DIACORRECT: END-TO-END ERROR CORRECTION FOR SPEAKER DIARIZATION

Jiangyu Han¹, Yuhang Cao¹, Heng Lu¹, Yanhua Long²*

¹Ximalaya Inc., Shanghai, China
²Shanghai Normal University, Shanghai, China

ABSTRACT

In recent years, speaker diarization has attracted widespread attention. To achieve better performance, some studies propose to diarize speech in multiple stages. Although these methods might bring additional benefits, most of them are quite complex. Motivated by spelling correction in automatic speech recognition (ASR), in this paper, we propose an end-to-end error correction framework, termed DiaCorrect, to refine the initial diarization results in a simple but efficient way. By exploiting the acoustic interactions between input mixture and its corresponding speaker activity, DiaCorrect could automatically adapt the initial speaker activity to minimize the diarization errors. Without bells and whistles, experiments on LibriSpeech based 2-speaker meeting-like data show that, the self-attentive end-to-end neural diarization (SA-EEND) baseline with DiaCorrect could reduce its diarization error rate (DER) by over 62.4% from 12.31% to 4.63%. Our source code is available online at https://github.com/jyhan03/diacorrect

Index Terms— DiaCorrect, speaker activity, end-to-end, error correction, speaker diarization

1. INTRODUCTION

Speaker diarization aims to address “who spoke when” by logging speaker-specific events from long mixed speech [1]. It’s necessary for many speech related applications, such as automatic meeting transcription, retrieval information from broadcast media, and medical dialogue summarization. Traditionally, speaker diarization is performed by clustering all short speech segments into different speakers. Although these clustering-based methods perform well in some challenging scenarios [2,3], they are inherently unable to handle overlapped speech and hard to optimize to minimize the diarization errors directly.

Recently, two typical neural network based frameworks are proposed to solve the above problems. The first one is end-to-end neural diarization (EEND) [5] which directly predicts the joint speech activities of all speakers at each time frame. Many recent EEND extensions or modifications [6-10] have been proposed because of its excellent performance over clustering-based diarization. Another well-known framework is target-speaker voice activity detection (TS-VAD) [11], it estimates voice activity of all speakers at the same time with the help of their speaker embeddings. TS-VAD has shown promising performance in many tasks, such as CHiME-6 [2], DIRHARD-III [3], and AliMeeting [12], etc.

To further improve speaker diarization performance, several studies propose to deal with the mixture using multi-stage diarization strategies, which can be regarded as an error correction pipeline. Among them, VBHMM x-vectors diarization (VBx) [13] is one of the state-of-the-art representatives for clustering-based methods. In VBx, a bayesian hidden markov model (BHMM) that initialized with agglomerative hierarchical clustering (AHC) is used to find speaker clusters in a sequence of x-vectors [14]. Although VBx is good at dealing with non-overlapped tasks, it still cannot handle overlapped speech and decoding long recordings with VBx is usually quite slow. Moreover, a reliable x-vector extractor is also required and needs to be well-trained before the formal VBx process. In order to exploit the advantages of VBx and handle overlapped speech at the same time, the most common diarization error correction is to apply VBx at first and then extract speaker embeddings (i-vectors [15] or x-vectors) from the initial outputs. These speaker embeddings are then used to train a TS-VAD model. Such a multi-stage diarization has achieved promising benefits in many tasks [16,18]. However, the whole process is quite cumbersome and would inherit some drawbacks from VBx, such as the slow inference and strong dependence on a pre-trained speaker embedding extractor (sometimes even needs two, one for extracting x-vectors of VBx, and the other for extracting i-vectors of TS-VAD). Considering these problems, we wonder if it’s possible to correct the initial diarization errors in a simpler but still efficient way.

Actually, the error correction techniques are very common in ASR tasks. In [19], the recognized results of CTC-based system are used as inputs to train a transformer [21] corrector with encoder-decoder architecture. In [22], an end-to-end spelling correction system that accepts acoustic features and the recognized results as inputs is proposed to improve code-switching ASR performance. In [23], a non-autoregressive error correction model based on edit alignment, termed FastCorrect, is proposed to refine the ASR output sequences. Different from ASR task, the outputs of speaker diarization are speaker activities instead of text sequence or lattices, which means that applying the error correction methods in ASR to speaker diarization tasks is challenging and still an open question.

In this paper, motivated by the spelling correction in ASR, we propose an end-to-end error correction framework called DiaCorrect for speaker diarization. It refines the initial diarization results in a hidden way, by exploiting the interactions between the mixed input acoustic features and their corresponding initial speaker activity with a parallel encoder and a very simple decoder architecture. During inference, the refined speaker activities can also be further fine-tuned by iteratively feeding them into the DiaCorrect. Different from previous methods, DiaCorrect tends to correct the initial speaker activities in an end-to-end manner. There are neither complicated training tricks nor any dependence on the pre-trained speaker embedding extractors in our approach. These characteristics make DiaCorrect more lightweight. We evaluate the proposed DiaCorrect on the 2-speaker meeting-like data that simulated using LibriSpeech [24]. Compared with SA-EEND [6,7] baseline, DiaCorrect can improve the original diarization performance more than 62.4%.

