public domain audio books,” in Proc. ICASSP, 2015, pp. 5206–5210.
[36] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Molicek, Yanmin Qian, Petr Schwarz, et al., “The Kaldi speech recognition toolkit,” in ASRU, 2011.
[37] Tom Ko, Vijayaditya Peddinti, Daniel Povey, Michael L Seltzer, and Sanjeev Khudanpur, “A study on data augmentation of reverberant speech for robust speech recognition,” in Proc. ICASSP, 2017, pp. 5220–5224.
[38] Emanuel AP Habets and Sharon Gannot, “Generating sensor signals in isotropic noise fields,” The Journal of the Acoustical Society of America, vol. 122, no. 6, pp. 3464–3470, 2007.
[39] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Voxceleb: A large-scale speaker identification dataset,” in Proc. Interspeech, 2017, pp. 2616–2620.
[40] Joon Son Chung, Arsha Nagrani, and Andrew Zisserman, “Voxceleb2: Deep speaker recognition,” in Proc. Interspeech, 2018, pp. 1086–1090.
[41] Tianyan Zhou, Yong Zhao, Jinyu Li, Yifan Gong, and Jian Wu, “CNN with phonetic attention for text-independent speaker verification,” in Proc. ASRU, 2019, pp. 718–725.
[42] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton, “Layer normalization,” arXiv preprint arXiv:1607.06450, 2016.