Comprehensive Report on Speaker Verification, Multi-Speaker Separation, and Combined Pipeline

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Abstract

This report provides an extensive investigation of speaker separation and verification using three related tasks. In Task I, a pre-trained `Wavlm-base-plus` model is tested on VoxCeleb1 and fine-tuned on VoxCeleb2 with Low-Rank Adaptation (LoRA) and ArcFace loss. In Task II, the speaker separation is performed with the pre-trained SepFormer model on a multi-speaker mixed dataset generated by combining utterances of VoxCeleb2, followed by speaker identification evaluation. In Task III, a new pipeline is presented that integrates the speaker identification model with the SepFormer for collaborative speaker separation and speech enhancement. Comprehensive experimental results, observations, and analyses are presented

1 Introduction

Speaker verification and speaker separation are extremely important tasks for contemporary speech processing systems. In this report, three experimental tasks are described:

1. **Task I:** Evaluate a pre-trained `Wavlm-base-plus` model on VoxCeleb1 and fine-tune it using VoxCeleb2 with LoRA and ArcFace loss.
2. **Task II:** Construct a multi-speaker scenario dataset by overlapping utterances from VoxCeleb2, and apply speaker separation with a pre-trained SepFormer model. The separated speech is tested using separation metrics and then identified using both the pre-trained and fine-tuned speaker identification models.
3. **Task III:** Design and train a new pipeline that integrates speaker identification with the SepFormer model to perform speaker separation and speech enhancement jointly. The pipeline is trained on the multi-speaker dataset and tested using separation metrics and speaker identification accuracy.

2 Theory and Background

This section provides the theoretical basis and background for the experimental setup.

2.1 Speaker Verification and Fine-Tuning

Speaker verification is the process of authenticating a speaker's identity using unique voice characteristics. In this test, a pre-trained model (`Wavlm-base-plus`) is first assessed for speaker verification on the VoxCeleb1 (cleaned) dataset. Then, the model is further fine-tuned on the VoxCeleb2 dataset using Low-Rank Adaptation (LoRA) to efficiently update the model parameters and ArcFace loss to learn discriminative embeddings. Testing is carried out using measurements like Equal Error Rate (EER), True Acceptance Rate at 1% False Acceptance Rate (TAR@1%FAR), and Speaker Identification Accuracy.

2.2 Source Separation Metrics

When evaluating speaker separation, the following metrics are employed:

- **SDR (Signal-to-Distortion Ratio):** It measures the quality of the separated signal as a whole by comparing the target signal with the distortion (noise and interference).
- **SIR (Signal-to-Interference Ratio):** It measures the suppression capability of interfering sources over the target signal.
- **SAR (Signal-to-Artifacts Ratio):** Measures the amount of artifacts added during the separation process.
- **PESQ (Perceptual Evaluation of Speech Quality):** This gives a perception-based measurement of speech quality according to human auditory models.

3 Datasets

3.1 VoxCeleb1 (Cleaned)

- **Purpose:** Baseline evaluation of speaker verification.
- **Content:** Audio files with trial pairs for enrollment and testing.

3.2 VoxCeleb2

- **Purpose:** Fine-tuning the speaker verification model and creating a multi-speaker scenario.
- **Data Splits:**
  - **Speaker Verification Fine-tuning:** First 100 identities for training; remaining 18 identities for testing.
  - **Multi-Speaker Dataset Creation:**
    - **Training Set:** First 50 identities.
    - **Testing Set:** Next 50 identities.

4 Methodology

4.1 Pre-trained Model Selection and Baseline Evaluation

In this experiment, the `Wavlm-base-plus` model has been chosen as the pre-trained model. The decision to select `Wavlm-base-plus` was based on the following reasons:

- **Performance:** It has shown robust performance in various audio processing tasks.
- **Model Size:** `Wavlm-base-plus` is relatively smaller in size compared to other candidate models such as `hubert large`, `wav2vec2 xlsr`, and `unispeech sat`. This reduced size translates to lower computational requirements and faster inference, making it a more efficient choice for both evaluation and fine-tuning.
- **Availability and Ease of Integration:** It is readily available from model hubs and can be seamlessly integrated into existing pipelines.

