Online End-to-End Neural Diarization with Speaker-Tracing Buffer

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Abstract

End-to-end speaker diarization using a fully supervised self-attention mechanism (SA-EEND) has achieved significant improvement from the state-of-art clustering-based methods, especially for the overlapping case. However, applications of original SA-EEND are limited since it has been developed based on offline self-attention algorithms. In this paper, we propose a novel speaker-tracing mechanism to extend SA-EEND to online speaker diarization for practical use. First, this paper demonstrates oracle experiments to show that a straightforward online extension, in which SA-EEND is performed independently for each chunked recording, results in degrading the diarization error rate (DER) due to the speaker permutation inconsistency across the chunk. To circumvent this inconsistency issue, our proposed method, called speaker-tracing buffer, maintains the speaker permutation information determined in previous chunks within the self-attention mechanism for correct speaker-tracing. Our experimental results show that the proposed online SA-EEND with speaker-tracing buffer achieved the DERS of 12.84% for CALLHOME and 21.64% for Corpus of Spontaneous Japanese with 1 s latency. These results are significantly better than the conventional online clustering method based on x-vector with 1.5 s latency, which achieved the DERS of 26.90% and 25.45%, respectively.

1. Introduction

When building an audio-based human-computer interaction (HCI) system, it is important to provide the speaker turn information as well as speech transcription information. Speaker diarization can locate speaker turn information and use it to identify the speaker in a corresponding segment, which is defined as “who spoke when” [1][3]. Speaker diarization has been widely applied to meetings, call-center telephone conversations, and the home environment (CHiME-5) [4–7].

Online speaker diarization outputs the diarization result as soon as the audio segment arrives, which means no future information is available when analyzing the current segment. In contrast, in an offline mode, the whole recording is processed so that all segments can be compared and clustered at the same time [8]. Currently, few speaker diarization systems can be applied in practical scenarios because most of them work well only under specific conditions such as long latency, no overlapping, or no noise level. [9][10]. An online speaker diarization system with low latency is still an open technical problem.

State-of-art speaker diarization systems mostly concentrate on integrating several components: voice activity detection, speaker change detection, feature representation, and clustering [11][12]. Current research focuses primarily on the speaker model or speaker embeddings, such as Gaussian mixture models (GMM) [8][13], i-vector [14][16], d-vector [17][18], and x-vector [19][20], and on a better clustering method such as agglomerative hierarchical clustering or spectral clustering [19][21][22]. The issue with these methods is that they cannot directly minimize the diarization error because they are based on an unsupervised algorithm. Zhang, et al [12][24] proposed a supervised online speaker diarization approach while the method still assumes only one speaker in one segment (no overlap).

To solve these issues, Fujita, et al. [23][27] proposed an end-to-end speaker diarization system that directly minimizes the diarization error by training a neural network using Permutation Invariant Training (PIT) with multi-speaker recordings. Their experimental results show that the self-attention based end-to-end speaker diarization (SA-EEND) system [26][27] outperformed the state-of-art i-vector and x-vector clustering and long short-term memory (LSTM) [25] based end-to-end method. Although SA-EEND has achieved significant improvement, it is only working in the offline condition due to the self-attention mechanism, which outputs speaker labels only after the whole recording is provided.

This paper first investigates a straightforward online extension of SA-EEND by performing diarization independently for each chunked recording. However, this straightforward online extension degrades the diarization error rate (DER) due to the speaker permutation inconsistency across the chunk, especially for short-duration chunks. Therefore, we propose a method called speaker-tracing buffer, which can track speaker information consistently across the chunk by extending a self-attention mechanism to maintain the speaker permutation information determined in previous chunks. More specifically, we select a fixed number of input frames in the previous chunk that have dominant speaker permutation information based on the diarization output probability. These additional input frames are fed into the self attention layer to take over the speaker permutation information determined in the previous chunk. Our experimental results show that choosing the buffer frames using the absolute probability difference of the output speaker labels yields the best results compared with other methods. The code of SA-EEND with speaker tracing buffer will be available at https://github.com/hitachi-speech/EEND.

