North America Bixby Speaker Diarization System for the VoxCeleb Speaker Recognition Challenge 2021

Myungjong Kim, Taeyeon Ki, Aviral Anshu, Vijendra Raj Apsingekar
Samsung Research America, USA
{myungjong.k, taeyeon.ki, aviral.anshu, v.akar}@samsung.com

Abstract

This paper describes the submission to the speaker diarization track of VoxCeleb Speaker Recognition Challenge 2021 done by North America Bixby Lab of Samsung Research America. Our speaker diarization system consists of four main components such as overlap speech detection and speech separation, robust speaker embedding extraction, spectral clustering with fused affinity matrix, and leakage filtering-based postprocessing. We evaluated our system on the VoxConverse dataset and the challenge evaluation set, which contain natural conversations of multiple talkers collected from YouTube. Our system obtained 4.46%, 6.39%, and 6.16% of the diarization error rate on the VoxConverse development, test, and the challenge evaluation set, respectively.

Index Terms: speaker diarization, speech separation

1. Introduction

Speaker diarization is the process of labeling different speakers given an audio stream, determining “who spoke when” in a multi-speaker conversation [1]. Speaker diarization has potential to be widely utilized in a variety of applications such as meeting conversation analysis and multi-media information retrieval. It can be used as a front-end component of automatic speech recognition (ASR), providing improved ASR accuracy, and more rich analysis depending on speakers.

In general, one of the most important components of speaker diarization is speaker embedding extraction. Speaker embeddings are generally extracted from short speech segments (e.g., 1.5 seconds) and directly used for speaker clustering. Therefore, extracting reliable speaker embeddings is critical in achieving better speaker diarization.

There are several challenges to extract better speaker embeddings in a multi-speaker conversation in the real world. Conversation often can happen in adverse noisy environment and multiple speakers can speak at the same time. In this situation, speaker embeddings could have low capacity to represent speaker identity. To overcome this problem, integrating additional components such as speech enhancement [2] and speech separation [3] into speaker diarization has shown good improvements in speaker diarization of natural conversations.

In this paper, we propose an integrated speaker diarization system, consisting of overlap speech detection and separation, robust speaker embedding extraction, effective spectral clustering and fusion methods, and postprocessing to handle incorrectly clustered results. We evaluate our system on the VoxConverse dataset [4], which is used in VoxCeleb Speaker Recognition Challenge 2020. VoxConverse [5] is a large-scale diarization dataset, collected from YouTube videos including talk-shows, panel discussions, political debates and celebrity interviews.

The organizer shared ground truth data of the dev & test set of VoxConverse as a validation set for this year. The VoxConverse dev & test set consists of 216 recordings (20.3 hours in total) and 232 recordings (43.5 hours in total), respectively. The number of speakers in one recording varies from 1 to 21. We report diarization error rates (DERs) and Jaccard error rates (JERs) using the scoring tool provided by the organizer [2] on the VoxConverse dev and test set, respectively. Our best system on the VoxConverse set is submitted to the challenge.

2. System Description

2.1. Speech enhancement

Our system starts with preprocessing, which is a speech enhancement technique to reduce background noise and improve speech quality, especially retaining speaker specific information as much as possible. According to recent research [2, 5], the long short-term memory (LSTM) network-based speech enhancement method trained on simulated data improves performance in speaker diarization. In our experiments, our diarization accuracy was also consistently improved by 3% on average on the VoxConverse set, so we take advantage of this approach.

2.2. Voice activity detection

We use the pretrained Silero voice activity detection (VAD) model [6] as our baseline. The model architecture is based on convolutional neural networks and transformers. To improve voice detection accuracy in cases where our preprocessing does not remove diverse background or foreground noise properly, the pretrained model is retrained with the AVA speech dataset [7]. The AVA speech dataset is collected from YouTube, and contains 300 audios with 16000 clean and noisy speech, and 17000 non-speech frames in a variety of environment.

We have compared our retrained VAD model with the AVA speech data to the baseline model. Table 1 shows missed speech (MS) rates and false alarm (FA) rates on the VoxConverse dev and test sets. As shown in Table 1, the retrained VAD model performs better than the baseline on both MS and FA. The error rates show relative improvements of 5.45% and 5.75%, respectively.