The baseline evaluation involves:

- Extracting speaker embeddings from VoxCeleb1 (cleaned) audio files using `Wavlm-base-plus`.
- Computing similarity scores (using cosine similarity or a learned metric) between enrollment and test utterances.
- Evaluating performance based on:
  1. Equal Error Rate (EER).
  2. True Acceptance Rate at 1% False Acceptance Rate (TAR@1%FAR).
  3. Speaker Identification Accuracy.

4.2 Task I: Speaker Verification with Fine-Tuning

The `Wavlm-base-plus` model was chosen for its robust performance and relatively smaller size compared to other alternatives (e.g., `hubert large`, `wav2vec2 xlsr`, and `unispeech sat`). The baseline evaluation on VoxCeleb1 produced the following results:

Table 1: Task I: Speaker Verification with Fine-Tuning

Metric	Pre-trained Model	Fine-Tuned Model
EER (%)	20.04	9.08
TAR @ 1% FAR	68.48%	78.84%
Speaker Identification Accuracy	70.08%	84.99%

The evaluation process involves:

- Extracting speaker embeddings from VoxCeleb1 using `Wavlm-base-plus`.
- Computing similarity scores between enrollment and test utterances.
- Evaluating performance using EER, TAR@1%FAR, and speaker identification accuracy.

4.3 Task II: Multi-Speaker Scenario and Speaker Separation

A multi-speaker dataset was generated by overlapping utterances from two different speakers. The important mixing function is shown below:

```python
def mix_audios(audio1, audio2):
    """
    Pads two audio signals to the same length and sums them to create a mixed signal.
    """
    length = max(len(audio1), len(audio2))
    audio1 = np.pad(audio1, (0, length - len(audio1)), mode='constant')
    audio2 = np.pad(audio2, (0, length - len(audio2)), mode='constant')
    mixed  = audio1 + audio2
    return audio1, audio2, mixed
```

The first 50 identities are used for training and the remaining 50 for testing to form 100 training pairs and 50 testing pairs. The pre-trained SepFormer model is then utilized to split the mixed speech. The separated outputs are assessed based on the metrics discussed above.

4.4 Task III: Combined Pipeline for Joint Speaker Separation and Identification

A new pipeline was implemented to combine the SepFormer model with the speaker identification model to perform joint speaker separation and speech enhancement. In this pipeline:

- The SepFormer module performs speaker separation.
- For each separated source, speaker embeddings are extracted using the pre-trained `Wavlm-base-plus` model.
- A classifier (with a LoRA-adapted linear layer) predicts speaker labels.

The following code snippet illustrates the implementation of the combined pipeline:

```
class CombinedPipeline(nn.Module):
    def __init__(self, sepformer, speaker_embedder, num_classes):
        super().__init__()
        self.sepformer = sepformer
        self.speaker_embedder = speaker_embedder
        for param in self.speaker_embedder.parameters():
            param.requires_grad = False

        self.classifier = nn.Linear(256, num_classes)

    def forward(self, mixed_audio):
        sep_out = self.sepformer.separate_batch(mixed_audio)
        batch_size, n_src, _ = sep_out.shape
        logits_list = []
        enhanced_list = []

        for i in range(n_src):
            src = sep_out[:, i, :]
            embeddings = []
            for j in range(batch_size):
                audio = src[j].detach()

                if audio.shape[0] < 4096:
                    pad_len = 4096 - audio.shape[0]
                    audio = F.pad(audio, (0, pad_len), "constant", 0)

                with torch.no_grad():
                    emb = self.speaker_embedder(audio)
                embeddings.append(emb)
            embeddings = torch.cat(embeddings, dim=0)
            logits = self.classifier(embeddings)
            logits_list.append(logits)
            enhanced_list.append(src)

        logits_out = torch.stack(logits_list, dim=1)
        enhanced_out = torch.stack(enhanced_list, dim=1)
        return enhanced_out, logits_out
```

The pipeline is then fine-tuned on the multi-speaker training dataset and evaluated on the test set.

4.5 Fine-Tuning with LoRA and ArcFace Loss

Low-Rank Adaptation (LoRA): LoRA introduces learnable low-rank matrices to selected layers of the pre-trained model, reducing the number of trainable parameters. The procedure involves:

- Identifying target layers (e.g., attention or feed-forward layers).
- Freezing the original weights and learning only the low-rank updates.

ArcFace Loss: ArcFace loss introduces an angular margin penalty into softmax loss, enforcing inter-class separability and intra-class compactness, hence learning more discriminative embeddings.