2. Analysis of online SA-EEND

2.1. SA-EEND

In SA-EEND [26], the speaker diarization task is formulated as a probabilistic multi-label classification problem. Given the T-length acoustic feature $X = (x_t \in \mathbb{R}^D | t = 1, \cdots, T)$, with a D-dimensional observation feature vector at time index $t$, SA-EEND predicts the corresponding speaker label sequence $\hat{Y}_t = (\hat{y}_t | t = 1, \cdots, T)$. Here, speaker label $\hat{y}_t = \hat{y}_{t,s} \in \{0, 1\} | s = 1, \cdots, S$ represents a joint activity for multiple speakers (S) at time t. For example, $\hat{y}_{t,s} = \hat{y}_{t,s'} \equiv 1(s \neq s')$ means both $s$ and $s'$ spoke at time $t$. Thus, determining $\hat{Y}$ is the key for determining the speaker diarization information as
follows:
\[
\hat{Y} = SA(X) \in (0, 1)^{S \times T},
\]
where SA(\cdot) is a multi-head self-attention based neural network.

Note that the vanilla self-attention layers has to wait the processing of all speech features in an entire recording to compute the output speaker labels. Thus, this method causes very large latency determined by the length of the recording, and cannot be adequate for online/real-time speech interface.

### 2.2. Chunk-wise SA-EEND for online inference

This paper first investigates the use of SA-EEND as shown in Eq. (1) for chunked recordings with chunk size \( \Delta \), as follows:
\[
\hat{Y}_{t_i+1:t_i+\Delta} = SA(X_{t_i+1:t_i+\Delta}) \in (0, 1)^{S \times \Delta}.
\]

\( i \) denotes a chunk index, and \( t_{i+1} \neq 0 \). \( X_t \) and \( \hat{Y}_t \) denote subsequences of \( X \) and \( Y \) at chunk \( i \), respectively. The latency can be suppressed by chunk size \( \Delta \) instead of the entire recording length \( T \). We first investigate the influence of chunk size \( \Delta \) in terms of the diarization performance.

#### 2.2.1. Model configuration and dataset

The SA-EEND system was trained using simulated training/test sets for two speakers and following the procedure in [27]. Here two encoder blocks with 256 attention units containing four heads without residual connections were trained. The input features are 23-dimensional log-Mel-filterbanks concatenated with previous seven frames and subsequent seven frames with a 25-ms frame length and 10-ms frame shift. And then subsampling with a factor of ten. In a word, a \((23 \times 15)\)-dimensional input feature is inputted into the neural network every 100 ms which means the duration length of one chunk is 100 ms.

Two datasets are used for this analysis. The first one, CALLHOME [6], consists of actual two-speaker telephone conversations. Following the steps in [27], we split CALLHOME into the two parts: 155 recordings for adaptation and 148 recordings for evaluation. The average overlap ratio with the test set is 13.0%. The average duration of recordings in CALLHOME is 72.1 s. The second dataset is the Corpus of Spontaneous Japanese (CSJ) dataset [28] which consists of interviews, natural conversations, etc. We used 54 recordings in this evaluation and their average overlap ratio is 20.1%. There are two speakers in each recording and the average duration is 767.0 s.

#### 2.2.2. Analysis results

In this section, we analyze the relationship between chunk size \( \Delta \) in Eq. (2) and DER. The recordings to be evaluated were first divided according to chunk size and then fed into a SA-EEND system one by one to obtain the diarization result of each chunk. These chunk-wise diarization results were then combined as the final diarization result of the whole recording. We call it as recording-wise DER calculated on the entire recording. When computing the DER, a 0.25 s collar tolerance was used at the start and the end of each segment. We also evaluated overlapping speech and non-speech regions.