2.3. Overlapped speech detection and separation

In the natural daily conversations or meetings, it is observed that people often speak together at the same time (i.e., overlapping utterances) [4, 8]. However, a speaker embedding vector represents a single speaker’s acoustic characteristics in general.
So, handling a speech segment that contains multiple speakers’ speech is one of the major challenges in speaker diarization. This is because multiple speakers are mingled in a speech segment, and it is hard to extract each speaker embedding vector correctly. In some cases, non-dominant speaker’s characteristics can be missing as well.

Neural network-based speech separation models such as ConvTasNet 9, Sepformer 10, DPTNet 11, and DPRNN 12 have been widely studied, and show good performance. However, the latency of speech separation still remains as an issue. Thus, processing an entire audio signal with speech separation model is not ideal.

To address this issue, we exploit pretrained overlapped speech detection (OSD) model 13 to determine whether a segment has multiple speakers’ utterance. If it does, we conduct speech separation to find each speaker’s voice. Going into details, the OSD takes segments as input from VAD, and splits into subsegments, 1.5 seconds long window with a shift of 0.75 seconds. The pretrained OSD model is trained with a subset of the AMI corpus 14, recording in a quiet environment. We have fine-tuned the hyper parameters of the model to make a good fit for the VoxConverse dataset.

We conduct an experiment to see how well our fine-tuned OSD module works with the VoxConverse dataset. We have extracted 100 overlapped and non-overlapped speech segments from the VoxConverse dev set, and obtained 75% classification accuracy on this set with our fine-tuning OSD model.

We consider two speech separation architectures to find a better fit for our speaker diarization system in terms of latency and accuracy. One is ConvTasNet 9, a fully-convolutional time-domain audio separation network, and the other is Sepformer 10, an RNN-free Transformer-based neural network. Both models consist of three main components including an encoder, a masknet, and a decoder. Our ConvTasNet model is trained with the combination of WSJ0-2, WHAMR! 15, and VoxConverse datasets, but our Sepformer model is trained with only WHAM! 16 dataset. From our experiment, regarding latency, ConvTasNet is a better option, but Sepformer shows better performance on the VoxConverse dev and test sets.

We add a signal energy-based segment filter to our Sepformer model in order to handle a false detection case, which is that the OSD classifies a single voice in a segment into multiple voices. In the cases, we observed one of the separated signals often contains the active speaker’s voice while the other contains residual signals with low energy. Thus, this energy-based residual segment filtering helps to compensate a false detection case. Also, we add one more VAD round based on WebRTC with the most aggressiveness mode to cover the corner case, which is a short partially overlapped speech in a subsegment. With the additional VAD round, the non-speech part is filtered out in the separated signals.

After speech separation, if a segment is determined as a single speaker (i.e., when the decision of energy-based residual filtering is true), we use the original audio. This is because the speech acoustic characteristics can be subject to change.

### 2.4. Speaker embedding extraction

ECAPA-TDN-based speaker embedding models were recently introduced 17, and have shown a great success on speaker verification 18 19 as well as speaker diarization tasks 20. It is based on TDNN-based x-vector speaker embeddings 21 with several advancements by incorporating a channel- and context-dependent attention mechanism in the pooling layer, 1-dimensional Squeeze-Exitation (SE) blocks, 1-dimensional Res2Net blocks, and multi-layer feature aggregation. In addition, the model is optimized with the AAM-softmax loss 22 to effectively classify speaker identities. Also, it directly optimizes the cosine distance between the speaker embeddings, and therefore, it is beneficial to use cosine similarities as a similarity measure during spectral clustering.

We consider three ECAPA-TDN models with slightly different variants: 1) large version of ECAPA-TDN, 2) light version of ECAPA-TDN, and 3) light version of ECAPA-TDN with retraining. The large version of ECAPA-TDN has the same structure as in 17 20 with 80 dimensional log Mel filterbank energies as acoustic features and TDNN channel size of 1024. This model is trained on VoxCeleb 1 23 2 24 data with RIRs 1 and MUSAN 25 datasets for data augmentation. We use the data augmentation strategies 20: waveform and frequency dropout, speech perturbation, reverberation, additive noise, and noise + reverberation. All corrupted data is added to our train set, and our training data is six times the original data. To train the model, the data is cropped into 3 seconds audios. We used the Adam optimizer with a cyclical learning rate using a triangular policy 26. AAM-softmax is used with a margin of 0.2. Training is done for 10 epochs with batches of 32 segments.