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2. METHODS

2.1. SA-EEND baseline

We take the self-attentive end-to-end neural diarization (SA-EEND) as our baseline because of its excellent performance. It is one of the state-of-the-art methods of EEND framework. As shown in Fig. 1, transformer is used to capture speaker interactions along time axis. Different from clustering-based methods, SA-EEND formulates speaker diarization as a multi-label classification task, and directly outputs the joint speech activities of all speakers at the same time for an input multi-speaker recording. During training, permutation-invariant training (PIT) is applied to solve the output label ambiguity problem. More details can be found in [6, 7].

2.2. Proposed DiaCorrect

2.2.1. Motivation

Unlike the context bias refined by spelling correction in ASR [22], the proposed DiaCorrect aims to improve the diarization results from the initial model outputs. Although there are not strong contextual alignments between model hypothesis and ground-truth as in ASR, we still believe that it is possible to learn the hidden dependence of the initial speaker activities and their ground-truth patterns. Because for neural network based speaker diarization system, the generated speaker activity usually consists of a series of probabilities, where a higher value means that speaker has a higher possibility to speak at the current time. Intuitively, if a speaker has a large probability to utter words at the current time, then he/she is expected to have a large chance to utter words at the next time. We also speculate that there should be some rules behind the outputs of diarization model to avoid some unreasonable results, such as 0 and 1 appear alternately. In addition, we believe that the additional input mixture is expected to provide richer acoustic information for refining the initial speaker activity. This inspires us to model the original acoustic representation and initial diarization outputs simultaneously to improve the speaker diarization performance in DiaCorrect.

2.2.2. Math definition

Given a T-length, F-dimensional input acoustic feature sequence \( X = \{x_t \in \mathbb{R}^F \mid t = 1, ..., T\} \) and its initial speaker activity sequence \( \hat{Z} = \{z_t \mid t = 1, ..., T\} \), DiaCorrect aims to align the initial speaker activity \( Z \) to the ground-truth label sequence \( Y = \{y_t \mid t = 1, ..., T\} \). Here, \( z_t = [z_{t,c} \in [0, 1] \mid c = 1, ..., C] \) means a joint utter probability of \( C \) speakers at time \( t \). \( y_t = [y_{t,c} \in \{0, 1\} \mid c = 1, ..., C] \) denotes the binary ground-truth speaker activity of \( z_t \).

During DiaCorrect error correction, the refined speaker activity sequence \( \hat{Z} \) is generated as follows:

\[
\hat{Z} = \arg \max_{\tilde{Z}} P(\tilde{Z} | X, Z)
\]

With the conditional independence assumption, \( P(\tilde{Z} | X, Z) \) can be factorized as:

\[
P(\tilde{Z} | X, Z) = \prod_t P(\tilde{z}_t | \tilde{z}_1, ..., \tilde{z}_{t-1}, X, Z) \\
\approx \prod_t P(\tilde{z}_t | X, Z) \approx \prod_t \prod_c P(\tilde{z}_{t,c} | X, Z)
\]

As in SA-EEND [6, 7], we also assume that the frame-wise posterior \( P(\tilde{z}_{t,c} | X, Z) \) is conditioned on all inputs and each speaker utters independently. This probability will be estimated by the DiaCorrect neural network model.

During network training, we also use PIT to alleviate the output label ambiguity, with a standard binary cross entropy (BCE), the whole DiaCorrect loss function is defined as follows:

\[
\mathcal{L} = \frac{1}{TC} \min_{\phi \in \mathcal{P}} \sum_{t=1}^{T} \text{BCE}(\hat{z}_{t}^{\phi}, y_t)
\]

where \( \mathcal{P} \) is output permutation set of \( C \) speakers, \( \phi \) is one of the permutation, \( \hat{z}_{t}^{\phi} \) means the output speaker activity label with permutation \( \phi \) at time \( t \).

2.2.3. Model design

The whole process of 2-speaker DiaCorrect is shown in Fig 2. It has two encoders, one is the “SAS encoder” to model the statistics of initial diarization results, the other is a “speech encoder” to capture the original speaker interaction acoustics. The “SAS encoder” is able to accept two types of initial diarization outputs, where they...
can be the general 0 or 1 speaker activity sequence SAS, that obtained from a Rich Transcription Time Marked (RTTM) file, or the posterior probability sequence SAS, that directly derived from the pre-trained SA-EEND model. The input of “speech encoder“ is the same Log-Mel feature as SA-EEND.