Note that this chunk-wise SA-EEND method does not guarantee that the speaker labels obtained across the chunk are the same due to the speaker permutation ambiguity underlying in

The general speaker diarization problem. Thus, the recording-wise DER would be degraded due to this across-chunk speaker inconsistency. To measure this degradation, we also computed the oracle DER in each chunk separately (chunk-wise DER), which does not include the across-chunk speaker inconsistency error.

The analytical results are shown in Figure 1 for the CALLHOME and CSJ datasets. In these figures, the x-axis represents chunk size \( \Delta \) during inference. Here, one chunk unit corresponds to 0.1 s, which means the latency of the system is 1 s when the chunk size is 10 (i.e. 0.1 s \times 10 = 1 s). The y-axis represents the final DER of the whole dataset. As shown in Figure 1, the recording-wise DER decreased as the chunk size increased for both datasets. When the chunk size was larger than 800, the recording-wise DER tended to converge for CALLHOME. On the other hand, the oracle chunk-wise DER was much smaller and more stable than the recording-wise DER even when the chunk size was small, for both datasets. This indicates that the main degradation of online chunk-wise SA-EEND comes from the across-chunk speaker permutation inconsistency. Based on these findings, the next section explores how to solve this across-chunk speaker permutation issue.

### 3. Speaker-tracing buffer

In this section, we propose a method called speaker-tracing buffer, that utilizes previous information as a clue to solve the across-chunk permutation issue.

#### 3.1. Speaker-tracing with buffer

Let \( X_{buf} \in \mathbb{R}^{D \times L} \) and \( Y_{buf} \in (0, 1)^{S \times L} \) be \( L \)-length acoustic feature buffer and the corresponding SA-EEND outputs, respectively, which contain the speaker-tracing information. At the initial stage, \( X_{buf} \) and \( Y_{buf} \) are empty. Our online diarization is performed by referring and updating this speaker-tracing buffer, as shown in Algorithm 1. The input of the SA-EEND system is the concatenation of acoustic feature subsequence \( X_t \in \mathbb{R}^{D \times L} \) at current chunk \( i \) and the acoustic features in buffer \( X_{buf} \), i.e., \( [X_{buf}; X_t] \in \mathbb{R}^{D \times (L+\Delta)} \). The corresponding output of SA-EEND is \( [Y_{buf}; \hat{Y}_t] \in (0, 1)^{S \times (L+\Delta)} \). If \( Y_{buf} \) is not empty, the correlation coefficient \( CC(C, \cdot) \) between \( Y_{buf} \) and current buffer output \( \hat{Y}_{buf} \) at output speaker permutation \( \phi \) is calculated as

\[
CC(Y_{buf}, \hat{Y}_{buf}^\phi) = \frac{\sum_{s=1}^{S} \sum_{l=1}^{L} (y_{buf,s,l} - \bar{y}_{buf})(\hat{y}_{buf,s,l} - \bar{\hat{y}}_{buf})}{\sqrt{\sum_{s=1}^{S} \sum_{l=1}^{L} (y_{buf,s,l} - \bar{y}_{buf})^2} \sqrt{\sum_{s=1}^{S} \sum_{l=1}^{L} (\hat{y}_{buf,s,l} - \bar{\hat{y}}_{buf})^2}}.
\]
If chunk size $\Delta$ is not larger than the pre-defined buffer size $L$, and the corresponding selection rules are shown in Fig.

The maximum value of $\delta_m$ is $1$ is realized in either case of $y_{i,m} = 1, y_{i,m} = 0$ or $y_{i,m} = 1$. This means that we try to find

where $\phi \in \text{perm}(S)$ generates all permutations according to the number of speakers $S$. The corresponding buffer output $Y_{i+1}$ is chosen as the final output $Y_i$ of chunk $i$, which can maintain the consistent speaker permeation across the chunk. The obtained output $Y_i$ is stacked with the previously estimated output to form the whole recording’s output $Y$. An example of applying the speaker-tracing buffer to SA-EEND in the first two chunks is shown in Fig.

where $\phi \in \text{perm}(S)$.

where perm(S) generates all permutations according to the number of speakers $S$. The corresponding buffer output $Y_{i+1}$ is chosen as the final output $Y_i$ of chunk $i$, which can maintain the consistent speaker permeation across the chunk. The obtained output $Y_i$ is stacked with the previously estimated output to form the whole recording’s output $Y$. An example of applying the speaker-tracing buffer to SA-EEND in the first two chunks is shown in Fig. where $\Delta$ is equal to 10, the buffer size $L$ is 5, and the speaker number $S$ is 2.

