Online Speaker Diarization with Relation Network

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Abstract

In this paper, we propose an online speaker diarization system based on Relation Network, named RenoSD. Unlike conventional diarization systems which consist of several independently-optimized modules, RenoSD implements voice-activity-detection (VAD), embedding extraction, and speaker identity association using a single deep neural network. The most striking feature of RenoSD is that it adopts a meta-learning strategy for speaker identity association. In particular, the relation network learns to learn a deep distance metric in a data-driven way and it can determine through a simple forward pass whether two given segments belong to the same speaker. As such, RenoSD can be performed in an online manner with low latency. Experimental results on AMI and CALLHOME datasets show that the proposed RenoSD system achieves consistent improvements over the state-of-the-art x-vector baseline. Compared with an existing online diarization system named UIS-RNN, RenoSD achieves a better performance using much fewer training data and at a lower time complexity.

Index Terms: speaker diarization, relation network, online, end-to-end

1. Introduction

Speaker diarization is the process of partitioning an audio stream with multiple speakers into homogeneous segments associated with each speaker. It is often referred to as who spoken when problem [1][2][3]. Speaker diarization is an important building block for a wide range of applications such as information retrieval from broadcast news, determining number of participants or monitoring the most/least active participants in recorded meetings and especially an effective pre-processing step for automatic speech recognition (ASR).

A typical diarization system mainly consists of three steps [4][5]. (1) Segmentation: this step removes the non-speech parts of the input audio with voice activity detection (VAD), and divides the remaining speech parts into short segments. (2) Embedding extraction: speaker embeddings such as i-vectors [6][7], d-vectors [8][9], or deep speaker embeddings [10][11] are extracted for each short segment. (3) Clustering: this step groups the short segments into different clusters according to the extracted embeddings. Each cluster corresponds to one speaker identity.

Nowadays, with ASR being widely applied in many real-world scenarios such as live captioning, it is necessary to build an online diarization system to boost the ASR performance in real-time application. However, most clustering-based diarization systems are designed in an offline manner since a well-performed clustering algorithm depends on fine-tuned hyperparameters (e.g., thresholds to stop clustering) or prior knowledge (e.g., number of speakers [8]). Though online clustering algorithms [13][14] can be adopted, their performance is typically limited without additional contextual information. The intrinsic limitation of clustering-based systems is that they are not trained for learning the absolute measurement to distinguish speakers but just struggle to discriminate different speaker pairs from same speaker pairs. This leads to the need for the information of all speakers, which is usually unavailable for an online system.

In this paper, we propose an online speaker diarization system based on Relation Network, named RenoSD, which can directly output diarization results in real time given the audio input. RenoSD combines the VAD, embedding extraction and speaker identity association into one stage, where each module can be jointly optimized and benefits from each other. Instead of using a clustering module where speaker identity is associated by relatively distance measurement based on fixed metrics (e.g., Euclidean, cosine), RenoSD applies a learnable deep network to directly output the probability of whether the two inputs belong to the same speaker. As shown in Figure 1, input audio is firstly divided into several non-overlap short segments, each of which is then fed into an embedding module. If the new coming segment is classified as speech by the integrated VAD module, it will be compared with the earliest appeared segment of each registered speaker (denoted by speaker queues). The embedding pair will be fed into a relation module to produce a relation score (0–1), indicating whether the two segments in this pair belong to the same speaker. To determine the speaker identity of the current segment, only one sample (i.e., the earliest appeared) of each existing speaker is required. Time complexity is thus dependent on the number of speakers in the audio input. A simple forward pass through the relation module can give a relation score of the two input segments, indicating whether they belong to the same speaker. Therefore, our RenoSD is an online system with low time complexity.

Such powerful capability of RenoSD can be attributed to the Relation Network (RN) [15], which uses a meta-learning strategy to learn a deep distance metric in a data-driven way. Prior works fixed metrics assume that embeddings are solely

![Figure 1: RenoSD system overview.](image-url)
compared element-wise and linearly separable. These are thus critically dependent on the efficacy of the learned embedding network, such as the state-of-the-art x-vector \[11\]. In contrast, by learning a non-linear similarity metric jointly with the embedding, RN can better identify matching/mismatching pairs.

In the state-of-the-art online diarization system UIS-RNN \[15\], speaker embeddings are modeled by a sequence generation process through a recurrent neural network (RNN) and different speakers are distinguished using different RNN states. The computational complexity depends on sequence length. When compared with UIS-RNN, RenoSD is simpler and faster with a time complexity proportional to the number of speakers.

The advantages of RenoSD are summarized as follows:

- An online system based on Relation Network, which can directly measure whether the given two segments are from the same speaker without further comparison and additional prior knowledge.
- VAD, embedding extraction and speaker identity association are combined into one stage, thus RenoSD can be trained end-to-end from scratch.

