DNN Speaker Tracking with Embeddings

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Abstract

In multi-speaker applications is common to have pre-computed models from enrolled speakers. Using these models to identify the instances in which these speakers intervene in a recording is the task of speaker tracking. In this paper, we propose a novel embedding-based speaker tracking method. Specifically, our design is based on a convolutional neural network that mimics a typical speaker verification PLDA (probabilistic linear discriminant analysis) classifier and finds the regions uttered by the target speakers in an online fashion. The system was studied from two different perspectives: diarization and tracking; results on both show a significant improvement over the PLDA baseline under the same experimental conditions. Two standard public datasets, CALLHOME and DIHARD II single channel, were modified to create two-speaker subsets with overlapping and non-overlapping regions. We evaluate the robustness of our supervised approach with models generated from different segment lengths. A relative improvement of 17% in DER for DIHARD II single channel shows promising performance. Furthermore, to make the baseline system similar to a speaker tracking, non-target speakers were added to the recordings. Even in these adverse conditions, our approach is robust enough to outperform the PLDA baseline.

Index Terms: speaker diarization, speaker identification, speaker verification, speaker tracking, i-vector, x-vector, deep learning

1. Introduction

Speaker tracking is the process of identifying all regions uttered by a target speaker in an audio [1]. Similarly to speaker diarization, which answers the question "who spoke when?" [179], speaker tracking searches for those regions, but assigns speaker identities. This process is an important pre-processing step for many multi-speaker applications such as virtual assistants and broadcast news transcription and indexing [3].

As shown in [3], diarization and tracking are two methods closely related. Although tracking would benefit from the diarization, in this research, we explored the possibility to include a neural network as a robust classifier that can operate similarly to the PLDA. The goal is that it can naturally provide results for diarization and tracking. Since there are just a few studies on speaker tracking [1, 2, 4], we use diarization as the main background and inspiration of this work.

Most of the standard speaker diarization systems focus on offline clustering as it uses all the contextual information to label the speech regions. Examples of such algorithms include agglomerative hierarchical clustering (AHC) [5, 6], k-means [7, 8], spectral clustering [9, 10], etc. These clustering methods cannot be used in real-time applications since they require the complete speech data upfront. If the application is latency-sensitive it requires to have speaker labels generated as soon as speech segments are available for the system. [11] presents an embedding based speaker diarization system. d-vectors were used [12] along with an LSTM-based speaker verification in combination with spectral clustering to successfully perform offline diarization; however, the diarization error rate almost doubles in its online modality. Another online diarization approach is introduced in [13]. They propose a DNN (deep neural network) embedding suitable for online processing referred as speaker-corrupted embedding. The diarization algorithm uses cosine similarity to compare the speaker models and the embedding in order to make the labeling decisions.

In this paper, we propose an online speaker tracking pipeline by replacing the unsupervised offline clustering module from the standard diarization system with a online tracking method that uses a DNN as an embedding robust classifier. As shown in Figure [1] our speaker tracking system shares many of its components with the standard diarization pipeline [14, 15, 16], with the main difference being the clustering algorithm.

The experimental results on CALLHOME and DIHARD II single channel reveal that our method achieves significant improvements over the PLDA baseline.

2. Methodology

In this section, we introduce our speaker tracking framework. Figure [1] illustrates the overall steps of our tracking pipeline.

- Speech segmentation and embedding extraction.
- Speaker model generation.
- Speaker segment identification.
- Post-processing.

1 Our code is available at https://github.com/CarlosRCS9/kaldi/tree/paper-dnn-tracking
2.1. Speech segmentation and embedding extraction

The first module in our pipeline is inspired by the standard di-

arization system, it uses a Voice Activity Detector (VAD) to
determine the speech regions in the input audio signal, exclud-
ing the non-speech regions from subsequent processing. A slid-
ing window, further divides these regions into a set of smaller,
overlapping speech segments, establishing the temporal resolu-
tion of the speaker tracking results. The output of this module
is a set of voiced-speech segments. We decided to use an or-
acle VAD as segmentation mechanism to focus our efforts on
checking whether our proposed architecture can track speakers
accurately.

2.1.1. Embedding extraction

The next step in the pipeline is to extract an embedding from
each segment. Our system was tested following the i-vector-
and x-vector-based approaches [17, 18]. The i-vector, intro-
duced by Dehak et al. [19], is a speaker representation that
provides a way to reduce large-dimensional input speech data
to a small-dimensional feature vector that retains most of the
relevant channel and speaker information. The x-vector, intro-
duced by Snyder et al. [20, 18] is an embedding extracted from
a deep neural network trained to discriminate between speak-
ers, mapping variable-length speech segments to a fixed-length
feature vector. Nowadays, the x-vector approach provides state-
of-the-art performance in many speaker recognition fields, such
as, speaker verification and speaker diarization [21, 22, 23, 24].

