

Enhancing Low-latency Speaker Diarization with Spatial Dictionary Learning

Weiguang Chen¹, Tran The Anh², Xionghu Zhong¹, Eng Siong Chng²



PAPER ID: 6144

¹College of Computer Science and Electronic Engineering, Hunan University, China ²School of Computer Science and Engineering, Nanyang Technological University, Singapore

INTRODUCTION

- Speaker diarization serves as a crucial precursor for downstream applications, such as multi-speaker automatic speech recognition.
- Recent advancements have focused on adapting existing frameworks to online diarization by buffering speakers' acoustic representations.
- Despite this, online diarization based on acoustic features encounters several challenges:
 - The latency in acquiring a reliable acoustic embedding for a new speaker can extend up to several seconds.
 - As the number of speakers increases, distinguishing between speakers with similar timbres becomes more challenging.

RESULTS AND CONCLUSION

• We evaluated our SDL-TS-VAD on the AliMeeting[1] dataset. The results for Diarization Error Rate (DER) are presented in Table 1.

Table 1. The performance of different systems on Alimeeting Eval and Test set in terms of DER (%). † and ‡ denote the 1st-ranked and 2nd-ranked methods from Alimeeting challenge respectively. Results marked with $^{\land}$ are sourced from [2].

Model	Туре	Input Channels	Eval				Test
			FA (%)	MISS (%)	SC (%)	DER (%)	DER (%)
Official baseline[1]	offline	single-	-	-	-	15.24	15.60
BeamformIt [3] +VBx [4] ^	offline	multi-	0.00	13.10	0.47	13.57	13.51
BeamformIt [3] +VBx [4] +OSD[5] $^{\wedge}$	offline	multi-	1.09	4.17	2.84	8.10	9.45
Target-DOA[6] ^	offline	multi-	1.17	3.92	4.15	9.23	11.95
TS-VAD [7] †	offline	single-	1.00	2.50	0.70	4.12	-
TS-VAD [7] †	offline	multi-	1.10	1.10	0.10	2.26	2.98
FFM-TS-VAD $[2]$ [‡]	offline	multi-	0.83	2.55	0.26	3.64	5.63
Online TS-VAD [8]	online	single-	-	-	-	8.14	11.42
SDL-TS-VAD	online	multi-	2.35	2.73	0.95	6.04	6.19

 To address these issues, this paper introduces a novel spatial dictionary learning method for online speaker diarization.

METHOD

• Overall Framework --- SDL-TS-VAD

During training, the left part of the input is utilized to generate speaker embeddings, which are then used for predicting the right portion via the Conformer based TS-VAD model.



 We also conducted ablation studies on the SDL and MWF modules, with the results summarized in Table 2. "MagPhase" denotes the combination of magnitude and phase spectra, while "RealImag" signifies the concatenation of real and imaginary spectra.



- We compared our method with re-implemented Online TS-VAD under various latencies, as shown in Figure 1.
- Additionally, we visualized the speaker embeddings aggregated from each block of session "R8002_M8002_MS802" in the Alimeeting test set, as depicted in Figure 2.
- Two novel modules are proposed --- Spatial dictionary learning (SDL) and Magnitude-weighted fusion (MWF)
 - SDL projects the complex vector at each time-frequency point onto a hypersphere.
 - MWF fuses the magnitude spectrum with the result obtained from SDL.

• Spatial Dictionary Learning





Figure 2. The t-SNE plots of aggregated speaker embeddings from each block of session "R8002 M8002 MS802".

- The experiments demonstrated that our method achieved a significant improvement compared to the single-channel method, and SDL-TS-VAD exhibited performance comparable to the second-ranked offline method of the AliMeeting challenge[1].
- In the future, we will extend our method to scenarios where speakers can move in the meeting and the number of speakers is greater.



- > The spatial dictionary is composed of a complex tensor with dimensions $N \times M(Size_D \times Channel)$.
- The input at each time-frequency point is a complex vector, encompassing both amplitude and phase information.
- The cosine similarity is calculated between the input complex vector and the items in the spatial dictionary.
- Magnitude-Weighted Fusion
- Average pooling is applied to multichannel magnitude spectra.
- The features from SDL and the averaged magnitude are then fused by multiplication.





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