ONLINE END-TO-END NEURAL DIARIZATION
HANDLING OVERLAPPING SPEECH AND FLEXIBLE NUMBERS OF SPEAKERS

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ABSTRACT

This paper proposes an online end-to-end diarization that can handle overlapping speech and flexible numbers of speakers. The end-to-end neural speaker diarization (EEND) model has already achieved significant improvement when compared with conventional clustering-based methods. However, the original EEND has two limitations: i) EEND does not perform well in online scenarios; ii) the number of speakers must be fixed in advance. This paper solves both problems by applying a modified extension of the speaker-tracing buffer method that deals with variable numbers of speakers. Experiments on CALLHOME and DIHARD II datasets show that the proposed online method achieves comparable performance to the offline EEND method. Compared with the state-of-the-art online method based on a fully supervised approach (UIS-RNN), the proposed method shows better performance on the DIHARD II dataset.

Index Terms— Online speaker diarization, EEND

1. INTRODUCTION

Speaker diarization is a challenging technique that relates audio regions to speaker labels. It responds to the question “who spoke when” [1]. Diarization produces outcomes that downstream tasks can utilize. It can provide the turn-taking information and build a pre-processing pipeline for automatic speech recognition in meetings [2,3], call-center telephonic communications [4,5], and home environment (CHiME-5, CHiME-6) [6,8].

In real conditions, speaker diarization should consider overlapping speech and unknown numbers of speakers. However, it is still an open problem to solve these conditions at once. Conventional clustering-based systems primarily focus on clustering algorithms and speaker embeddings such as Gaussian mixture models (GMM) [2,10], i-vector [11,13], d-vector [14], and x-vector [15,17]. However, most clustering-based systems assume that there is only one speaker in one segment. As a result, most systems cannot deal with the overlapping speech except for a handful (e.g., [18]).

To solve the overlapping issue, an end-to-end neural diarization model (EEND) was proposed [19]. EEND directly minimizes the diarization error by mapping the multi-speaker mixture recording to joint speech activities using a single neural network. Since each speaker has its own speech activity channel in the model, EEND can detect overlapping speech using multiple speech activity channels. EEND has already shown significant performance improvement than the conventional clustering-based method, especially after adopting the self-attention mechanism (SA-EEND) [20], in the setting of a fixed number of speakers.

Table 1: Comparison of speaker diarization methods.

| Method                  | Online | Overlapping | Flexible #speakers |
|-------------------------|--------|-------------|--------------------|
| x-vector+clustering     | –      | –           | ✓                  |
| UIS-RNN [14,15]        | ✓      | ✓           | ✓                  |
| RSAN [25,26]           | ✓      | ✓           | ✓                  |
| EEND/SA-EEND [19,20,27] | –      | ✓           | ✓                  |
| EEND-EDA/SC-EEND [21,22]| –      | ✓           | ✓                  |
| This work               | ✓      | ✓           | ✓                  |

To deal with flexible numbers of speakers, Horiguchi et al. introduced the encoder-decoder based attractor (EDA) module to SA-EEND [21], and Fujita et al. extended the SA-EEND to speaker-wise conditional EEND (SC-EEND) [22]. Moreover, to reduce the computational cost of EEND, a faster loss calculation approach has been proposed [23]. All the above extensions have only been evaluated in offline mode. Later, the speaker-tracing buffer (STB) was proposed to make the EEND work in an online manner with acceptable results, while this method was limited to two-speaker recordings [24].

To improve the potential of the EEND-based system, in this work, we extend the EEND models, such as EEND-EDA and SC-EEND, to operate in an online mode using STB for variable numbers of speakers. An extension of STB was also designed to deal with variable numbers of speakers at a reasonable computational cost. Table 1 shows a comparison of speaker diarization methods. Among these methods, the Recurrent Selective Attention Network (RSAN) [25,26] can deal with the online mode, overlapping speech, and flexible numbers of speakers. However, due to the speech separation-based training objective, which is hard to adapt to real recordings, the evaluations under real scenarios are limited. In this work, we propose a diarization system that can operate in an online mode handling overlapping speech and flexible numbers of speakers, enabling it to work in real scenarios such as CALLHOME and DIHARD II.

2. PRELIMINARY

In this section, we briefly explain EEND for flexible numbers of speakers and the conventional STB that are the key elements of our system.