After transforming the initial speaker activity and acoustic features into a high-dimensional embedding space by two encoders, a decoder is designed to learn the alignment or dependence between these concatenated high-level feature embeddings and the ground-truth speaker label sequence. If necessary, the DiaCorrect process can be performed iteratively during speaker activity inference.

Detailed structure of “SAS encoder” is shown in Fig(2b), where we use temporal convolutional network (TCN) [26,27] to model each speaker activity along time. For speech encoder, as shown in Fig(2c), we choose 2-D convolutional network to attend both temporal and spectral dynamics in a spectrogram. Finally, a 2-layer transformer [21] based decoder shown in Fig(2d) is used to predict the refined speaker activity detection results.

3. EXPERIMENTS

3.1. Dataset

We use a 2-speaker simulated dataset from LirbiSpeech-100 [23] to verify the effectiveness of our proposed DiaCorrect. The simulation procedure is identical to the one introduced in [5]. In this paper, we set \( \beta = 2, N_{\text{spk}} = 2, N_{\text{umax}} = 20, \) and \( N_{\text{umin}} = 10.\) The ratio to add reverberation was set to 0.5. All simulated recordings are sampled at 8 kHz. Table 1 presents all detail information of our simulated dataset. The dev set is only used to tune the hyper-parameters during model training. All our results reported in this paper are evaluated on the test set.

| Dataset | #Spks | #Uts | Hours | Sec/utt | Overlap Ratio |
|---------|-------|------|-------|---------|---------------|
| train   | 251   | 10000 | 696.7 | 250.8   | 59.3%         |
| dev     | 40    | 500   | 23.4  | 168.5   | 46.5%         |
| test    | 40    | 500   | 25.3  | 183.6   | 44.6%         |

3.2. Configurations

We use the public open source software [2] to train SA-EEND. The best configuration in [7] is applied. For SAS encoder, the input/output dimensions of Linear and TCN are set to 256/512 and 1/256, respectively. For speech encoder, the strides, kernel size, and paddings of the Conv2d are set to (3, 7), (1, 5), and (1, 0). The input/output channels of two Conv2d and Linear are 1/256, 256/256, respectively. For decoder, the input/output dimension of two Linear are set to 768/256 and 256/2. Except for the number of blocks, the transformer structure used in DiaCorrect decoder is identical to the one used in SA-EEND. More details about DiaCorrect implementation can be found in our source code.

All models are trained using Equation (3) within 50 epochs and the model averaging of the last 10 models is applied. We use 11-frame median filtering to prevent the unreasonable short segments. The remaining training details of DiaCorrect are keep same with SA-EEND [7]. We use diarization error rate (DER) [23] and Jaccard error rate (JER) [2] to evaluate the performance.

3.3. Results and discussion

3.3.1. Baseline

As the diarization network output is a probability sequence of speaker activity for each speaker, a threshold is required to determine whether the current probability value denotes active or not. Therefore, the setup of the decision threshold can greatly affect the overall diarization performance.

| Threshold | FA | MISS | SC | DER | JER |
|-----------|----|------|----|-----|-----|
| 0.3       | 22.69 | 1.38 | 0.38 | 24.46 | 24.12 |
| 0.4       | 17.57 | 2.10 | 0.51 | 20.17 | 22.16 |
| 0.5       | 12.83 | 3.07 | 0.67 | 16.57 | 20.57 |
| 0.6       | 8.20  | 4.58 | 0.82 | 13.61 | 19.56 |
| 0.7       | 4.28  | 7.02 | 1.00 | 12.31 | 19.97 |
| 0.8       | 1.54  | 11.64 | 0.99 | 14.18 | 22.92 |

To obtain a strong baseline result, we first compare the performance of different decision thresholds on SA-EEND baseline. Results are shown in Table 2. As expected, we can see that a higher threshold tends to produce lower false alarm (FA) and higher missed (MISS) detection errors of speaker. Compared with FA and MISS, the speaker confusion (SC) error only accounts for a small part of diarization errors in our task. We take the best result (threshold=0.7) in Table 2 as our baseline. In the following experiments, we only present the results when decision threshold is set to 0.7, which achieves the best performance in almost all our experiments.