Speaker-tracing buffer $(X_{\text{buf}}, Y_{\text{buf}})$ for the next chunk $i+1$ is selected from $\{Y_{\text{buf}}; Y_i\}$ and $\{X_{\text{buf}}; X_i\}$ in the current chunk. We consider three selection strategies, as explained in the next section.

3.2. Selection strategy for speaker-defined buffer

If chunk size $\Delta$ is not larger than the pre-defined buffer size $L$, we can simply store all the features in the buffer until the number of stored features reaches the buffer size. Once the number of accumulated features becomes larger than buffer size $L$, we have to select and store informative features that contain the speaker permutation information from $[X_{\text{buf}}; X_i]$ and $[Y_{\text{buf}}; Y_i]$. In this section, three selection rules for updating the buffer are listed. Here we assume that the number of speaker $S$ is 2.

- Uniform sampling (US). $L$ acoustic features from $[X_{\text{buf}}; X_i]$ and the corresponding diarization results $[Y_{\text{buf}}; Y_i]$ are randomly extracted based on the uniform distribution.

- Deterministic selection (DS) using the absolute difference of probabilities of speakers, as

$$\delta_m = |y_{1,m} - y_{2,m}|, \quad (5)$$

where $y_{1,m}, y_{2,m}$ are the probabilities of the first and second speakers at time index $m$. The maximum value of $\delta_m$ is 2.

4. Experimental results

4.1. Effect of selection strategy

We analyzed the effect of the selection strategy using the same chunk size $\Delta = 10$ and several buffer sizes $L$ from 10 to 600. In Table 1, the number in the left column (10-500) represent the chunk size $\Delta$ for offline system but the buffer size $L$ for online situation. As shown in Table 1, applying the speaker-tracing buffer improved the performance of online SA-EEND performance regardless of which selection strategy was used. As for the strategies, WS performed best for both datasets at most cases when $L$ was large (larger than 100). Therefore, we considered WS as the selection strategy for future analysis.

4.2. Effect of buffer and chunk size

Next, we analyzed the effect of buffer and chunk size. The DER results for the CALLHOME and CSJ when applying the weighted sampling (WS) selection strategy are shown in Fig. Chunk sizes $\Delta$ were 10 and 20 and had the latency time of 1 s and 2 s respectively. Regarding the chunk size in Fig.

where $\phi \in \text{perm}(S)$.

where perm(S) generates all permutations according to the number of speakers $S$. The corresponding buffer output $Y_{i+1}$ is chosen as the final output $Y_i$ of chunk $i$, which can maintain the consistent speaker permeation across the chunk. The obtained output $Y_i$ is stacked with the previously estimated output to form the whole recording’s output $Y$. An example of applying the speaker-tracing buffer to SA-EEND in the first two chunks is shown in Fig.

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where $\phi \in \text{perm}(S)$.
Output for 1st chunk

The simulated datasets were created by using two speakers’ segments. The background noise and room impulse response were from MUSAN corpus [29] and Simulated Room Response corpus [30] following the procedure in [26]. Three kinds of simulated datasets were created with overlap ratios equal to 34.4%, 27.2% and 19.5%, respectively.

For the offline i-vector and x-vector method, we applied the Kaldi CALLHOME diarization v1 and v2 recipe [19][31][32]. They are offline diarization methods that apply probabilistic linear discriminant analysis [33] along with an agglomerative-cluster method with TDNN-based speech activity detection [34] and oracle number of speakers. Offline SA-EEND is referred to as a chunk size of the entire recording. The system in [27] which achieved the best performance is applied here, not only for the offline SA-EEND but also for the online SA-EEND (Δ = 10) and all proposed methods.

