Leveraging Speech Separation for Conversational Telephone Speaker Diarization

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Abstract

Speech separation and speaker diarization have strong similarities. In particular with respect to end-to-end neural diarization (EEND) methods. Separation aims at extracting each speaker from overlapped speech, while diarization identifies time boundaries of speech segments produced by the same speaker. In this paper, we carry out an analysis of the use of speech separation guided diarization (SSGD) where diarization is performed simply by separating the speakers signals and applying voice activity detection. In particular we compare two speech separation (SSep) models, both in offline and online settings. In the online setting we consider both the use of continuous source separation (CSS) and causal SSep models architectures. As an additional contribution, we show a simple post-processing algorithm which reduces significantly the false alarm errors of a SSGD pipeline. We perform our experiments on Fisher Corpus Part 1 and CALLHOME datasets evaluating both separation and diarization metrics. Notably, without fine-tuning, our SSGD DPRNN-based online model achieves 12.7% DER on CALLHOME, comparable with state-of-the-art EEND models despite having considerably lower latency, i.e., 50 ms vs 1 s.

Index Terms: online speaker diarization, speech separation, overlapped speech, deep learning, conversational telephone speech

1. Introduction

Speaker diarization (or “who spoke when”) is the task of segmenting a recording into homogeneous speaker-specific regions \cite{2}. It constitutes an important preprocessing step for many applications, such as meeting summary \cite{3}, live captioning, speaker-based indexing \cite{4} and telephone conversation analysis \cite{4}.

Diarization methods can be broadly divided into two categories: clustering-based and end-to-end supervised systems. The former typically employs a pipeline comprised of voice activity detection (VAD), speaker embedding extraction and clustering \cite{5,7}. End-to-end neural diarization \cite{9,11} reformulates the task as a multi-label classification, which is trained directly to perform diarization using permutation invariant training (PIT) \cite{13}. There also exist methods such as target-speaker VAD \cite{14} and region proposal networks \cite{15} which lie at the intersection of these two categories.

With enough simulated training data, end-to-end approaches have been shown to outperform state-of-the-art clustering-based systems \cite{16}, but at the cost of requiring significant memory consumption for long recordings (for e.g., longer than 10 minutes). Chunk-wise processing can help to reduce the memory footprint but it leads to inter-window speaker label permutation problem due to the PIT training objective \cite{17,20}. Several recent approaches have been proposed to address this problem, such as employing a speaker tracing buffer \cite{17,18} or a hybrid end-to-end/clustering framework \cite{19,21}. However, most of these methods, with the exception of \cite{17,18}, are offline methods and are thus not suitable for streaming applications such as e.g. live captioning.

A key reason for the adoption of end-to-end diarization is its advantage over clustering-based methods in handling overlapped speech. Conventional clustering algorithms inherently assume single-speaker segments, and are thus prone to missing out on overlapping speakers (which may constitute as high as 20% of the speech in real conversations \cite{22}). Although researchers have proposed techniques for overlap assignment in VBx \cite{23} and spectral clustering \cite{24}, these methods depend heavily on an accurate overlap detection, which is often challenging to train. Furthermore, embedding extractors trained on single-speaker utterances may not produce reliable representations for overlapping segments, resulting in speaker confusion errors in these regions \cite{24}.

An alternate framework to deal with overlapped speech is continuous speech separation (CSS) \cite{24}. CSS extends traditional monaural separation to long recording scenarios, by applying separation in a chunk-wise manner, where each chunk is assumed to contain a fixed number of speakers (usually 2-3). Since the underlying separator is trained via a PIT objective, output permutation consistency between chunks is not guaranteed. CSS solves this problem by performing overlapping inference (i.e., using strides shorter than chunk sizes) and re-ordering adjacent chunks based on a similarity measure over the portion in which they overlap. Several recent works have proposed diarization systems based on CSS by applying clustering techniques across the separated audio streams \cite{26,27}. Fang et al. \cite{28} proposed speech separation guided diarization (SSGD), where diarization is performed by first separating the input mixture and applying a conventional VAD to detect speech segments in each channel. SSGD is a particularly appealing approach as separated sources could be readily used for downstream tasks such as automatic speech recognition (ASR), with diarization coming almost “for free”.