2.1. EEND for flexible numbers of speakers

As the original EEND cannot deal with flexible numbers of speakers due to its neural network structure, to our knowledge, two extensions of EEND systems have been proposed to solve this problem. The first system applies EDA to the speaker embedding sequences derived from SA-EEND [21]. The second system is the

index terms — Online speaker diarization, EEND
3. PROPOSED METHOD

Our proposed method has three advantages compared with previous works mentioned in Section 2.2. Firstly, we solve the varying number of speakers among chunks by increasing the number of speakers of the speaker tracing buffer with the zero-padding. When the system detects the new speakers, the system adds new speaker elements with the zero speaker activity to the buffer. Secondly, we improve the efficiency of the system by using the covariance instead of the correlation coefficient to calculate the similarity between the previous and the current outputs. Lastly, we propose four selection strategies for updating the buffer to extend the application scope of the system.

3.1. STB for flexible numbers of speakers

Online diarization for flexible numbers of speakers was performed by referring and updating STB, as shown in Algorithm 1. Let $X_i \in \mathbb{R}^{D \times T}$ represent the subsequence of $X$ at chunk $i$, where $\Delta$ is the chunk size and $\hat{Y}_i$ be the corresponding outputs of $X_i$. We define $L_{\max}$ to be the maximum number of frames in the buffer.

At the initial stage, the acoustic features and the corresponding outputs are defined as

\[ X_{\text{buf}}^i \in \mathbb{R}^{D \times L} (0 \leq L \leq L_{\max}) , \]
\[ Y_{\text{buf}}^i \in (0, 1)^{S_{\text{buf}}^i \times L} (0 \leq L \leq L_{\max}) , \]

in STB are empty, where $S_{\text{buf}}^i$ is the estimated number of speakers in a buffer. The input of the FS-EEND system is the concatenation of features of the buffer and the acoustic features of the buffer $X_{\text{buf}}^i$ as shown in Eq. (2). The corresponding output of FS-EEND is expressed as follows:

\[ \hat{X}_{\text{buf}}^i ; X_i \in \mathbb{R}^{D \times (L+\Delta)} , \]
\[ \hat{Y}_{\text{buf}}^i ; \hat{Y}_i \in (0, 1)^{\hat{S}_i \times (L+\Delta)} , \]

where $\hat{S}_i$ is the estimated number of speakers of the current chunk. We define $\mathcal{D}(\cdot)$ function to calculate the number of speakers from the network output. As the number of speakers $S_{\text{buf}}^i$ in the previously computed outputs $Y_{\text{buf}}^i$ and $\hat{S}_i$ in the newly computed outputs $\hat{Y}_{\text{buf}}^i$ may be varied when the system is used for flexible numbers of speakers case. A zero-padding ZP($Y, S$) function is applied to force the number of speakers in $Y$ to be $S$. If $S_{\text{buf}}^i < \hat{S}_i$, which means there are new speakers coming in, we pad $((\hat{S}_i - S_{\text{buf}}^i) \times L)$ zero-values to all lacking dimensions in $Y_{\text{buf}}^i$. If the number of speakers is reduced in the current chunk (seldom but a few cases), we apply the zero-padding function to $Y_{\text{buf}}^i$. One example of the first
two chunks is shown in Figure 1, where \( \Delta = 10 \), \( L_{\text{max}} = 5 \), and the number of speakers is increased in the second chunk.

To solve the speaker permutation ambiguity, the original STB used the correlation coefficient to find the optimal correspondence between \( Y^{\text{buf}} \) and \( x^{\text{buf}} \). In this study, we adopt the covariance instead to avoid time-consuming calculation. The covariance between the output stored in the buffer \( Y^{\text{buf}} := (y_{\phi,s,t}^{\text{buf}})_{s,t} \in (0,1) \cdot S_i \times L \) and the current output with the speaker permutation \( \phi \in \text{perm}(S_i) \), i.e., \( Y_{\phi} := (y_{\phi,s,t}^{\text{buf}})_{s,t} \in (0,1) \cdot S_i \times L \) is defined as:

\[
\text{Cov} \left( Y^{\text{buf}}, Y_{\phi} \right) = \frac{1}{S_i L} \sum_{s=1}^{S_i} \sum_{t=1}^{L} (y_{\phi,s,t}^{\text{buf}} - \bar{y}^{\text{buf}})(y_{\phi,s,t}^{\text{buf}} - \bar{y}_{\phi}^{\text{buf}}),
\]

where \( \text{perm}(S_i) \) generates all permutations according to the number of speakers \( S_i \). Then, the permutation \( \psi \in \text{perm}(S_i) \) with the largest covariance is chosen, and the corresponding buffer output \( Y_{\psi}^{\text{buf}} \) is selected as the final output \( Y_i \) of chunk \( i \), which can maintain a consistent speaker permutation across the chunk. The obtained output \( Y_i \) is stacked with the previously estimated output to form the whole recording’s output \( \tilde{Y} \) in the end. Lastly, the current acoustic features \( X_i \) and corresponding output \( \tilde{Y} \) will be saved into the buffer.

