LOW-LATENCY SPEECH SEPARATION GUIDED DIARIZATION FOR TELEPHONE CONVERSATIONS

Giovanni Morrone∗1, Samuele Cornell∗1, Desh Raj2, Luca Serafini1, Enrico Zovato3, Alessio Brutti1, Stefano Squartini1

1Università Politecnica delle Marche, Ancona, Italy 2Johns Hopkins University, Baltimore, USA 3PerVoice S.p.A., Trento, Italy 4Fondazione Bruno Kessler, Trento, Italy

ABSTRACT
In this paper, we carry out an analysis on the use of speech separation guided diarization (SSGD) in telephone conversations. SSGD performs diarization by separating the speakers signals and then applying voice activity detection on each estimated speaker signal. In particular, we compare two low-latency speech separation models. Moreover, we show a post-processing algorithm that significantly reduces the false alarm errors of a SSGD pipeline. We perform our experiments on two datasets: Fisher Corpus Part 1 and CALLHOME, evaluating both separation and diarization metrics. Notably, our SSGD DPRNN-based online model achieves 11.1% DER on CALLHOME, comparable with most state-of-the-art end-to-end neural diarization models despite being trained on an order of magnitude less data and having considerably lower latency, i.e., 0.1 vs. 10 seconds. We also show that the separated signals can be readily fed to a speech recognition back-end with performance close to the oracle source signals.

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 [1, 2]. It constitutes an important preprocessing step for many applications, such as meeting summary, live captioning, speaker-based indexing, and telephone conversation analysis.

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 [3–6]. End-to-end neural diarization (EEND) reformulates the task as a multi-label classification. The majority of these systems [7–9] are trained directly to perform diarization using permutation invariant training (PIT) [10]. There also exist methods such as target-speaker VAD [11] and region proposal networks [12] which lie at the intersection of these two categories.

With enough training data, end-to-end approaches have been shown to outperform state-of-the-art clustering-based systems [13], but at the cost of requiring significant memory for long recordings (e.g., longer than 10 minutes). Chunk-wise processing can help reduce the memory footprint but it leads to inter-window speaker label permutation problem due to the PIT training objective [14–17]. Several recent approaches have been proposed to address this problem, such as employing a speaker tracing buffer [14, 16], a hybrid end-to-end/clustering framework [17] or chunk-level recurrence in the chunk hidden states [15]. Another system [18] iteratively builds embeddings for each speaker which are exploited to condition the following VAD module. However, most of EEND methods, with the exception of [14–16], work offline and are thus not suitable for streaming applications such as 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 [19]). Although researchers have proposed techniques for overlap assignment in VBx [20] and spectral clustering [21], 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 [21].

An alternative framework to deal with overlapped speech is continuous speech separation (CSS) [22, 23]. CSS extends PIT-based speech separation (SSep) 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 reordering 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 [24, 25]. Fang et al. [26] have 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”. We show this in Section 4.4.

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 causal SSep models and CSS. Both these techniques allow the processing of arbitrarily long recordings that could not fit in memory making SSGD viable in practical applications. Additionally, we introduce an effective, causal leakage removal post-processing algorithm that reduces the SSGD VAD false alarm errors generated by imperfect separation. This algorithm has negligible computational overhead. We carry out an extensive experimental analysis focusing on conversational telephone speech (CTS).
2. SYSTEM DESCRIPTION

The adopted SSGD pipeline is composed of three modules: speech separation, leakage removal 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

We consider in our experiments SSGD based on causal separation models (i.e., Conv-TasNet [32] and DPRNN [33]). Since the majority of diarization approaches work offline, we also experiment with non-causal separation models (as used in [26]) to carry out a more comprehensive comparison with clustering-based and EEND state-of-the-art systems. Additionally, we analyze the application of CSS with non-causal SSep models. In such configuration, the latency of these models is tied to the CSS window size and thus can be used online. CSS is not applied to causal SSep models since they are already capable to process the input in a streaming fashion with low latency.

Briefly, CSS 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 $I = \left\lceil \frac{T}{H} \right\rceil$, where $W$ and $H$ are the window and hop sizes, respectively. Then, the separation 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, the 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 an Hanning window.

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 higher 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.

Algorithm 1 Leakage Removal

Input: $Y$, $X^1$, $X^2$, $T$, $L$, $t_{tr}$
Output: $\hat{X}^1$, $\hat{X}^2$

for $i \leftarrow 0$ to $T$ by $L$ do

$\ell_1 \leftarrow \text{SL-SDR}(Y[i:i+L], X^1[i:i+L])$

$\ell_2 \leftarrow \text{SL-SDR}(Y[i:i+L], X^2[i:i+L])$

if $\ell_1 > t_{tr}$ and $\ell_2 > t_{tr}$ then

if $s^1_1 > s^2_1$ then

$\hat{X}^1[i:i+L] \leftarrow 0$

else

$\hat{X}^2[i:i+L] \leftarrow 0$

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 $\hat{X}_f$ independently but future work could also consider a multi-source VAD. We experiment with two different VAD models: an energy-based VAD [35], and a neural model which employs a temporal convolutional network (TCN), as proposed in [36].