\textsuperscript{*} denotes equal contribution.
In this work, we build upon the SSGD framework and attempt to deal with its limitations. We extend SSGD to online processing by considering the use of CSS and causal speech separation models. Both these techniques allow the processing of arbitrarily long recordings that could not fit in memory making SSGD viable in practical applications. We carry out an extensive experimental analysis using real-world telephone conversation datasets such as Fisher [29] and CALLHOME [30], comparing offline and online approaches and studying the effect of the CSS window size. Last but not least, we introduce an effective, causal leakage removal post-processing algorithm which reduces false alarm errors generated by separators with negligible computational overhead. Results show that by using just separation and a simple VAD, it is possible to obtain competitive diarization results on CALLHOME with extremely low-latency (e.g., 50 ms). Our code is made available through the Asteroid toolkit [31].

2. System Description

The adopted SSGD pipeline is composed of three modules: speech separation, post-processing and VAD, as shown in Fig. 1. The input of the system is a single-channel mixed audio stream, denoted as $Y \in \mathbb{R}^{1 \times T}$, where $T$ is the number of audio samples.

2.1. Speech Separation Module

As said, we consider in our experiments SSGD based on non-causal separation models (as used in [28]), causal separation models (such as causal Conv-TasNet [32]) and CSS. Briefly, CSS [33] consists of three stages as shown in Fig. 1: framing, separation and stitching. In the framing stage, a windowing operation splits $Y$ into $I$ overlapped frames $Y_i \in \mathbb{R}^{1 \times W}$, $i = 1, \ldots, I$, with $I = \lceil \frac{T}{W} \rceil$, where $W$ and $H$ are the window and hop size, respectively. Window size defines the memory footprint and hop size defines the minimum latency of the system. Then, speech separation (SSep) is performed independently on each frame $Y_i$, generating separated output frames $O_i \in \mathbb{R}^{C \times W}$, where $C$ is the number of output channels. In this work, $C$ is fixed to 2, meaning that we assume that the maximum number of speakers in any frame is 2. This is a common assumption made for CSS systems, and is also valid in general for telephone conversations (which is the focus of this work).

To solve the permutation ambiguity between consecutive frame outputs, a stitching module aligns channels of two separation outputs $O_i$ and $O_{i+1}$ according to the cross-correlation computed on the overlapped part of consecutive frames. The final output stream $X \in \mathbb{R}^{C \times T}$ is generated by an overlap-add operation with a Hanning window.

In this preliminary work, we consider the application of CSS only to non-causal SSep models, which are generally more performant than their causal counterpart [32]. In such configuration, the latency of these models will be tied to the CSS stride and thus can be used online. On the other hand, causal separation models are already capable to process the input in a streaming fashion with small latency.

2.2. Leakage Removal Post-Processing

In the presence of long input recordings, even state-of-the-art separation models are prone to channel leakage when only one speaker is active (e.g., see estimated sources in Fig. 1). As a result, the “leaked” segments are detected as speech by the following VAD module, leading to a large false alarm error in the final diarization output. To alleviate this problem, we propose a post-processing algorithm to reduce false alarms without significantly affecting missed speech, speaker confusion errors, and separation quality. It does not introduce additional latency and its computational overhead is negligible.

