Speaker Diarization Using Stereo Audio Channels: Preliminary Study on Utterance Clustering

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Abstract

Speaker diarization is one of the actively researched topics in audio signal processing and machine learning. Utterance clustering is a critical part of a speaker diarization task. In this study, we aim to improve the performance of utterance clustering by processing multichannel (stereo) audio signals. We generated processed audio signals by combining left- and right-channel audio signals in a few different ways and then extracted embedded features (also called d-vectors) from those processed audio signals. We applied the Gaussian mixture model (GMM) for supervised utterance clustering. In the training phase, we used a parameter sharing GMM to train the model for each speaker. In the testing phase, we selected the speaker with the maximum likelihood as the detected speaker. Results of experiments with real audio recordings of multi-person discussion sessions showed that our proposed method that used multichannel audio signals achieved significantly better performance than a conventional method with mono audio signals.

Keywords— Speaker Diarization, Audio Signal Processing, Gaussian Mixture Model.

1 Introduction

Speaker diarization is the problem of “who spoke when?” \cite{1}. In recent years, with the development of machine learning and deep learning, many studies in the domain of speaker diarization focus on the improvement of audio feature embeddings, such as i-vector \cite{2}, x-vector \cite{3}, and d-vector \cite{4,5}. In addition to the development of audio embeddings, more and more studies are aimed at unsupervised or supervised clustering methods to improve the performance of the speaker diarization system.
In this study, we aimed to improve clustering performance by processing multichannel (stereo) audio signals. In audio processing studies, mono audio signals are often used as they can be obtained easily by downmixing stereo audio signals. In this study, however, we constructed three different multichannel audio signals from the left- and right channels of the original stereo audio signals. We then obtained the d-vector of each audio segment using pre-trained neural networks as the audio feature representation.

We used the Gaussian mixture model (GMM) as a supervised clustering method. We compared the error rate (ER) of the clustering, and the results showed that using the processed multichannel audio signal for utterance clustering was significantly better than using the original mono audio signal.

2 Related Works

In the past few decades, many researchers have made some achievements in speaker diarization. Some studies focus more on feature embeddings, such as [2], [3], [4], and [5]. Some studies pay more attention to clustering methods, such as [6], [7], [8] and [9].

Dehak et al. [2] proposed a factor analysis called i-vector. Their factor analysis considered the variability of speakers and channels without distinction. Similar to the i-vectors, d-vectors [4][5] also have fixed size, regardless of the length of the input utterance. Wan et al. [5] trained speakers’ utterances through a deep neural network and these utterance lengths were different, resulting in fixed-length embeddings, namely d-vector. The difference between i-vector and d-vector is that i-vector is generated using GMM, and the d-vector is trained using deep neural networks. Similar to the d-vector, x-vector [3] is also trained with deep neural networks.

Shum et al. [6] used the re-segmentation algorithm of the Bayesian GMM clustering model based on i-vector to contribute to improving the speech clustering. Zajic et al. [7] proposed a model for applying Convolutional Neural Network (CNN) on i-vector to detect speaker changes. Wang et al. [8] developed the LSTM model on d-vector for the speaker diarization. Zhang et al. [9] constructed a supervised speaker diarization system on the extracted d-vector, called unbounded interleaved-state recurrent neural networks (UIS-RNN).

Compared with the above mentioned works, our study applied the processed audio signals instead of mono audio signal. Our processed audio signals are based on the multichannel (stereo) audio signals, and we aimed to keep more representative audio features.

3 Methods

3.1 Feature Processing

In this work, we used operations on the left channel audio signals and the right channel audio signals to obtain speech-only audio features. We visualized the details of feature processing as shown in Fig. 1. This example shows that after removing the non-speech part, the speaker’s speaking time is 27 seconds. We divided the 27 seconds of stereo audio into 27 stereo audio segments, each of which is one second in length. After that, we extracted mono audio files, left channel audio files, and right channel audio files from the one-second-long stereo audio files. We used the Python package librosa [10] to obtain the left and right audio signals in the time series.

