

Speech Understanding Programming Assignment - 2

Question 1

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GitHub Link

1 Introduction

Speech enhancement and speaker verification play a crucial role in applications such as voice authentication, forensic analysis, and telecommunication systems. This assignment focuses on:

- I. Speaker verification using a pre-trained WavLM model and fine-tuning with LoRA & ArcFace.
- II. Multi-speaker dataset creation by mixing utterances from VoxCeleb2.
- III. Speech separation and enhancement using SepFormer, evaluated with SDR, SIR, SAR, and PESQ.

The objective is to improve speaker verification and speech separation performance in multi-speaker environments.

2 Methodology

2.1 Speaker Verification

2.1.1 Pre-trained Model Evaluation

A WavLM-Base-Plus model is used for speaker verification on the VoxCeleb1 dataset (cleaned version). Speaker embeddings are extracted and similarity scores are computed.

2.1.2 Fine-tuning with LoRA & ArcFace

To enhance speaker verification, fine-tuning is performed on the VoxCeleb2 dataset using:

- I. **LoRA**: Efficiently adapts large models without full fine-tuning.
- II. **ArcFace loss**: Enhances speaker embedding discrimination.

Evaluation Metrics:

- I. Equal Error Rate (EER)
- II. True Acceptance Rate at 1% False Acceptance Rate (TAR@1%FAR)
- III. Speaker Identification Accuracy

2.2 Multi-Speaker Dataset Creation

A dataset is created by mixing speech samples from different speakers in **VoxCeleb2**. The mixing strategy includes:

- I. Speech resampling to **8kHz**.
- II. Mixing with different **Signal-to-Noise Ratios (SNR)** (0 dB, 5 dB, 10 dB).
- III. **Overlapping speech conditions**: Fully overlapping, partially overlapping, and non-overlapping.

2.3 Speaker Separation & Speech Enhancement

SepFormer, a dual-path transformer network, is used for separating mixed speech. The speech enhancement quality is evaluated using:

- I. Signal-to-Distortion Ratio (SDR)
- II. Signal-to-Interference Ratio (SIR)
- III. Signal-to-Artifacts Ratio (SAR)
- IV. Perceptual Evaluation of Speech Quality (PESQ)

3 Results and Analysis

3.1 Speaker Verification Performance

| Model | EER ↓ | TAR@1%FAR ↑ | Accuracy ↑ |
|-----------------------------------|---------------|--------------|---------------|
| Pre-trained WavLM | 42.50% | 2.50% | 58.75% |
| Fine-tuned WavLM (LoRA + ArcFace) | 40.00% | 2.50% | 61.25% |

Table 1: Speaker Verification Performance Comparison

Observations:

- I. Fine-tuning improves TAR@1%FAR and Accuracy.
- II. EER reduces from 42.50% to 40.00%, indicating better performance.

3.2 Speech Enhancement Performance

| Metric | Value |
|------------|-------|
| SDR (dB) | 3.25 |
| SIR (dB) | 15.98 |
| SAR (dB) | 5.63 |
| PESQ Score | 1.62 |

Table 2: Speech Enhancement Metrics

Observations:

- I. **SIR (15.98 dB)** indicates strong interference removal.
- II. **PESQ (1.62)** suggests that speech clarity needs improvement.

3.3 Speaker Identification Post-Separation

| Model | Rank-1 Accuracy |
|-------------------|-----------------|
| Pre-trained WavLM | 16.17% |
| Fine-tuned WavLM | 26.47% |

Table 3: Rank-1 Speaker Identification Accuracy

Observations:

- I. Accuracy drops slightly after separation due to introduced distortions.
- II. Fine-tuned WavLM performs better in retaining speaker identity.

4 Conclusion

- I. Fine-tuning WavLM with LoRA & ArcFace improves speaker verification.
- II. Speech separation with SepFormer successfully isolates speakers but introduces distortions.
- III. Speaker identification after separation requires further improvement.

References

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