Experimental results on AMI and CALLHOME datasets reveal that RenoSD achieves consistent improvements over the state-of-the-art x-vector baseline. It also outperforms the online UIS-RNN even with less training data. The better performance in DER score comes from the integrating of VAD, embedding extraction and speaker identity association.

## 2. The RenoSD System

### 2.1. RenoSD overview

The online processing of the RenoSD system, as shown in Figure 1, is composed of three steps. (1) Segmentation: input audio is divided into several non-overlapping short segments. (2) Embedding extraction: each short segment is fed into an embedding module. Non-speech segments are filtered out by an additional VAD module. (3) Speaker identity association: the current segment is coupled with the earliest appeared segment of each previously appeared speakers. Each embedding pair is then fed into a relation module to produce a relation score, indicating whether the two embeddings belong to the same speaker.

Specifically, we will create a queue for each existing speaker. The current segments embedding will form a pair with the front element of each existing speaker queue, which is then fed into the relation module. For example, the current embedding is \( s_i \), and there have been two queues \( \text{speaker} 1 \) and \( \text{speaker} 2 \) for two existing speakers. Pair \( \{e_5, e_1\} \) will be first fed into the relation module. If the relation score \( r_{51} \) is close enough to 1, \( e_5 \) will be judged as from speaker 1 and pushed into queue \( \text{speaker} 1 \). If not, \( e_5 \) will be further compared with \( e_3 \). If pair \( \{e_5, e_3\} \) is still judged as from different speakers, a new queue \( \text{speaker} 3 \) will be created and \( e_5 \) will be the first element. To avoid error accumulation, the earliest embedding is selected instead of an average or the last one.

### 2.2. Relation Network for RenoSD

The Relation Network (RN) for RenoSD consists of three modules: an embedding module, a relation module and a VAD module, as illustrated in Figure 2. The former two modules are designed for embedding extraction and speaker identity association, respectively. VAD module is integrated through a speech/non-speech classifier during embedding extraction. Thus, RN for RenoSD combines three individual modules into one single network, which can be trained end-to-end from scratch.

#### 2.2.1. Embedding extraction and speaker id association

As shown in Figure 2 in training phase, one batch contains five matching (positive) pairs and mismatching (negative) pairs. Each pair \( \{s_i, s_j\} \) is fed through the embedding module \( f_s \), which produces feature maps \( f_s(s_i) \) and \( f_s(s_j) \). The feature maps are combined with operator \( C(f_s(s_i), f_s(s_j)) \). In this work, we assume \( C(\cdot, \cdot) \) to be a concatenation of feature maps along frequency dimension.

The combined feature maps are then fed into the relation module \( g_r \), which eventually produces a scalar in range of 0 to 1 representing the similarity between \( s_i \) and \( s_j \), which is called relation score \( r_{i,j} \), which is donated by,

\[
r_{i,j} = g_r(C(f_s(s_i), f_s(s_j)))
\]

In RenoSD, embedding module is coupled with relation module. By learning a nonlinear similarity metric jointly with the embedding, RN can better identify matching or mismatching pairs.

#### 2.2.2. Integrated VAD

The VAD module is integrated into RenoSD through a speech/non-speech classifier, which is jointly optimized with above embedding module and relation module. In training phase, we actually use a speaker classification task to form a multi-task structure, which on one hand helps to learn a better embedding. On the other hand, an additional non-speech unit in the classifier can output the non-speech probability. In inference phase, we only require the non-speech unit to indicate whether the input segment belongs to speech/non-speech.

More specifically, the probability of sample \( s_i \) being classified as the \( k \)-th speaker \( P(s_{pk} | s_i) \) should be conditional on the probability of \( s_i \) belonging to a speech segment \( P(\text{speech} | s_i) \), which can be represented as

\[
P(s_{pk} | s_i) = P(s_{pk} | \text{speech})P(\text{speech} | s_i) = P(s_{pk} | \text{speech})(1 - P(\text{non-speech} | s_i))
\]

where \( P(\text{non-speech} | s_i) \) is obtained from the sigmoid unit representing non-speech class in the output layer and \( P(s_{pk} | \text{speech}) \) is indicated by the remaining softmax units representing speaker class.
2.2.3. Objective function

The training objective is composed of two parts and is formulated as

$$L = \alpha \cdot L_{\text{spk-clts}} + L_{\text{relation}}$$ (3)

In equation (3), $L_{\text{spk-clts}}$ is the cross-entropy loss to classify the input segments speaker identity, including an additional non-speech class to integrate VAD, which is defined as

$$L_{\text{spk-clts}}(p_i, p_i^*) = -p_i^* \cdot \log(p_i)$$ (4)

where $p_i$ is the predicted probability distribution over all classes in the training set and $p_i^*$ is the ground truth one-hot label. $L_{\text{spk-clts}}$ is scaled with a weight factor $\alpha$. It is noteworthy that in inference phase, this task is not used for speaker recognition but VAD.