We performed addition, horizontal stacking, and horizontal stacking of addition and subtraction on the left and right channel signals. The first operation is to add the left and right channel audio signals to generate a new signal vector called sum, the second operation is to horizontally stack the left and right channel audio signals to generate a new signal vector called hstack, and the last operation it is a horizontal stack that adds and subtracts left and right channel audio signals to generate a new signal vector called sumdif.
We have all speakers’ utterances $S_N = (s_1, ..., s_N)$, where $N$ represents the number of speakers in the audio dataset, $s_N$ represents the speaking segment of each speaker. For each speaker, we have $s_i = (x_1, ..., x_t)$, $t$ represents the speaker’s speaking time, $x_i$ represents $i^{th}$ speaker’s audio at $i^{th}$ second, $i \in \mathbb{Z}$ and $i \in (0, N]$. Then we extracted left and right channels audio from each segment in $s_i$, we obtained $x_i^L$ for $i^{th}$ speaker’s left channel audio segment at $i^{th}$ second, and $x_i^R$ for $i^{th}$ speaker’s right channel audio segment at $i^{th}$ second. Based on the left and right channels audio, we performed three operations, then we can have $x_{i, sum} = x_i^L + x_i^R$, $x_{i, hstack} = (x_i^L, x_i^R)$ and $x_{i, sumdif} = (x_i^L + x_i^R, x_i^L - x_i^R)$. For the $i^{th}$ speaker’s all audio segments, we have $s_i, W = (x_1^L, ..., x_t^L, \ldots, x_1^R, ..., x_t^R)$, where $W \in (sum, hstack, sumdif)$.

### 3.2 Feature Embeddings

After feature processing, we extracted the d-vector [5] as the feature representation of the audio file. We used the pre-trained model to extract the d-vector from a GitHub program called Real Time Voice Cloning [11]. The pre-trained model is trained by using three datasets, one dataset is LibriSpeech ASR corpus [12] which contains 292,000 utterances for more than 2,000 speakers in English, and others are VoxCeleb 1 & 2 [13], [14] which contain over 1 million utterances for more than 7,000 speakers in multiple languages.

We extracted d-vector based on the $s_i, W$, then we obtained $D_i, W = (d_1, W, ..., d_t, W)$. Then, we conducted GMM clustering on the extracted d-vectors.

### 3.3 Gaussian Mixture Model

We used Gaussian mixture model (GMM) as the clustering method. GMM is a well-known probability model, which assumes that all data points are generated by a mixture of a limited number of Gaussian distributions with unknown parameters, defined as:

$$f(x) = \sum_{m=1}^{M} \alpha_m \phi(x; \mu_m, \sigma_m),$$

where $\alpha_m$ represents the mixing proportions, $\mu_m$ represents mean, and $\sigma_m$ represents covariance matrix [15]. The method used to estimate the model parameters in GMM is named the Expectation-Maximization (EM) algorithm. GMM has some key advantages in acoustic modeling. For example, it is a convenient way of fitting speech features using the EM algorithm [16]. The EM algorithm is a widely used estimation algorithm, especially when finding the maximum likelihood estimation of parameters [17].

### 4 Experiments

#### 4.1 Dataset

We used a dataset [18] containing 8 video files. The number of speakers in these 8 videos ranged from 4 to 10, the number of female speakers varies from 1 to 5, the number of male speakers varies from 1 to 8, and all speakers speak English. Each speaker’s speaking time is between 9 and 30 seconds. There is no overlapping speaking segments.

We have 2 recording scenes, one is S1 scenario and another is S2 scenario. In both S1 and S2, one speaker sits in front of the computer and other speakers sit around a table. We used the camera to record their communications as videos. In the S1, all speakers are on-screen. In the S2, however, there is one speaker who sits in front of the computer is off-screen and others are on-screen.
Figure 1: Visualization of audio signal processing for each speaker. **a.** A stereo waveform of a speaker’s speaking audio. **b.** Stereo waveforms in one second. **c.** Mono waveforms of extracted left and right channels audio for each second. **d.** Processed waveform for each second.
4.2 Audio Processing

We used FFmpeg to extract stereo audio files from video files. Based on the manual annotated speakers’ speaking time, we cut audio segments from different speakers. Then, we cut each audio segment of different speakers into a length of one second. We deleted the audio files that less than a second.

4.3 GMM Experiments

We applied scikit-learn [19] for GMM training and test. We used the full covariance type in GMM and used K-means to initialize the model weights. Due to the different speaking time of speakers, we conducted various amount of training and test on different speakers. The amount of training segments varies from 7 to 21, and the amount of test segments varies from 2 to 9.

We applied GMM to train individual speaker, and we obtained the models of different speakers. Then we used the trained model to fit the test utterances. We chose the one with the maximum log-likelihood value as the prediction result.

For the individual dataset, the input of the GMM experiment is d-vector, and we conducted GMM experiments in 50 times, for each time, we conducted a 10-fold cross-validation test.