3. EXPERIMENTAL SETUP

3.1. Datasets

Since the focus of our work is on the CTS scenario, we use the Fisher Corpus Part I [28] for both training and test purposes. Fisher consists of 5850 telephone conversations in English, 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 the SI-SDR improvement (SI-SDRi) [34]. Training, validation and test sets are created by drawing 5728, 61, and 61 conversations, respectively, with no overlap between speaker identities. The amount of overlapped speech is around 14% of the total speech duration. In addition, we generate a simulated fully-overlapped version of Fisher for the purpose of training the SSep models. This portion is derived from the training set and amounts to 30000 mixtures for a total of 44 hours.

We also test the proposed methods on the portion of the 2000 NIST SRE 2015 denoted as CALLHOME, consisting of real-world multilingual telephone conversations. Following the recipe in [7], we use the 2-speaker subset of CALLHOME and the adaptation/test split that allows to compare with most end-to-end diarization methods mentioned previously. The amount of overlapped speech is around 13% of total speech duration.

3.2. Architecture, Training and Inference Details

We employ the Asteroid toolkit [38] to experiment with 2 SSep architectures: Conv-TasNet and DPRNN, both in online (causal) and offline (non-causal) configurations (for a total of 4). For both, we use the best hyperparameter configuration as found in [32, 33] with these exceptions: to reduce memory footprint we employ a 16 analysis/synthesis kernel size for encoder/decoder also for DPRNN and, regarding causal models, we use standard layer normalization versus the non-causal global layer normalization employed in non-causal models. Additionally, we set the DPRNN chunk and hop sizes to 100 and 50, respectively. These models are trained on the simulated fully overlapped Fisher dataset using the SI-SDR objective to separate two speakers. We use Adam optimizer [39], batch size 4 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 10 epochs. If no improvement is observed for 20 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 adopt the TCN VAD from [36], 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 to estimated sources. We train on random 2 s long segments with a batch size of 256. The rest of training hyperparameters are the same as those 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 SSep model, we tune the median filter, leakage removal threshold and \( t_s \) parameters on the Fisher validation set (CALLHOME adaptation set for CALLHOME models). The segment length \( L \) of the leakage removal algorithm is set to 10 ms, which results in the same latency as the TCN VAD.

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 [7]. The evaluation is carried out using the standard NIST mid-eval scoring tool [40]. For the Fisher test set we also report the SI-SDRi [34] source separation metric since oracle sources are available.

4.1. Online Separation/Diarization

The results for online 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. We carry out the oracle evaluation only for Fisher, as for CALLHOME separated sources are not provided. For the CALLHOME evaluation, we also show DERs obtained by EEND, as reported in the original papers.

We observed that the Conv-TasNet model failed to deal with long recordings, generating large false alarm errors. This is due to the fact that, being fully convolutional, it has a limited ~1.5 s receptive field. On the other hand, the DPRNN, being based on recurrent neural networks, has no such limitations and was effectively able to track the speakers for much longer and generate better diarization results. The proposed leakage removal algorithm was highly effective for both architectures. This was especially true in the case of TCN-based VAD since it was more prone to false alarms caused by leaked speech due to being trained on real Fisher data and not on the output of the separators. Although the algorithm was only partially able to mitigate the low separation capability of the Conv-TasNet, it improved the DER by 50.3% and 50.7% on Fisher and CALLHOME, respectively. For DPRNN, the improvement was lower as the system

Table 1. Speech separation and diarization results on the Fisher and CALLHOME test sets in the online 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). Latency of the system is reported in seconds. The best results among proposed techniques are shown in bold, and among EEND methods are underlined.