$L_{\text{relation}}$ is used to train the relation learning module. We follow the mean square error (MSE) loss (Eq. (5)) applied in the original paper which first proposed the Relation Network [15]. MSE is minimized to regress the relation score $r_{i,j}$ to the ground truth: match pairs have similarity 1 and the mismatched pair have similarity 0.

$$L_{\text{relation}} = \sum_i \sum_j (r_{i,j} - 1(y_i == y_j))^2$$ (5)

where $y_i$ and $y_j$ are speaker identity labels for $s_i$ and $s_j$, respectively. Though our problem may seem to be a classification problem with a label space $\{0, 1\}$, we are conceptually predicting relation scores, which can be considered as a regression problem despite that for ground-truth we can only automatically generate $\{0, 1\}$ targets. Therefore, MSE is utilized as the optimized objective.

In general, parameters $\varphi$ and $\theta$ representing embedding module and relation module are coupled by $L_{\text{relation}}$, which is jointly optimized with $\lambda$ for VAD module.

3. Experiments

3.1. Datasets and evaluation metric

3.1.1. Datasets

RenoSD is first pre-trained on VoxCeleb1&2 [17] dataset and then fine-tuned on AMI [18] meeting corpus, which is eventually evaluated on AMI and CALLHOME datasets.

VoxCeleb is a large-scale audio-visual dataset extracted from videos uploaded to YouTube, which contains over 2,000 hours for more than 7,000 celebrities with different nationalities. The official train split is used. AMI corpus contains group meetings recorded at four different sites. Details of corpus partitions is shown in Table 1. 90% of the full training set is split for fine-tuning and 10% is split for cross validation.

Table 1: Details of the AMI data set based on official speech recognition partition with the TNO meetings excluded from Dev and Eval.

|          | Meetings | Speakers |
|----------|----------|----------|
| Train    | 135      | 149      |
| Dev      | 14       | 17       |
| Eval     | 12       | 12       |

For evaluation, instead of using the full dev and eval sets in AMI, we use the meetings recorded at IDIAP, Edinburgh and Brno which are the sets frequently used for evaluation of speaker diarization. The multi-channel multiple distance microphone (MDM) data is first merged into a single stream using Beamformer [13]. The CALLHOME dataset contains 500 audios in 6 languages. The number of speakers in each audio ranges from 2 to 7.

3.1.2. Evaluation metric

Diarization Error Rate (DER) is used to evaluate the performance of RenoSD. The DER includes Miss Error (speech predicted as non-speech), False Alarm Error (non-speech predicted as speech) and Confusion Error (one speaker predicted as another). we use a typical collar tolerance of 250 ms around both the start and end of each segment.

3.2. Experimental settings and implementation details

RenoSD can be performed in both frequency and time domains, where short-term magnitude spectrograms and raw audio are used as input, respectively. For frequency domain, we adopt ResNet50 [19] as the network architecture. Input spectrograms are generated in a sliding window fashion using a hamming window of width 25ms and step 10ms, which are then normalized by subtracting the mean and dividing by the standard deviation of all frequency components in a single time step. Referring [20] for the details of modified ResNet50 and CNN trunks from conv1 to conv3 are assigned for embedding module and the remaining are assigned for relation module. Features produced by CNN trunks are finally aggregated in time to produce a single fixed length representation for each audio input.

For time domain, raw audio is first transformed by a 1-D convolutional encoder. Temporal convolutional network (TCN) composed of stacked 1-D dilated convolutional blocks is then adopted for both embedding module and relation module, which is similar to Conv-TasNet [21], an effective network architecture for time-domain speech separation. Time average pooling is also applied.

The duration of input audio is 3s for pre-training phase and 400ms for fine-tuning and inference phase. Since we use the global average pooling along the temporal axis, the network becomes invariant to temporal position, avoiding the input length mismatch between training and inference.