Given an input mixture $Y$ and two estimated sources $X^1$ and $X^2$, we split each signal in disjoint segments $Y_t, X^1_t, X^2_t$ of length $L$. For each segment, we compute the SI-SDRs $s^1_t, s^2_t$ between segments of every source $X^1_t, X^2_t$ with the associated segment $Y_t$ of input mixture. If both $s^1_t, s^2_t$ are above a threshold $t_{fa}$, a segment with leakage is detected. Leakage is removed by filling with zeros the segment with lower SI-SDR. This process results in new estimated sources $\hat{X}_t$, which are passed as input to the VAD module. The leakage removal algorithm is summarized in the pseudocode below.

```
Algorithm 1 Leakage Removal
Input: $Y, X^1, X^2, T, t_f, t_{fa}$
Output: $\hat{X}_t^1, \hat{X}_t^2$
for $i \leftarrow 0$ to $T$ by $L$ do
    $s^1_t \leftarrow$ SI-SDR$(Y_{i:i+L}, X^1_{i:i+L})$
    $s^2_t \leftarrow$ SI-SDR$(Y_{i:i+L}, X^2_{i:i+L})$
    if $s^1_t > t_{fa}$ and $s^2_t > t_{fa}$ then
        if $s^1_t > s^2_t$ then
            $\hat{X}_t^2_{[i:i+L]} \leftarrow 0$
        else
            $\hat{X}_t^1_{[i:i+L]} \leftarrow 0$
```

2.3. Voice Activity Detection (VAD)

The VAD module is used to extract active speech segments from the post-processed estimated sources and generate the diarization output. It is applied on each estimated source $\hat{X}_t$ independently but future work could consider a multi-source VAD. We experiment with two different VAD models: an energy-based VAD [34], and a neural model which employs a temporal convolutional network (TCN), proposed earlier in [35].

3. Experimental Setup

3.1. Datasets

We used the Fisher Corpus Part I [29] for both training and test purposes. Fisher consists of 5850 telephone conversations, sampled at 8 kHz, between two participants. It provides a separated signal for each of the two speakers. This allows training a separation model directly on this dataset and computing source separation metrics such as Scale-Invariant Signal-to-Distortion improvement (SI-SDR) [36]. Training, validation and test sets are created by drawing 5000, 61, and 61 conversations, respec-
Table 1: Speech separation and diarization results on the Fisher and CALLHOME test sets in the offline scenario. Separation is assessed using the SI-SDR (dB) improvements over the input mixtures. Diarization is assessed using diarization error rate (DER), missed speech (MS), false alarm (FA) and speaker confusion errors (SC). The best results among proposed techniques are shown in bold, and those among baselines are underlined.

| Method          | VAD          | Fisher SI-SDRi | MS | FA | SC | DER | CALLHOME MS | FA | SC | DER |
|-----------------|--------------|----------------|----|----|----|-----|-------------|----|----|-----|
| VBx [9]         | TCN          | 10.0           | 0.3 | 0.5 | 10.8 | 7.3 | 1.9         | 3.1 | 12.3 |
| VBx [9] +       | Kaldi        | 8.9            | 0.4 | 0.9 | 10.2 | 8.3 | 0.9         | 2.6 | 11.7 |
| + Overlap assignment [23] | Kaldi | 4.4 | 2.1 | 0.9 | 7.4 | 5.3 | 2.5 | 2.4 | 10.3 |
| Spectral clustering [8] | Kaldi | 8.9 | 0.4 | 0.9 | 9.5 | 8.3 | 0.9 | 5.3 | 14.5 |
| + Overlap assignment [24] | Kaldi | 5.2 | 2.0 | 0.2 | 7.4 | 5.7 | 2.7 | 5.8 | 14.1 |
| SA-EEND [10]    | Kaldi        | 8.8            | 0.0 | 0.0 | 5.0 | 5.0 | 8.8         | 0.8 | 0.8 |
| SA-EEND + EDA [12] | TCN    | 7.9            | 0.0 | 0.0 | 4.6 | 4.6 | 7.9         | 0.0 | 0.0 |
| EEND + VC [19, 20] | TCN | 7.8 | 0.0 | 0.0 | 4.3 | 4.3 | 7.8 | 0.0 | 0.0 |