**Algorithm 1:** Online diarization using STB for flexible numbers of speakers.

```
Input: \( \{X_1, \ldots\} \) // Chunked acoustic subsequences
\( L_{\text{max}} \) // Buffer size
FS-EEND(\() // EEND-EDA or SC-EEND
Output: \( \tilde{Y} \) // Diarization results
1 \( X^{\text{buf}} \leftarrow \emptyset \), \( Y^{\text{buf}} \leftarrow \emptyset \) // Initialize buffer
2 for \( i = 1, \ldots \) do
3 \( [Y^{\text{buf}}, \tilde{Y}_i] \leftarrow \text{FS-EEND} \left( [X^{\text{buf}}, X_i] \right) \)
4 if \( Y^{\text{buf}} \neq \emptyset \) then
5 \( \bar{S}^{\text{buf}} \leftarrow D \left( Y^{\text{buf}}, \tilde{S}_i \right) \) // #Speakers
6 \( \text{if } \bar{S}^{\text{buf}} < \tilde{S}_i \text{ then} \)
7 \( Y^{\text{buf}} \leftarrow ZP \left( Y^{\text{buf}}, \tilde{S}_i \right) \) // Zero-padding
8 \( \text{else if } \bar{S}^{\text{buf}} > \tilde{S}_i \text{ then} \)
9 \( Y^{\text{buf}} \leftarrow ZP \left( Y^{\text{buf}}, \bar{S}^{\text{buf}} \right) \) // Zero-padding
10 \( \psi \leftarrow \arg \max_{\phi \in \text{perm}(S_i)} \text{Cov} \left( Y^{\text{buf}}, Y_{\phi} \right) \)
11 \( \tilde{Y}_i \leftarrow Y^{\text{buf}}_{\psi} \)
12 \( Y \leftarrow [\tilde{Y}; \tilde{Y}_i] \)
13 \( X^{\text{buf}} \leftarrow [X^{\text{buf}}, X_i], Y^{\text{buf}} \leftarrow [Y^{\text{buf}}, \tilde{Y}_i] \)
14 Update \( X^{\text{buf}} \) and \( Y^{\text{buf}} \) according to the selection strategy // Sec. 3.2
```

### 3.2. Selection strategy

When the number of accumulated features \( L \) becomes larger than the buffer size \( L_{\text{max}} \), some selection strategy is needed for keeping informative features that contain the speaker permutation information from \( [X^{\text{buf}}; X_i] \) and \( [Y^{\text{buf}}; \tilde{Y}_i] \). In this section, four selection rules for updating the buffer are proposed, especially for flexible numbers of speakers.

- **First-in-first-out:** the most recent \( L_{\text{max}} \) features and the corresponding diarization results are stored in the buffer, which follows the first-in-first-out manner.
- **Kullback-Leibler divergence based selection:** we think of the Kullback-Leibler divergence (KLD) as the distance metric that quantifies the difference between two probability distributions as follows:

\[
\text{KLD}_i = \sum_{s=1}^{S_i} p_{s,t} \log \frac{p_{s,t}}{q_{s,t}},
\]

\[
p_{s,t} = \frac{\exp(y_{s,t}^{\text{buf}})}{\sum_{s'=1}^{S_i} \exp(y_{s',t}^{\text{buf}})},
\]

\[
q_{s,t} = \frac{\exp(u_{s,t})}{\sum_{s'=1}^{S_i} \exp(u_{s',t})} = \frac{1}{S_i}
\]

where \( u_{s,t} \) is the uniform distribution, i.e., \( u_{s,t} = \frac{1}{S_i} \). Top \( L_{\text{max}} \) samples with the highest KLD values are selected from \( [X^{\text{buf}}; X_i] \) and \( [Y^{\text{buf}}; \tilde{Y}_i] \).

- **Uniform sampling.** Uniform distribution sampling is applied to extract \( L_{\text{max}} \) frames.
- **Weighted sampling using KLD selection:** the combination of uniform sampling and KLD based selection.

### 4. EXPERIMENTAL RESULTS

#### 4.1. Data

We used 100k simulated mixtures of variable-speaker sets for training. These mixtures were generated following the procedure in [21]. For speech, we used the utterances from the Switchboard-2, Switchboard Cellular, and the NIST Speaker Recognition Evaluation. Additionally, the MUSAN corpus [28] was employed for noise with simulated room impulse responses used in [29]. Then, we applied our proposed methods to two real conversation data: the CALLHOME (CH) [4] and the DIHARD II [1] for evaluation.