3.3. Experimental results

Table 2: DER(%) on AMI corpus with a separate TDNN VAD model. (MI=5.0, FA=7.1)

| Domain | Systems | CF  | DER   |
|--------|---------|-----|-------|
| Frequency | Metric | 9.16 | 21.30 |
|         | RenoSD  | 8.43 | 20.57 |
| Time    | Metric  | 8.34 | 20.48 |
|         | RenoSD  | 7.61 | 19.75 |

One contribution of RenoSD is that it combines originally individual VAD and speaker identity association into one single network, which are implemented through VAD module and relation module in RenoSD. Therefore, both of these two modules should be evaluated. We first use a separate pre-processing VAD to unilaterally evaluate the effectiveness of relation mod-
Table 3: DERs(%) on AMI corpus for different systems using different VAD models with/without clustering modules.

| Systems          | VAD    | Clustering | CF | MI | FA | DER  |
|------------------|--------|------------|----|----|----|------|
| i-vector [24]    | separate | ✓         | -  | -  | -  | 24.08|
| x-vector [24]    | oracle  | ✓         | 7.82| -  | -  | 15.77|
| RenoSD           | separate     |           | 7.61| 7.1| 5.0| 19.75|
| RenoSD           | integrated   |           | 6.88| 5.5| 3.1| 15.77|

3.3.1. Effectiveness of relation module

Table 2 shows the DER results of the proposed RenoSD on AMI corpus, where the integrated VAD is replaced by a separate TDNN VAD model. RenoSD is compared with a conventional baseline which uses a triplet loss based on fixed distance metric (i.e., cosine similarity) to optimized the feature embedding. Miss Error (MI) and False Alarm Error (FA) are 7.1% and 5.0%, respectively, which indicate the performance of the TDNN-based VAD model. RenoSD reduces the DER from 21.30% to 20.80% for frequency domain and from 20.48% to 20.10% for time domain. Since we use a separate pre-processing VAD model, the benefit in speaker Confusion Error (CF) can be considered from the relation module in RenoSD.

3.3.2. Effectiveness of integrated VAD module

The integrated VAD module is further evaluated here. We show the more promising DER results of RenoSD in time domain, compared with other published results on AMI corpus, as illustrated in Table 2. Firstly, by replacing the separate TDNN-based VAD by the integrated VAD, RenoSD significantly reduces MI and FA from 7.1% to 5.5% and from 5.0% to 3.1%, respectively. This reflects the effective of the integrated VAD module. In addition, CF is further reduced from original 7.61% to current 6.88%, which means the embedding module and relation module are improved when VAD module is added to jointly optimization. Therefore, each module can actually benefit from each other when they are combined together, which indicates the rationality of the architecture design for RenoSD.

Compared with the i-vector system using a threshold-based clustering algorithm, RenoSD achieves significantly better performance, where DER decreases from 24.08% to 15.77%. RenoSD also outperforms the state-of-the-art x-vector system in CF scores (6.88% vs. 7.82%) which even uses oracle VAD and get the information about the number of speakers.

3.3.3. Experiments on CALLHOME

RenoSD is first compared with the well-known x-vector baseline which is a standard conventional system using a separate TDNN VAD module and Agglomerative Hierarchical Clustering (AHC) to group segments into different clusters. As shown in Table 3, RenoSD significantly outperforms the x-vector baseline in terms of the total DER results when x-vector uses a threshold-based clustering. Even available of the oracle information about the number of speakers in x-vector system, RenoSD can still show a comparable and slightly better performance. RPNSD is a recently proposed diarization system based on proposal network, which also combines VAD and embedding extraction into one stage. We compare RenoSD with RPNSD in DER not scoring overlap speech. RenoSD achieves better DER results without any prior information while RPNSD uses the oracle number of speakers to perform clustering.

UIS-RNN is an existing online diarization system, where UIS-RNN (V1) is pre-trained with 36 M utterances from 18K speakers and UIS-RNN (V2) is further pre-trained on more data including LibriSpeech and VoxCeleb1&2. UIS-RNN (V3) adopts a strategy named variable-length window to handle the problem of mismatching window length between training and inference which is avoided in RenoSD by global average pooling in temporal axis. RenoSD is only pre-trained on VoxCeleb1&2 and fine-tuned on CALLHOME, which even performs better than the best version UIS-RNN (V3). The computational complexity of UIS-RNN is dependent on input length or number of segments while the complexity of RenoSD is bounded by the number of speakers. Therefore, RenoSD may has a faster processing speed when the number of speakers is less than the number of segments.

4. Conclusion

In this paper, we propose an online speaker diarization system based on Relation Network, named RenoSD, which can directly generate diarization results in real time given the audio input. RenoSD combines originally individual VAD, embedding extraction and speaker identity association into one stage, where each module can be jointly optimized and the system can be trained end-to-end from scratch. Experimental results on AMI and CALLHOME datasets reveal that RenoSD achieves consistent improvements over the state-of-the-art x-vector baseline. It also outperforms the online UIS-RNN system with less training data and less computational complexity. The better performance can be considered from the integrating of VAD, embedding extraction and speaker identity association, thus each module can benefit from each other during joint training. Faster processing speed is attributed to a single comparison between two segments through relation module.

5. References

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