| Oracle sources | VAD          | Fisher SI-SDRi | MS | FA | SC | DER | CALLHOME MS | FA | SC | DER |
|----------------|--------------|----------------|----|----|----|-----|-------------|----|----|-----|
| Energy         | TCN          | 4.5            | 0.8 | 0.0 | 5.3 | 5.3 | 8.0         | 0.8 | 0.8 |
| Oracle sources | TCN          | 17.54          | 8.0 | 4.5 | 1.6 | 14.1 | 6.0 | 12.0 | 2.8 | 20.6 |
| Conv-TasNet    | TCN          | 17.54          | 6.2 | 5.0 | 1.1 | 12.4 | 6.1 | 13.6 | 1.8 | 21.6 |
| + Leakage removal | TCN | 17.09 | 5.5 | 2.5 | 2.0 | 10.1 | 6.0 | 10.1 | 2.8 | 18.9 |
| DPRNN           | Energy       | 21.25          | 7.8 | 2.3 | 1.0 | 11.1 | 5.4 | 5.9 | 0.6 | 12.0 |
| + Leakage removal | TCN    | 21.25 | 4.1 | 3.1 | 0.9 | 8.1 | 4.8 | 9.0 | 0.2 | 14.1 |

3.2. Architecture, Training and Inference Details

We consider 2 separation model architectures: Conv-TasNet and DPRNN, both in causal and non-causal configurations (for a total of 4). For both, we use the best hyperparameter configuration as found in [32, 37] with these exceptions: to reduce memory footprint we use a 16x synthesis kernel size also for DPRNN and, regarding causal models, we use standard layer normalization versus the non-causal global layer normalization employed in non-causal models. These models are trained on the synthetic fully overlapped Fisher dataset using the SI-SDR objective to separate two speakers. We use Adam optimizer [38], batch size 8 and learning rate 0.001. We clip gradients with $l_2$ norm greater than 5. Learning rate is halved if SI-SDR does not improve on validation for 5 epochs. If no improvement is observed for 10 epochs, training is stopped. Each SSep model is then fine-tuned using a learning rate of 0.0001 and batch size 1 on the real Fisher data, by taking 60 s long random segments from each recording.

We employ the TCN VAD from [35], which is causal and for which the latency amounts to 10 ms. This model is trained on the original Fisher data, using each speaker source separately, as the VAD is then applied on estimated sources. We train on random 2 s long segments with a batch size of 256. The rest of training hyperparameters is the same as used for SSep models. In inference we employ a median filter to smooth the VAD predictions. In addition, we remove segments shorter than a threshold $t_s$ to further reduce false alarm errors. For each SSgd model, we tune the median filter, leakage removal threshold and $t_s$ parameters on the Fisher validation set (CALLHOME adaptation for CALLHOME models). The leakage removal algorithm is applied on 10 ms segments, the same latency as the TCN VAD.

3.3. Baseline Methods

We compared our approach with clustering-based and EEND methods. For the former, we used VBx [9] and spectral clustering [8], along with their overlap-aware counterparts [23, 24]. For VAD in these systems, we used the publicly available Kaldi ASpIRE model [39]. For overlap detection, we fine-tuned the Pyannote [40] segmentation model on the full CALLHOME development set. The hyperparameters for each task were tuned on the corresponding validation set. The scripts for reproducing the baseline results are publicly available [51]. For fair comparison, we also report the performance of VBx with the TCN VAD, which however leads to degraded performance for this system.

For the CALLHOME evaluation, we also show DERs obtained by EEND, as reported in the original papers.

4. Results

We evaluate the performance on Fisher and CALLHOME test sets in terms of diarization error rate (DER) including overlapped speech and using a collar tolerance of 0.25 s, as in [10]. For the Fisher test set we also report the SI-SDR score separation metric since oracle sources are available.