3.3.2. DiaCorrect with SAS

Table 3 presents the results of DiaCorrect with input speaker activity that directly obtained from a RTTM file of baseline output. The 2nd line results are from DiaCorrect framework that only includes a SAS encoder and a decoder. In this situation, we only feed the initial speaker activity of each speaker that consists of 0/1 sequence to the network. We find that the SAS, alone has little effect on diarization error correction. It’s reasonable because there is almost no information available between elements of input 0/1 sequence. Although provided with the ground-truth supervision, in this case, we speculate that the network tends to behave like an all-pass filter to keep the network output the same as its input.

| System | Type | #Params | FA | MISS | SC | DER | JER |
|--------|------|--------|----|------|----|-----|-----|
| Baseline | - | 5.35 M | 4.28 | 7.02 | 1.00 | 12.31 | 19.97 |
| SAS, alone | - | 3.03 M | 4.13 | 6.60 | 1.06 | 11.80 | 20.11 |
| DiaCorrect | Linear | 3.18 M | 4.73 | 5.14 | **0.92** | 10.79 | 17.86 |
| Conv2d | 5.33 M | **2.86** | **3.79** | 0.93 | **7.58** | **14.45** |

In Table 3 we also investigate the effects of two types of speech encoder in DiaCorrect, where the first one is a single linear layer that used in SA-EEND [6] and the second one is our proposed 2-D convolution network as shown in Fig(2c). Results are shown in the 3rd and 4th lines. We can see that the additional acoustic features really help to correct diarization errors and the proposed 2-D convolution network can encode speech characteristic more effectively. Compared with SA-EEND baseline, the proposed DiaCorrect with SAS, (4th line) greatly reduces the initial diarization errors, especially for the false alarm and the miss detection.

1 https://github.com/Xflick/EEND_PyTorch
2 https://github.com/nryant/dscore
Furthermore, as shown in the purple line of Fig. 2, we also extract the new SAS from the refined RTTM file of DiaCorrect output to iterative adapt the speaker activity. Results are shown in Table 4. We can see that the system performance can be further improved within several iterations and the 2nd iteration achieves the best.

3.3.3. DiaCorrect with SAS$_p$

Table 5 shows the DiaCorrect performance when SAS$_p$ is available. Different from SAS$_r$, SAS$_p$ is obtained directly from the model output without any post-processing like threshold decision or median filtering. Each value in SAS$_p$ describes the speaker activity from a possibility perspective. Theoretically, SAS$_p$ is expected to provide more valuable information than SAS$_r$.

Table 5. Performance of DiaCorrect with SAS$_p$.

| System | #Iter | FA  | MISS | SC | DER | JER |
|--------|-------|-----|------|----|-----|-----|
| Baseline | -     | 4.28 | 7.02 | 1.00 | 12.31 | 19.97 |
| DiaCorrect | 1     | 2.86 | 3.79 | **0.93** | 7.58 | 14.45 |
|           | 2     | 2.21 | 3.97 | 1.01 | 7.19 | 14.43 |
|           | 3     | 1.97 | 3.84 | 1.05 | 6.86 | 14.07 |

3.4. Visualization

To better understand the diarization error correction idea in this paper, we randomly select a 2-speaker mixture from our test simulation set, then process it with different diarization systems and visualize the speaker activity from their corresponding output RTTM files. Results are shown in Fig. 3 where the visualizations are obtained from ground-truth, SA-EEND baseline, correction with SAS$_p$ alone, and the best DiaCorrect that with SAS$_p$ in the 2nd iteration, respectively. As shown in Fig 3(c), the FA/MISS/SC performance of the selected speech with the baseline, corrected with SAS$_p$ alone, and our DiaCorrect are 0.70/18.76/10.40%, 0.53/9.12/0.19%, and 1.05/1.22/0.00%, respectively. We use orange and dark blue colors to represent two different speakers.

Compared with the ground-truth, as shown in Fig 3(c), it’s clear that there are many unexpected silent areas in baseline results, which leads to a high MISS error of 18.76%. Although this phenomenon can be greatly alleviated by just correction with SAS$_p$, we can still find out several remained silent areas in Fig 3(d). But when refined with the proposed DiaCorrect, Fig 3(e) indicates that the most unreasonable silences are corrected with their corresponding speaker activity, which significantly reduces the MISS to 1.22%. Furthermore, our DiaCorrect also reduces the SC error from 0.40% to 0.00%. Although DiaCorrect introduces slightly FA error during correction, the 1.05% error rate is still good enough for most cases.

4. CONCLUSION

In this study, we propose DiaCorrect to refine speaker diarization errors in an end-to-end way. The initial speaker activity can be refined automatically by modeling it with the mixture acoustic features together. Different from previous work, DiaCorrect does not require sophisticated training tricks and well-trained speaker embedding extractors. We investigate the influence of two kinds of speaker activities, SAS, and SAS$_p$, in the diarization error correction. Experiments on the LibriSpeech based 2-speaker simulation set demonstrate that the SAS$_p$ is more discriminative and our proposed DiaCorrect can significantly improve the initial diarization performance. Our future work will focus on generalizing DiaCorrect to different speaker diarization tasks.
5. REFERENCES

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