For the online x-vector, the speech segments are firstly divided into subsequent 1.5 s chunk. And then judging whether the entire chunk is speech or silence using the energy-based VAD for real datasets and oracle VAD for simulated datasets. The following part will be skipped if the entire chunk is considered as silence whose the If the percentage of voiced frames of the entire chunk are fewer than 20%, it will be considered as silence and the following chunk is voiced chunk, we will extract x-vector and assign it to the first cluster until a dissimilar x-vector arrives according to the probabilistic linear discriminant analysis (PLDA) score. Here we applied a threshold 0 as the dissimilar criterion. After two clusters exist, when a new x-vector comes, calculating the PLDA score between the new segment and the

### Table 2: DERs (%) on simulated mixtures and real dataset.

| System                | Simulated | Real |
|-----------------------|-----------|------|
| Offline i-vector      | 33.73     | 30.93 | 25.96 | 12.10 | 27.99 |
| Offline x-vector      | 28.77     | 24.46 | 17.78 | 11.53 | 22.96 |
| Offline SA-EEND       | 4.56      | 4.50  | 3.85  | 9.54  | 20.48 |
| Online x-vector (Δ = 15) | 36.94   | 34.94 | 33.19 | 26.90 | 25.45 |
| Online SA-EEND (Δ = 10) | 33.18   | 37.31 | 41.41 | 36.93 | 47.57 |
| Proposed (Δ = 10, L = 500) | 7.91   | 7.31  | 6.91  | 12.84 | 21.64 |
| Proposed (Δ = 5, L = 600) | 7.75   | 7.39  | 7.03  | 12.81 | 22.75 |

### Table 3: DERs (%) on real datasets with calibration period (30s).

| System                | Within 30s | After 30s | All       |
|-----------------------|------------|-----------|-----------|
| Offline SA-EEND       | 9.38       | 23.43     | 9.53      | 20.23     | 9.54  | 20.48 |
| Proposed (Δ = 10, L = 500) | 15.91   | 25.37     | 10.05     | 21.30     | 12.84 | 21.64 |

For a comparison with other methods, we evaluated our proposed methods using two real datasets (CALLHOME (CH) and CSJ), and three simulated datasets which are shown in Table 2. The simulated datasets were created by using two speakers’ segments. The background noise and room impulse response were from MUSAN corpus [29] and Simulated Room Response corpus [30] following the procedure in [26]. Three kinds of simulated datasets were created with overlap ratios equal to 34.4%, 27.2% and 19.5%, respectively.

4.4. Comparison with other methods

As shown in Table 2, comparing with x-vector based online system, the proposed method obtained the best results for the online situations. The proposed method performed even better on CH than the offline clustering i-vector and the x-vector based methods. The online method increased the DER by 3.27 and 1.16 point comparing with the offline SA-EEND system for two real dataset when buffer size is 500 and the latency time is 1 s. In order to explore the increased DER, the broken down DER with a calibration period of 30 s is calculated and shown in Table 3. Comparing with offline SA-EEND, the proposed method only increases the DERs of 0.52 and 1.07 point for two datasets with a 30 s calibration period. Therefore, we can conclude that our proposed method can improve latency of the SA-EEND system from the entire duration of recording to only 1 s or even 0.5 s with comparable diarization performance.

### Figure 2: Applying speaker-tracing buffer for SA-EEND.

![Figure 2: Applying speaker-tracing buffer for SA-EEND.](image)

### Figure 3: Relationship among DER, chunk size and buffer size.

(a) CALLHOME  
(b) CSJ

5. Conclusion

In this paper, we proposed a speaker-tracing buffer to memory previous speaker permutation information which enable the pre-trained offline SA-EEND system directly work online. The latency time can reduce to 500 ms with comparable diarization performance. Future work will be concentrated to flexible speaker as current method is limited to two-speaker case.
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