| Method                        | VAD Latency (s) | Fisher   | CALLHOME |
|-------------------------------|----------------|----------|----------|
|                               |                | SI-SDRi  | MS      | FA     | SC     | DER | MS | FA | SC | DER |
| Oracle sources                |                |          |         |        |        |     |    |    |    |     |
| Energy                        | Energy         |          |         |        |        |     |    |    |    |     |
| TCN                           | TCN            |          |         |        |        |     |    |    |    |     |
| Conv-TasNet                   | Energy         |          |         |        |        |     |    |    |    |     |
| 0.01                          | -0.9           | 11.5     | 39.1    | 9.5    | 60.1   | 7.3 | 55.8 | 5.6 | 68.7 |
| + Leakage removal TCN 0.1     | -3.1           | 5.2      | 5.6     | 25.9   | 36.8   | 6.2 | 21.9 | 15.5 | 42.6 |
| DPRNN                         | Energy         |          |         |        |        |     |    |    |    |     |
| 0.1                           | 22.6           | 7.6      | 14.0    | 0.8    | 9.7    | 5.5 | 6.9  | 1.9  | 14.3 |
| DPRNN + Leakage removal       | 22.6           | 3.8      | 2.6     | 0.8    | 7.1    | 5.9 | 4.5  | 1.6  | 12.0 |

We also test the proposed methods on the portion of the 2000 NIST SRE 2015 denoted as CALLHOME, consisting of real-world multilingual telephone conversations. Following the recipe in [7], we use the 2-speaker subset of CALLHOME and the adaptation/test split that allows to compare with most end-to-end diarization methods mentioned previously. The amount of overlapped speech is around 13% of total speech duration.

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We observed that the Conv-TasNet model failed to deal with long recordings, generating large false alarm errors. This is due to the fact that, being fully convolutional, it has a limited ~1.5 s receptive field. On the other hand, the DPRNN, being based on recurrent neural networks, has no such limitations and was effectively able to track the speakers for much longer and generate better diarization results. The proposed leakage removal algorithm was highly effective for both architectures. This was especially true in the case of TCN-based VAD since it was more prone to false alarms caused by leaked speech due to being trained on real Fisher data and not on the output of the separators. Although the algorithm was only partially able to mitigate the low separation capability of the Conv-TasNet, it improved the DER by 50.3% and 50.7% on Fisher and CALLHOME, respectively. For DPRNN, the improvement was lower as the system
Table 2. Speech separation and diarization results on the Fisher and CALLHOME test sets in the offline scenario. The best results among proposed techniques are shown in bold, and those among baselines are underlined. Oracle sources evaluation is the same of Table 1, as the VADs works online in both online and offline scenarios.

| Method          | VAD              | Fisher | CALLHOME |
|-----------------|------------------|--------|----------|
|                 | SI-SDR          | MS     | FA      | SC      | DER | MS     | FA     | SC     | DER   |
| VBx [6]         | TCN              | 10.0   | 0.3     | 0.5     | 10.8 | 7.3    | 1.9    | 3.1    | 12.3  |
| VBx [6]         | Kaldi            | 8.9    | 0.4     | 0.9     | 10.2 | 8.3    | 0.9    | 2.6    | 11.7  |
| + Overlap        | assignment [20]  | Kaldi  | 4.4     | 2.1     | 0.9  | 7.4    | 5.3    | 2.5    | 10.3  |
| Spectral        | clustering [5]   | Kaldi  | 8.9    | 0.4     | 0.2  | 9.5    | 8.3    | 0.9    | 5.3   |
| + Overlap        | assignment [21]  | Kaldi  | 5.2    | 2.0     | 0.2  | 7.4    | 5.7    | 2.7    | 5.8   |
| SA-EEND [7]     |                  |        |         |         |      |        |        |        |       |
| SA-EEND-EDA [9] |                  |        |         |         |      |        |        |        |       |
| EEND + VC [17]  |                  |        |         |         |      |        |        |        |       |
| DIVE [18]       |                  |        |         |         |      |        |        |        |       |
| Conv-TasNet     | Energy           | 17.5   | 8.0     | 4.5     | 1.6  | 14.1   | 6.0    | 12.0   | 2.8   |
| Conv-TasNet     | TCN              | 17.5   | 6.2     | 5.0     | 1.1  | 12.4   | 6.1    | 13.6   | 1.8   |
| + Leakage        | removal          | TCN    | 17.1   | 5.5     | 2.5  | 2.0    | 10.1   | 6.0    | 10.1  |
| DPRNN            | Energy           | 22.6   | 7.6     | 1.2     | 0.7  | 9.5    | 5.5    | 4.4    | 0.5   |
| DPRNN            | TCN              | 22.6   | 3.4     | 2.2     | 0.7  | 6.3    | 5.0    | 5.4    | 0.4   |
| + Leakage        | removal          | TCN    | 22.2   | 3.9     | 1.6  | 0.7    | 6.4    | 6.6    | 1.9   |

without leakage removal was already able to obtain good diarization performance. However, the proposed post-processing almost halved the false alarm error rates and improved the DER by 4.2% and 7.5% on Fisher and CALLHOME, respectively.