#### 4.2. Experiment setting

The EEND-EDA model was trained following the same procedure as [21] with four Transformer encoder blocks and 256 attention units containing four heads. The first pre-trained EEND-EDA model used a two-speaker dataset for 100 epochs and then finetuned with the concatenation of one- to four-speaker simulated datasets for 25 epochs. For training SC-EEND, we used four Transformer encoder blocks containing six heads by following [22]. SC-EEND model was trained using one- to four-speaker simulated datasets for 100 epochs. The models are finetuned using a development set of CALLHOME, or DIHARD II.

We evaluated all models with the diarization error rate (DER) in both overlapping and non-speech regions. A collar tolerance of...
250 ms was applied at the start and end of each segment for CALLHOME. For DIHARD II, to follow the regulation of the second DIHARD challenge [1], we did not use collar tolerance.

### 4.3. Results on flexible numbers of speakers

In Table 2, DERs on CALLHOME and DIHARD II using EEND-EDA and SC-EEND models are shown. Experiment conditions varied from four selection methods with buffer sizes equal to 10 s, 50 s and 100 s. It is shown that the larger buffer size obtained better results than the shorter buffer size, regardless of the selection strategy. EEND-EDA performed better than SC-EEND model when the buffer size was as large as 50 s on both datasets. The selection strategies based on KLD performed the best when the buffer size was small ($L_{\text{max}} = 10$ s). On the other hand, simple strategies, i.e., FIFO and the uniform sampling, performed better when the buffer size was large ($L_{\text{max}} \geq 50$ s).

The comparison results with offline systems are shown in Table 4. Comparing with the offline systems, DERs of the proposed online method could deal with flexible numbers of speakers. However, it cannot be applied to more than the four-speaker case, which was also found in offline EEND-EDA and SC-EEND systems [21, 22].

### 4.4. Real-time factor and latency

Our experiment was conducted using an Intel® Xeon® Gold 6132 CPU @ 2.60GHz with one thread. To calculate the average computing time of one buffer, we filled the buffer with dummy values for the first iteration to keep the buffer size always the same among chunks. The real-time factor was equal to 0.12 when we applied STB to SC-EEND with the chunk size equalled to 1 s, and the buffer size was 100 s. This means that the average computation duration of one 1 s chunk was 0.12 s so that the latency time was 1.12 s.

### 5. Conclusions

In this paper, we proposed an online speaker diarization method that handles overlapping speech and flexible numbers of speakers. Speaker tracing buffer was applied to ensure the permutation consistent among short input chunks. Experimental results showed that the proposed online system achieves comparable results with the offline method. For the DIHARD II track 1, it achieved better results than the offline baseline and also the online UIS-RNN method.
6. REFERENCES

[1] Neville Ryant, Kenneth Church, Christopher Cieri, Alejandra Cristia, Jun Du, Siriam Ganapathy, and Mark Liberman, “The second dihard diarization challenge: Dataset, task, and baselines,” in INTERSPEECH, 2019, pp. 978–982.

[2] Wonjune Kang, Brandon C Roy, and Wesley Chow, “Multimodal speaker diarization of real-world meetings using d-vectors with spatial features,” in ICASSP, 2020, pp. 6509–6513.

[3] Takuya Yoshioka, Igor Abramovski, Cem Aksoylar, Zhuo Chen, Moshe David, Dimitrios Dimitriadis, Yifan Gong, Ilya Gurvich, Xuedong Huang, Yan Huang, et al., “Advances in online audio-visual meeting transcription,” in 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). IEEE, 2019, pp. 276–283.

[4] “2000 NIST Speaker Recognition Evaluation,” https://catalog.ldc.upenn.edu/LDC2001S97

[5] Alvin Martin and Mark Przybocki, “The NIST 1999 speaker recognition evaluation—an overview,” Digital signal processing, vol. 10, no. 1-3, pp. 1–18, 2000.

[6] Jon Barker, Shinji Watanabe, Emmanuel Vincent, and Jan Trmal, “The fifth ‘CHiME’ speech separation and recognition challenge: Dataset, task and baselines,” in INTERSPEECH, 2018.

[7] Naoyuki Kanda, Rintaro Ikeshita, Shota Horiguchi, Yusuke Fujita, Kenji Nagamatsu, Xiaofei Wang, Vimal Manohar, Nelson Enrique Yalta Soplin, Matthew Maciejewski, Szu-Jui Chen, et al., “The Hitachi/JHU CHiME-5 system: Advances in speech recognition for everyday home environments using multiple microphone arrays,” in CHiME-5, 2018.