In the light version of ECAPA-TDN, acoustic features are replaced from 80 dimensional log Mel filterbank energies to 40, and TDNN channel size from 1024 to 512. This model is also trained on VoxCeleb data with the same data augmentation strategies, but MUSAN is replaced with WHAMR! noise set. Inspired by 18, we retrain the light version of ECAPA-TDN model with 1.5 seconds audio clips to match the em-

---

Table 1: Comparison between the retrained VAD model and the pretrained Silero VAD model on the VoxConverse set.

| Model          | Vox dev |     | Vox test |     |
|----------------|---------|-----|----------|-----|
|                | MS      | FA  | MS       | FA  |
| Baseline VAD   | 2.96    | 1.02| 3.02     | 2.08|
| Retrained VAD  | 2.87    | 0.96| 2.78     | 1.96|

---

Figure 1: System Diagram
bedding window size. In addition, we increased a margin of AAM-softmax from 0.2 to 0.5. Retraining is done for 2 more epochs based on the trained light version of ECAPA-TDNN.

All models contain an embedding layer with hidden unit size of 192 right before the softmax layer. After speaker embedding model training, we extract 192 speaker embedding vectors from 1.5 seconds window with a shift of 0.75 seconds.

### 2.5. Spectral clustering

Spectral clustering is a popular clustering method in speaker diarization [27, 28]. We apply the unnormalized spectral clustering approach as in [29]. The affinity matrix is calculated using the cosine similarity. We prune out the smaller values in the affinity matrix to focus more on prominent values. The symmetrized affinity matrix is used to estimate an unnormalized Laplacian matrix followed by eigendecomposition. The number of speakers $k$ is estimated using the maximum eigengap approach and we use the first $k$ eigenvectors. Specifically, the rows of the eigenvector matrix are the $k$ dimensional spectral embeddings corresponding to each speaker embedding vector of a segment. Finally, we use the standard $k$-means algorithm to cluster the estimated spectral embeddings.

Affinity matrix directly contributes in obtaining spectral embeddings to be clustered, therefore, manipulating the affinity matrix is one of the keys to achieve better diarization results. One widely used option is to prune out the smaller values in affinity matrix as our default setting [29]. Another option is to binarize the similarity values by converting non-zero values to 1 to have only 0 or 1 in the affinity matrix [30] or normalize the similarity values after pruning out the smaller values in affinity matrix.

In our experiments, there was no difference from these three methods in terms of DER. Instead, we add fixed values to the actual cosine similarity to boost the values after pruning out the smaller values in affinity matrix.

Spectral clustering is only applied to non-overlapped segments. After obtaining speaker clusters from non-overlapped speaker embeddings, the speaker embeddings are mapped from overlapped segments (speech separation outputs). We use cosine similarity between speaker embeddings and centroids of all speaker clusters, and the speaker embeddings are mapped to the cluster with the highest similarity.

### 2.6. Postprocessing

We perform postprocessing based on initial clustering results to obtain more fine-grained results. If the input audio includes non-stationary background/foreground noise recorded in different acoustic setup or speech separation signals, one speaker is likely to split into multiple clusters. To overcome this issue, we compare cosine similarity between centroids of all clusters, and if the similarity is larger than a threshold, we merge the clusters.

As noted in [31], speech separation outputs often have residual noise signals in one of separated signals especially when a single speaker is speaking with adverse background noises such as music. In addition, VAD may incorrectly detect noise or musical signals as speech. To reduce the errors coming from the residual noises or misdetected signals from VAD, we leverage leakage filtering [3] which means if maximum cosine similarity of a segment to the centroids of all clusters is below a threshold, the segment is removed from the diarization results. In addition, we further compute a centroid from the leakage filtered segments and remove segments if similarity with a leakage centroid is larger than a threshold. The threshold is set to 0.65, 0.2, and 0.7 which are tuned from the VoxConverse set, respectively.

### 2.7. Affinity matrix fusion

Three speaker embeddings are trained on slightly different configurations, and therefore, different speaker characteristics may be captured on the short speech segments to complement each other. Accordingly, affinity matrices might be estimated to focus on different views of relationship between speaker embeddings. Spectral embeddings to be clustered is directly modeled from the affinity matrix, so it is important to obtain a reliable affinity matrix in achieving a better accuracy in speaker diarization. To this end, we combine affinity matrices estimated from the three speaker embeddings by averaging them.

### 3. Results

We evaluated the proposed systems on the VoxConverse dev and test sets as well as the challenge evaluation set in terms of diarization error rates (DERs) and Jaccard error rates (JERs) [31] in Table 2. The baseline is the official baseline of the challenge shared by the organizer. We first compared the diarization results of single ECAPA-TDNN-based speaker embeddings. The large version of ECAPA-TDNN was better than the light version. Two light versions of ECAPA-TDNN were comparable, but the retrained ECAPA-TDNN showed slight improvement in the DER on the VoxConverse test set.

