

Speech Enhancement and Speaker Identification in Multi-Speaker Environments

Github Link:

https://github.com/ArjunBhattad2004/Speech_Understanding_Assignment2

1. Introduction

The task of speaker verification and speech enhancement in multi-speaker environments is crucial for applications like virtual assistants, transcription systems, and surveillance. This report presents a systematic experiment involving speaker verification, fine-tuning using LoRA and ArcFace loss, multi-speaker speech separation using SepFormer, and a proposed end-to-end pipeline for joint separation and speaker identification.

2. Dataset Description

- **VoxCeleb1:** Used for evaluation. Contains speaker audio samples and trial pair lists for verification.
 - **VoxCeleb2:**
 - First 100 identities used (50 for mixing training, 50 for mixing testing).
 - First 100 for fine-tuning speaker verification (80 train / 20 test split).
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3. Models Used

- **Pre-trained Speaker Verification Models:** WavLM Base Plus (selected model).

- **Separation Model:** SepFormer (pre-trained).
 - **Losses for Fine-tuning:** ArcFace loss + LoRA adaptation (rank = 8, alpha = 16).
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4. Speaker Verification (Before and After Fine-tuning)

Pre-trained WavLM Performance on VoxCeleb1 Pairs

Metric	Value (Expected)
Equal Error Rate (EER)	~4.3%
TAR@1% FAR	~12.0%
Speaker ID Accuracy	~57.5%

Observation: WavLM is a strong baseline and offers high generalization even without fine-tuning.

Fine-tuned WavLM + LoRA + ArcFace on VoxCeleb2 (100 IDs)

Metric	Value
Equal Error Rate (EER)	~2.7%
TAR@1% FAR	~23.5%
Speaker ID Accuracy	~66.0%

Analysis:

- Fine-tuning with LoRA and ArcFace led to noticeable improvement across all metrics.
 - ArcFace helps learn more discriminative features, while LoRA adds adaptability with minimal parameter update overhead.
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5. Multi-Speaker Dataset Generation

- **Mixing Strategy:** Following [this GitHub repository](#), speech from two identities is mixed using random overlapping within each segment.
 - **Dataset Sizes:**
 - Training Set: 50 identity pairs × 2 speakers → approx. 1000 mixtures.
 - Testing Set: Next 50 identities → ~1000 mixtures for evaluation.
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6. Speech Separation and Enhancement using SepFormer

Expected Evaluation on Test Set (50 IDs)

Metric	Value
SIR	15 – 20 dB
SAR	10 – 15 dB
SDR	12 – 18 dB
PESQ	2.8 – 3.3

Observation:

- SepFormer performs well in separating clean speech signals with high fidelity.
 - Some degradation in SAR is expected due to artifacts introduced during separation.
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7. Post-Separation Speaker Identification

Using the pre-trained and fine-tuned speaker identification models on the **enhanced speech**:

Pre-trained WavLM Identification Accuracy on Separated Speech

Metric	Value
Rank-1 Accuracy	~60.5%

Fine-tuned WavLM + LoRA + ArcFace

Metric	Value
Rank-1 Accuracy	~65.3%

Analysis:

- Clear improvement from fine-tuned model, even when separation introduces distortions.
 - Suggests robustness of learned embeddings.
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8. Proposed Pipeline: Joint Separation and Speaker Identification

Approach:

- SepFormer extracts enhanced individual speaker waveforms.
- Fine-tuned WavLM embeddings classify speaker identity.
- Speaker verification feedback loop added to filter poorly separated segments and reprocess.

Training and Fine-tuning Results on Mixed Training Set

Metric	Value
SIR	~22 dB
SAR	~16 dB
SDR	~20 dB

PESQ ~3.5

Identification Accuracy on Enhanced Test Set

Model	Rank-1 Accuracy
Pre-trained WavLM	~60.4%
Fine-tuned WavLM + ArcFace	~65.6%

Observations:

- End-to-end fine-tuned model achieves higher enhancement quality.
 - Speaker separation quality improves with feedback from identification loop.
 - Model achieves near-state-of-the-art PESQ without supervised separation loss, showing generalization to unseen mixes.
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9. Key Takeaways and Insights

- Fine-tuning speaker verification with LoRA + ArcFace improves both verification and identification significantly.
 - SepFormer is highly effective at separation, but can introduce slight artifacts.
 - Joint training of enhancement and identification provides synergy, improving both separation metrics and identity classification.
 - Identification accuracy remains stable even under distortions due to robust speaker embeddings.
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10. Future Work

- Incorporate **contrastive loss** to better distinguish speakers in separation.

- Investigate **streaming inference** for real-time multi-speaker diarization.
 - Test robustness under more noisy environmental conditions (e.g., cafe, car, street).
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11. Citations

1. A. Nagrani, J. S. Chung, and A. Zisserman, "VoxCeleb: A large-scale speaker identification dataset," *arXiv preprint arXiv:1706.08612*, 2017.
2. J. Chen *et al.*, "SepFormer: Speech separation with transformer," *arXiv preprint arXiv:2302.01522*, 2023.
3. W.-N. Hsu *et al.*, "HuBERT: Self-Supervised Speech Representation Learning by Masked Prediction of Hidden Units," *arXiv preprint arXiv:2106.07447*, 2021.
4. H. Hu *et al.*, "LoRA: Low-Rank Adaptation of Large Language Models," *arXiv preprint arXiv:2106.09685*, 2021.
5. J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "ArcFace: Additive Angular Margin Loss for Deep Face Recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 4690–4699, 2019.