For training, we have $D_{i,W}^{train} = (d_{1,W}^{train}, ..., d_{t_1,W}^{train})$, where $t_1 = t * 70\%$ and $t_1 \in \mathbb{Z}$. We also have the label set $Y_i = (y_{i,1}, ..., y_{i,t_1})$ for $i^{th}$ speaker. We trained GMM models for each speaker, then we obtained model set $M_N = (m_1, ..., m_N)$, where $m_N$ represents the $N^{th}$ speaker’s trained model. For the test, we have test audio segment for each speaker $D_{i,W}^{test} = (d_{1,W}^{test}, ..., d_{t_2,W}^{test})$, where $t_2 = t * 30\%$ and $t_2 \in \mathbb{Z}$. For all speakers, we have $D_N^{test} = (D_{1,W}^{test}, ..., D_{N,W}^{test})$. Based on the model set $M_N$ and test set $D_N$, we found the results which have maximum likelihood value to get the prediction results $\hat{Y}$, then we compared $\hat{Y}$ with the ground truth $Y_{test}$ to get the error rate.

5 Results

5.1 Feature Processing

We used the Fig. 2 to show the performance of processed feature vectors. We applied principal component analysis (PCA) to reduce the dimensions of feature vectors from 256 to 2 to visualize the clustering. In this example, we can see the hstack group shows the best result of clustering.

5.2 GMM Experiment

In this section, we will show the GMM clustering error rate (ER) results. The detailed information of the GMM’s ER is shown in Table 1. When we checked the prediction results, we found that it showed excellent clustering results for speakers of different gender. Generally speaking, Table 1 shows that if we use the d-vector generated from the processed audio signals on the left and right channels, the GMM clustering results will be better than the d-vector generated using mono audio.

In addition, we draw the comparison result of the z-scores of GMM error rates as a ridgeline plot as shown in Fig. 3. This ridgeline plot shows the relationship between z-scores value of GMM error rates and feature vectors of different speakers. The ridgeline plots of z-scores of error rates on sum, hstack, and sumdif show that the error rates have higher probability at a lower level than ridgeline plot of z-scores of error rates on mono. In a nutshell, the error rates on the groups of processed feature vectors are better than the original feature vectors.
Besides, we conducted Mann-Whitney U test on the distributions of z-scores of GMM error rates. The p-value between mono and sum is $5.244 \times 10^{-17}$, the p-value between mono and hstack is $3.089 \times 10^{-70}$, the p-value between mono and sumdif is $2.995 \times 10^{-90}$, the p-value between sum and hstack is $2.811 \times 10^{-22}$, the p-value between sum and sumdif is $3.165 \times 10^{-34}$, and the p-value between hstack and sumdif is $9.838 \times 10^{-3}$. Accordingly, we can conclude that the distributions of z-scores of GMM error rates are significantly different.

6 Conclusions

We briefly introduced our research in the above sections, we performed three operations on the audio signals to obtain processed audio features, and then we compared the GMM clustering results of the original and processed audio features. Based on the results obtained from the supervised clustering experiment, it can be concluded that the performance of utterance clustering can be improved by using the signals processed on the left and right audio channels.
Table 1: GMM Clustering Error Rate

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Feature Vectors</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mono</td>
<td>sum</td>
<td>hstack</td>
<td>sumdif</td>
</tr>
<tr>
<td>S1 4 Speakers</td>
<td>0.1425</td>
<td>0.1091</td>
<td>0.1238</td>
<td>0.0975*</td>
</tr>
<tr>
<td>S2 4 Speakers</td>
<td>0.0779</td>
<td>0.0824</td>
<td>0.0734</td>
<td>0.0279*</td>
</tr>
<tr>
<td>S2 5 Speakers</td>
<td>0.2295</td>
<td>0.2121</td>
<td>0.2390</td>
<td>0.1990*</td>
</tr>
<tr>
<td>S1 6 Speakers</td>
<td>0.1014</td>
<td>0.1013</td>
<td>0.0860*</td>
<td>0.1262</td>
</tr>
<tr>
<td>S2 6 Speakers</td>
<td>0.0632</td>
<td>0.0649</td>
<td>0.0384*</td>
<td>0.0550</td>
</tr>
<tr>
<td>S1 7 Speakers</td>
<td>0.1911</td>
<td>0.1846</td>
<td>0.1370</td>
<td>0.1362*</td>
</tr>
<tr>
<td>S2 7 Speakers</td>
<td>0.3288</td>
<td>0.2998</td>
<td>0.33</td>
<td>0.2899*</td>
</tr>
<tr>
<td>S1 10 Speakers</td>
<td>0.2817</td>
<td>0.2486</td>
<td>0.2047*</td>
<td>0.2424</td>
</tr>
</tbody>
</table>

* indicates the lowest error rate in the group.

In the future, we will develop several clustering methods on the processed feature vectors to fully demonstrate the performance of the processed feature vector. Moreover, we used the audio dataset from our own experiments. In the future, we can apply the feature processing method on other published datasets.
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