By combining three affinity matrices generated from the above three speaker embeddings, we obtained better accuracy than single speaker embeddings in terms of both DER and JER. The fusion system and the boosted affinity matrix together helped better improve performance. Leakage filtering helped contribute to diarization results by reducing both the DER and JER as well.

When we applied a series of components with fused and boosted affinity-based clustering, leakage filtering, and over-

| System                                              | Vox dev DER | Vox dev JER | Vox test DER | Vox test JER | Challenge set DER | Challenge set JER |
|-----------------------------------------------------|-------------|-------------|--------------|--------------|-------------------|------------------|
| Baseline                                            | -           | -           | -            | -            | 17.99             | 38.72            |
| ECAPA-TDNN                                          | 5.02        | 22.02       | 6.76         | 32.04        | -                 | -                |
| Light ECAPA-TDNN                                    | 5.17        | 22.70       | 6.84         | 31.91        | -                 | -                |
| Light ECAPA-TDNN retrained                          | 5.18        | 22.72       | 6.82         | 32.31        | -                 | -                |
| Fusion                                              | 4.98        | 22.00       | 6.70         | 31.31        | -                 | -                |
| Fusion + boosted affinity                            | 4.91        | 21.99       | 6.70         | 32.02        | -                 | -                |
| Fusion + boosted affinity + leakage filtering        | 4.82        | 21.90       | 6.46         | 31.90        | -                 | -                |
| Fusion + boosted affinity + leakage filtering + overlap handling | 4.46 | 21.09 | 6.39 | 32.19 | 6.16 | 27.95 |
lap handling, we were able to obtain the best diarization results, showing a DER of 4.46% on the VoxConverse dev set and a DER of 6.39% on the VoxConverse test set. Finally, we submitted this system to the challenge and obtained a DER of 6.16% and a JER of 27.95%, achieving relative improvements of 65.7% and 27.8% in the DER and JER, respectively, compared to the challenge baseline system.

4. Conclusions

This paper describes the speaker diarization system submitted by North America Bixby Lab of Samsung Research America. The system consists of a series of important components such as overlap speech detection and separation, ECAPA-TDNN-based speaker embeddings, fused and boosted affinity matrix-based spectral clustering, and leakage filtering-based postprocessing. The proposed system was evaluated with the data set provided by the VoxCeleb Speaker Recognition Challenge 2021, and we achieved DERs of 4.46%, 6.39%, and 6.16% on the VoxConverse dev & test set and the challenge evaluation set, respectively.