As a comparison, the current best performing online system on the CALLHOME dataset (i.e., SA-EEND-EDA with speaker tracking buffer [16]), obtains 10.0% DER, which is slightly better than ours but is obtained with significantly higher latency of 10 s. Our approach works with a latency of 0.1 s, making it appealing for applications where real-time requirements are very important (e.g., real-time captioning). Last but not least, the SSSG is trained using a dataset of ~900 hours of speech, which is considerably smaller than the ones used to train the state-of-the-art EEND models (i.e., ~10000 hours) and results in shorter training times and less burden regarding additional costs for the generation of simulated mixtures.

4.2. Offline Separation/Diarization

For the offline scenario, we compare our approach with clustering-based and EEND methods. For the former, we use VBx [6] and spectral clustering [5], along with their overlap-aware counterparts [20, 21]. For VAD in these systems, we use the publicly available Kaldi ASpIRE VAD model [41]. For overlap detection, we fine-tune the Pyannote segmentation model[2] on the full CALLHOME adaptation set. The hyperparameters for each task are tuned on the corresponding validation set. The scripts for reproducing the baseline results are publicly available [4]. For fair comparison, we also report the performance of VBx with the TCN VAD, which however leads to degraded performance for this system.

The results for baselines and the offline SSSG diarization models are reported in Table 2. As in Table 1, we show DERs of the EEND methods for the CALLHOME test set.

In contrast to the online scenario, Conv-TasNet obtained good separation capability. However, DPRNN-based SSSG strongly outperformed the Conv-TasNet version on all metrics on the Fisher dataset, and even surpassed the overlap-aware VBx which scored best among all clustering baselines. Regarding separation performance (SI-SDRi), we can see that the offline DPRNN did not improve over the online one. In general, the TCN VAD outperformed the energy-based one, especially when the former was used jointly with the proposed leakage removal, which continued to be effective in the offline configuration.

For the CALLHOME data, the best performing SSSG model is comparable with SA-EEND [7]. Although the diarization capability is good, it is not competitive with the current best performing approaches [17, 18], making it less attractive for offline applications. However, as we show in Section 4.4, it can be a more cost effective solution as the separated signals can be readily used in downstream applications such as ASR.

In future work we will consider several strategies to reduce this gap such as training with more data, comparable to the amount used in EEND models, and fine-tuning our models on the CALLHOME adaptation set (as done in [7,9]).

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 length of the CSS window. Therefore, it can be regarded as an alternative approach for performing diarization online. We use the best SSSG offline model from Table 2 (DPRNN+TCN+Leakage removal) to investigate the effect of varying window sizes on SSSG. Evaluation results are reported in Fig. 2 for both datasets. As expected, the DER consistently decreased as the window size increased. In particular, the performances were 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 SSSG by applying CSS on minute-long frames simultaneously, resulting in significant inference speed-ups and less memory consumption. The optimal chunk sizes are different for the two datasets because of the difference in their average recording duration (which is 10 minutes and 72 seconds for Fisher and CALLHOME, respectively).

As the window was shortened, missed speech and false alarm
error rates remained approximately constant while speaker confusion errors consistently increased, indicating that the main source of error comes from speaker permutation due to wrong channel re-ordering 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.

The CSS framework is not competitive with the online approach with causal SSep (Sec. 4.1) in terms of latency. However, it could be a convenient choice for applications in which better diarization accuracy is more desirable than the low-latency requirement, and memory footprint is an important concern, especially for very long recordings (e.g., > 10 minutes).

### 4.4. Automatic Speech Recognition Evaluation

A great advantage of the SSGD framework over other diarization methods is that separated sources together with the segmentation provided by the VAD can be readily fed into the back-end ASR system. To investigate ASR performance, we feed to a downstream ASR the estimated sources for the DPRNN models with and without leakage removal and using oracle segmentation or not. We use the pre-trained Kaldi ASPIRE ASR model [43] and report the performance in terms of word error rate (WER). We compare the results with the ones obtained with input mixtures and oracle sources, which ideally represent the upper and the lower bound for WER (%) evaluation.

The results are reported in Table 3. We can see that for all SSGD systems the degradation was small compared to using oracle signals. This suggests that the separation is highly effective. A large improvement was obtained over the mixture, and we can observe that the main source of performance degradation versus a fully oracle system (oracle VAD + oracle sources) comes from the VAD segmentation. This is consistent with what we observed for diarization in Sections 4.1 and 4.2. The leakage removal algorithm slightly degraded the performance, but, on the other hand, in the proposed framework it could be only used for obtaining the segmentation and avoided for ASR (+ Leakage removal (seg-only)). In this latter case the performance was slightly increased.

### 5. CONCLUSION AND FUTURE WORK

In this paper, we have performed an analysis of SSGD for real-world telephone conversations extending it to online and arbitrar-
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