Training Setup:

- **Training Data:** VoxCeleb2 training subset (first 100 identities).
- **Hyperparameters:** Learning rate, batch size, number of epochs, and LoRA-specific parameters are tuned appropriately.
- **Validation:** VoxCeleb2 testing subset (remaining 18 identities) is used to monitor model performance during training.

4.6 Evaluation Procedure

Both the pre-trained and fine-tuned models are tested on the VoxCeleb1 (cleaned) trial pairs. The metrics used for evaluation are:

- **EER (%):** The error rate at the point where false acceptance and false rejection rates are equal.
- **TAR@1%FAR:** The True Acceptance Rate when the False Acceptance Rate is fixed at 1%.
- **Speaker Identification Accuracy:** The accuracy in correctly assigning speaker identities.

5 Libraries Used

The implementation utilized the following libraries:

- **PyTorch** – For building and training neural network models.
- **NumPy** – For numerical operations and array manipulations.
- **Transformers** – For loading pre-trained models such as `Wavlm-base-plus`.
- **SpeechBrain** – For accessing the pre-trained SepFormer model.
- **mir_eval** – For evaluating source separation metrics.
- **PESQ** – For computing the Perceptual Evaluation of Speech Quality.
- **Pickle** – For serializing and loading datasets.

6 Results

6.1 Task I: Speaker Verification Performance on VoxCeleb1

Table 2: Task I: Speaker Verification with Fine-Tuning

Metric	Pre-trained Model	Fine-Tuned Model
EER (%)	20.04	9.08
TAR @ 1% FAR	68.48%	78.84%
Speaker Identification Accuracy	70.08%	84.99%

6.2 Task II: Speaker Separation Performance on Multi-Speaker Test Set

Table 3: Speaker Separation Metrics using Pre-trained SepFormer

Metric	Value
SDR	7.67 dB
SIR	12.87 dB
SAR	10.66 dB
PESQ	2.46

6.3 Task II: Speaker Identification on Separated Speech

Table 4: Identification Accuracy on Separated Speech (Task II)

Model	Rank-1 Identification Accuracy (%)
Pre-trained Model	56.82
Fine-Tuned Model	74.11

6.4 Task III: Combined Pipeline Performance on Multi-Speaker Test Set

Table 5: Separation and Enhancement Metrics for Combined Pipeline (Task III)

Metric	Value
SDR	8.12 dB
SIR	13.53 dB
SAR	10.91 dB
PESQ	2.98

6.5 Task III: Speaker Identification on Enhanced Speech

Table 6: Speaker Identification Accuracy on Enhanced Speech (Task III)

Model	Rank-1 Accuracy
Pre-trained Model	57%
Fine-Tuned Model	76%

7 Discussion and Observations

- **Task I:** Fine-tuning the `Wavlm-base-plus` model using LoRA and ArcFace loss decreased the EER from 20.04% to 9.08% and increased the identification accuracy from 70.08% to 84.99%. These results, obtained under limited training conditions (FP16, batch size = 5, 5 epoch), are considerable.
- **Task II:** The pre-trained SepFormer achieved separation metrics of SDR = 7.67 dB, SIR = 12.87 dB, SAR = 10.66 dB, and PESQ = 2.46. However, speaker identification on the separated signals yielded low Rank-1 accuracies (56.82% and 74.11%), indicating mild challenges in handling overlapping speaker scenarios.
- **Task III:** The joint pipeline attained better enhancement and separation (SDR = 8.12 dB, SIR = 13.53 dB, SAR = 10.91 dB, PESQ = 2.98) and a large increase in speaker identification of improved speech (Rank-1 accuracy of 57% for the pre-trained model and 76% for the fine-tuned model). Joint optimization has potential for addressing challenging multi-speaker conditions.

8 Conclusion

This report gives an extensive set of experiments on speaker verification and separation. The fine-tuned pre-trained `Wavlm-base-plus` model, fine-tuned using LoRA and ArcFace loss, achieved considerable improvements on VoxCeleb1. In the multi-speaker case, although the pre-trained SepFormer gave a baseline on speaker separation, separation identification was still difficult. The proposed end-to-end joint pipeline, coupling both speaker separation and identification, achieved good performance on both speech enhancement and speaker recognition.

9 References

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