5. References

[1] X. Anguera, S. Bozontet, N. Evans, C. Fredouille, G. Friedland, and O. Vinyals, “Speaker diarization: A review of recent research,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 20, no. 2, pp. 356–370, 2012.
[2] L. Sun, J. Du, C. Jiang, X. Zhang, S. He, B. Yin, and C.-H. Lee, “Speaker diarization with enhancing speech for the first dihard challenge.” in Interspeech, 2018, pp. 2793–2797.
[3] X. Xiao, N. Kanda, Z. Chen, T. Zhou, T. Yoshioka, S. Chen, Y. Zhao, G. Liu, Y. Wu, J. Wu et al., “Microsoft speaker diarization system for the voxceleb speaker recognition challenge 2020,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 5824–5828.
[4] J. S. Chung, J. Huh, A. Nagrani, T. Afouras, and A. Zisserman, “Spot the conversation: speaker diarisation in the wild,” arXiv preprint arXiv:2007.01216, 2020.
[5] F. Landini, O. Glembek, P. Maletjka, J. Rohdin, L. Burget, M. Diez, and A. Silnova, “Analysis of the but diarization system for voxconverse challenge,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 5819–5823.
[6] S. Team, “Siler-vad: pre-trained enterprise-grade voice activity detector (vad), number detector and language classifier,” [https://github.com/saekers4/siler-vad 2021].
[7] S. Chaudhuri, J. Roth, D. P. W. Ellis, A. Gallagher, L. Kaver, R. Marvin, C. Pantofaru, N. Reale, L. G. Reid, K. Wilson, and Z. Xu, “Ava-speech: A densely labeled dataset of speech activity in the wild,” 2018.
[8] O. Çetin and E. Shriberg, “Analysis of overlaps in meetings by dialog factors, hot spots, speakers, and collection site: Insights for automatic speech recognition,” in Ninth international conference on spoken language processing, 2006.
[9] Y. Luo and N. Mesgarani, “Fasnet: Surpassing ideal time-frequency masking for speech separation,” CoRR, vol. abs/1809.07454, 2018. [Online]. Available: [http://arxiv.org/abs/1809.07454](http://arxiv.org/abs/1809.07454)
[10] C. Subakan, M. Ravanelli, S. Cornell, M. Bronzi, and J. Zhong, “Attention is all you need in speech separation,” 2021.
[11] J. Chen, Q. Mao, and D. Liu, “Dual-path transformer network: Direct context-aware modeling for end-to-end monaural speech separation,” 2020.
[12] Y. Luo, Z. Chen, and T. Yoshioka, “Dual-path rnn: efficient long sequence modeling for time-domain single-channel speech separation,” 2020.
[13] L. Bullock, H. Bredin, and L. P. Garcia-Perera, “Overlap-aware diarization: resegmentation using neural end-to-end overlapped speech detection,” 2019.
[14] J. Carletta, “Unleashing the killer corpus: experiences in creating the multi-everything ami meeting corpus,” Language Resources and Evaluation Journal, p. 2007.
[15] M. Macieiewski, G. Wichern, and J. Le Roux, “Wham!: Noisy and reverberant single-channel speech separation,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2020.
[16] G. Wichern, J. Antognini, M. Flynn, L. R. Zhu, E. McQuinn, D. Crow, E. Manilow, and J. L. Roux, “Wham!: Extending speech separation to noisy environments,” arXiv preprint arXiv:1907.01160, 2019.
[17] B. Desplanches, J. Thienpondt, and K. Demuynck, “Ecapa-tmdn: Emphasized channel attention, propagation and aggregation in tdm based speaker verification,” arXiv preprint arXiv:2005.07143, 2020.
[18] J. Thienpondt, B. Desplanches, and K. Demuynck, “The iidlab voxsrc-20 submission: Large margin fine-tuning and quality-aware score calibration in dnn based speaker verification,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 5814–5818.
[19] ——, “The iidlab voxceleb speaker recognition challenge 2020 system description,” arXiv preprint arXiv:2010.12468, 2020.
[20] N. Dawalatabad, M. Ravanelli, F. Grondin, J. Thienpondt, B. Desplanches, and H. Na, “Ecapa-tmdn embeddings for speaker diarization,” arXiv preprint arXiv:2104.01466, 2021.
[21] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, and S. Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition,” in 2018 IEEE International Conference on Acoustics, Speaker and Signal Processing (ICASSP). IEEE, 2018, pp. 5329–5333.
[22] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, “Arcface: Additive angular margin loss for deep face recognition,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 4690–4699.
[23] A. Nagrani, S. J. Chung, and A. Zisserman, “Voxceleb: a large-scale speaker identification dataset,” arXiv preprint arXiv:1706.08612, 2017.
[24] J. S. Chung, A. Nagrani, and A. Zisserman, “Voxceleb2: Deep speaker recognition,” arXiv preprint arXiv:1806.05622, 2018.
[25] D. Snyder, G. Chen, and D. Povey, “Musan: A music, speech, and noise corpus,” arXiv preprint arXiv:1510.08484, 2015.
[26] L. N. Smith, “Cyclical learning rates for training neural networks,” arXiv, Preprint at https://arxiv.org/abs/1506.01186, 2015.
[27] Q. Wang, C. Downey, L. Wan, P. A. Mansfield, and I. L. Moreno, “Speaker diarization with lstm,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5239–5243.
[28] T. J. Park, N. Kanda, D. Dimitriadis, K. J. Han, S. Watanabe, and S. Narayanan, “A review of speaker diarization: Recent advances with deep learning,” arXiv preprint arXiv:2101.09624, 2021.
[29] U. V. Luxburg, “A tutorial on spectral clustering,” Statistics and Computing, vol. 27, no. 4, pp. 395–416, 2007.
[30] T. J. Park, K. J. Han, M. Kumar, and S. Narayanan, “Auto-tuning spectral clustering for speaker diarization using normalized maximum eigengap,” IEEE Signal Processing Letters, vol. 27, pp. 381–385, 2019.
[31] N. Ryant, K. Church, C. Cieri, A. Cristia, J. Du, S. Ganapathy, and M. Liberman, “First dihard challenge evaluation plan,” 2018, tech. rep., 2018.