4.1. Offline Separation/Diarization

The results for offline SSGD diarization models are reported in Table 1. Oracle sources refer to SSGD with oracle SSep, thus with error coming only from the VAD module. On the Fisher
dataset, DPRNN-based SSGD strongly outperformed the Conv-TasNet version on all metrics, and even surpassed the overlap-aware VBx which fares best among all clustering baselines. The proposed leakage removal algorithm was highly effective, halving the error rates due to false alarms for both architectures. This was especially true in the case of TCN-based VAD since it is more prone to false alarms caused by leaked speech due to being trained on real Fisher data.

For the CALLHOME data, the best performing SSGD model was comparable with SA-EEND [10]. However, since we did not fine-tune the separation networks on the CALLHOME development set (as done in [12, 20]), it failed to outperform these methods in terms of DER performance.

4.2. Online Separation/Diarization

For the online scenario (Table 2), the Conv-TasNet model failed to deal with long recordings. We found that the model generated large false alarms that could be only partially mitigated by the leakage removal algorithm. This is due to the fact that, being fully convolutional, it has a limited $\sim 5$ s receptive field, while DPRNN, being based on recurrent neural networks has no such limitations and can effectively track the speakers for much longer. As a result, DPRNN continued to be effective in the online scenario. Similar to the offline case, leakage removal added significant gains, improving the DER by 34.7% and 37.1% respectively on Fisher and CALLHOME, compared to the system without leakage removal. As a comparison, online variations of SA-EEND and SA-EEND-EDA using speaker tracing buffer [17, 18] obtain DERs 12.5% and 10.0% respectively, but with significantly higher latency of 1.0 s.

4.3. CSS Window Analysis

Recall from Section 2.1 that the CSS framework, besides allowing the processing of arbitrarily long recordings, also allows to use a non-causal separation model in an online fashion with latency reduced to the stride of the CSS window. We used the best SSGD offline model from Table 1 (DPRNN+TCN+leakage removal) to investigate the effect of varying window sizes on SSGD. Evaluation results are reported in Fig. 2 for both datasets. As expected, we see that the DER error consistently decreases with larger windows. In particular, the performances are almost on par with the offline models for windows larger than 60 and 30 seconds, respectively, for Fisher and CALLHOME. This suggests a possible parallelization scheme for offline SSGD by applying CSS on minute-long chunks simultaneously, resulting in possible inference speed-ups. We conjecture that the optimal chunk sizes are different for the two datasets because of difference in their average recording duration (which is 10 minutes and 72 seconds for CALLHOME and Fisher, respectively).

The MS and FA error rates remain approximately constant while speaker confusion errors consistently decrease, indicating that the main source of error comes from speaker permutation due to wrong channel reordering during the stitching stage of the CSS. For smaller windows, the cross-correlation used for reordering consecutive chunks is less reliable due to the smaller size of the overlapping portion.

5. Conclusion and Future Work

In this paper, we performed an analysis of SSGD for real-world telephone conversations extending it to online and arbitrarily long diarization scenarios. We showed that these systems achieve comparable performances with state-of-the-art methods based on clustering or EEND on the Fisher and CALLHOME datasets with significantly lower latencies (for instance, 50 ms compared to 1 s). Additionally, for the online scenario, we analyzed the impact of CSS window sizes on downstream diarization performance, and found that we can obtain DERs almost on par with the offline case with a sufficiently large window of 30 or 60 seconds. These findings open up several avenues worth exploring.

First, the gap between the best proposed system and the oracle source evaluation (Table 1) for Fisher suggests that error mainly comes from the VAD module. Future work could investigate joint fine-tuning of separation and VAD to reduce these errors. Another direction is to investigate the SSGD framework performance for higher number of speakers. This could require the development of new techniques since most current source separation methods struggle to track multiple speakers for very long inputs. Finally, SSGD is particularly appealing for multitalker speaker-attached ASR, since the estimated sources can be fed directly to an ASR module.

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