[8] Shinji Watanabe, Michael Mandel, Jon Barker, and Emmanuel Vincent, “CHiME-6 challenge: Tackling multispeaker speech recognition for unsegmented recordings,” in CHiME-6, 2020.

[9] Jürgen Geiger, Frank Wallhoff, and Gerhard Rigoll, “GMM-UBM based open-set online speaker diarization,” in INTERSPEECH, 2010.

[10] Konstantin Markov and Satoshi Nakamura, “Improved novelty detection for online gmm based speaker diarization,” in INTERSPEECH, 2008.

[11] Srikanth Madikeri, Ivan Himawan, Petr Motlicek, and Marc Ferras, “Integrating online i-vector extractor with information bottleneck based speaker diarization system,” in INTERSPEECH, 2015, pp. 3105–3109.

[12] Daniel Garcia-Romero, David Snyder, Gregory Sell, Daniel Povey, and Alan McCree, “Speaker diarization using deep neural network embeddings,” in ICASSP, 2017, pp. 4930–4934.

[13] Weizhong Zhu and Jason Pelecanos, “Online speaker diarization using adapted i-vector transforms,” in ICASSP, 2016, pp. 5045–5049.

[14] Aonan Zhang, Quan Wang, Zhenyao Zhu, John Paisley, and Chong Wang, “Fully supervised speaker diarization,” in ICASSP, 2019, pp. 6301–6305.

[15] Enrico Fini and Alessio Bruttì, “Supervised online diarization with sample mean loss for multi-domain data,” in ICASSP, 2020, pp. 7134–7138.

[16] Mireia Diez, Lukáš Burget, Shuai Wang, Johan Rohdin, and Jan Černocký, “Bayesian HMM based x-vector clustering for speaker diarization,” in INTERSPEECH, 2019, pp. 346–350.

[17] Alan McCree, Gregory Sell, and Daniel Garcia-Romero, “Speaker diarization using leave-one-out gaussian plda clustering of dnn embeddings,” in INTERSPEECH, 2019, pp. 381–385.

[18] Zili Huang, Shinji Watanabe, Yusuke Fujita, Paola García, Yifen Shao, Daniel Povey, and Sanjeev Khudanpur, “Speaker diarization with region proposal network,” in ICASSP. IEEE, 2020, pp. 6514–6518.

[19] Yusuke Fujita, Naoyuki Kanda, Shota Horiguchi, Kenji Nagamatsu, and Shinji Watanabe, “End-to-end neural speaker diarization with permutation-free objectives,” in INTERSPEECH, 2019, pp. 4300–4304.

[20] Yusuke Fujita, Shinji Watanabe, Shota Horiguchi, Yawen Xue, and Kenji Nagamatsu, “End-to-end neural diarization: Reformulating speaker diarization as simple multi-label classification,” arXiv preprint arXiv:2003.02966, 2020.

[21] Shota Horiguchi, Yusuke Fujita, Shinji Watanabe, Yawen Xue, and Kenji Nagamatsu, “End-to-end speaker diarization for an unknown number of speakers with encoder-decoder based attractors,” in INTERSPEECH, 2020, pp. 269–273.

[22] Yusuke Fujita, Shinji Watanabe, Shota Horiguchi, Yawen Xue, Jing Shi, and Kenji Nagamatsu, “Neural speaker diarization with speaker-wise chain rule,” arXiv preprint arXiv:2006.01796, 2020.

[23] Qingshan Lin, Tingle Li, Lin Yang, Junjie Wang, and Ming Li, “Optimal mapping loss: A faster loss for end-to-end speaker diarization,” in Odyssey, 2020, pp. 125–131.

[24] Yawen Xue, Shota Horiguchi, Yusuke Fujita, Shinji Watanabe, and Kenji Nagamatsu, “Online end-to-end neural diarization with speaker-tracing buffer,” arXiv preprint arXiv:2006.02616, 2020.

[25] 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 ICASSP, 2019, pp. 91–95.

[26] Keisuke Kinoshita, Marc Delcroix, Shoko Araki, and Tomohiro Nakatani, “Tackling real noisy reverberant meetings with all-neural source separation, counting, and diarization system,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 381–385.

[27] Yusuke Fujita, Naoyuki Kanda, Shota Horiguchi, Yawen Xue, Kenji Nagamatsu, and Shinji Watanabe, “End-to-end neural speaker diarization with self-attention,” in ASRU, 2019, pp. 296–303.

[28] David Snyder, Guoguo Chen, and Daniel Povey, “MU-SAN: A music, speech, and noise corpus,” arXiv preprint arXiv:1510.08484, 2015.

[29] 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 ICASSP, 2017, pp. 5220–5224.