2.2. Speaker model generation

After the segment embeddings are extracted, a speaker model
is generated for each tracked speaker. Such task is performed
by averaging the embeddings within a time window at the be-
ginning of each target speaker enrollment in the input audio.
We define model time as the window width used to generate the
speaker’s models. With this approach, the system operates in an
online fashion in which with a few labeled samples of the target
speakers it can find their appearances along the complete audio.

2.3. Speaker segment identification

The resulting segment embeddings and the speaker models are
then passed through a speaker identification/verification stage.
This task is performed by a speaker tracking DNN, the key
component of our pipeline. According to the run-time latency,
this module follows an online tracking strategy. It produces a
speaker label immediately after a segment is available without
the knowledge of future segments, making it easier for the sys-
tem to deal with large amounts of data.

2.3.1. Features

Figure 2 illustrates the structure of the network’s input and out-
put layers during the segmentation labeling process. For a given ut-
terance the input and output sequences of the network \((X', Y')\)
are defined as follows:

- The speech segmentation and embedding extraction module
  provides a sequence of embeddings \(X = (x_1, x_2, \ldots, x_p)\),
  where each \(x_i \in \mathbb{R}^b\) has a 1:1 cor-
  respondence to the \(T\) segments obtained from the input
  utterance, and \(b\) is the dimension of every embedding.
- The speaker model generation module provides the se-
  quence \(M = (m_1, m_2, \ldots, m_S)\) where \(m_s \in \mathbb{R}^b\), such

that each entry of the sequence is a model of one of the
\(S\) tracked speakers.

- The input sequence of our network is defined as the con-
catenation of \(M\) to each element of \(X\). \(X' = \{x_i, M|x_i \in X\}\).
- The sequence \(Y = (y_1, y_2, \ldots, y_T)\) is given by the
  speaker labels of the \(T\) segments.
- The output sequence is given by \(Y' = \{\Phi(y_i)|y_i \in Y\}\)
  where \(\Phi(y_i) = \{P(m_s|x_i, y_i)|m_s \in M\}\). At training
  time \(Y\) is given by the ground-truth labels. At inference,
  \(Y\) is computed by the estimated labels.

2.3.2. Architecture

Table 1 summarizes the final DNN architecture used in this
work. The first three convolutional layers of the network pro-
vide a comparison stream for each of the \(S\) speakers models,
where the similarity measure between the segment embedding
and a single speaker model is computed with the contextual in-
formation process. The fully-connected feed-forward layers use these streams to score the similarity of the
target speaker model and the incoming segment.

2.3.3. Training

During training, all possible permutations of the elements of \(M\)
are computed and appended to every input \(x_i\) with two main
goals: reduce overfitting by forcing all output neurons to score
the same speaker models, and augment the number of training
samples. This procedure ensures the DNN scoring to be inde-
pendent of the speaker model sequence order. Figure 3 shows
how the training data is furthermore augmented with the addi-
tion of zero padding as non-speaker model feature. This pro-
ducce simulates a verification task since the network has to

\[ \text{Table 1: DNN speaker tracking architecture.} \]

| Layer type | # filters | Kernel size | Input × output |
|------------|-----------|-------------|----------------|
| Conv1dReLU | 3         | \((b+1) \times (b-2)S^3\) | \((b-2)S^3 \times (b-4)S^2\) |
| Conv1dReLU | 3         | \((b-4)S^2 \times (b-6)S\) | \((b-6)S \times 2S\) |
| DenseReLU  | 3         | 32S \times 16S | 16S \times S |

\[ \text{We also tested recurrent neural network architectures (bidirectional LSTM), but it was discarded as it seemed to ignore the speaker model } \]

\[ \text{s} \text{equence time, and remembered the input sequence established at training phase.} \]
decide whether the current segment embedding belongs to one of the available models or not.

At inference time, the input layer of the network receives the incoming segment embedding and an array of target speakers models, the length of the array is the same as output neurons, so each score is related to an index in the speakers models array. In an identification setup we label the segment with the highest score index. If the task requires verification, a certainty threshold is used to label the segments.

Figure 3: Input layer with a non-speaker embedding during the network training.

### 2.4. PLDA

The baseline system uses probabilistic linear discriminant analysis (PLDA) scoring as the similarity measure\(^3\) since it has proven to achieve state-of-the-art performance in many speaker recognition tasks. It provides a powerful distortion-resistant mechanism to distinguish between different speakers, and robust to same speaker variability.\(^{[25][26][24][27]}\)

### 2.5. Post-processing

Due to the online nature of our pipeline, the post-processing step is applied as soon as a segment label is emitted, this step refines the tracking results by merging the same-speaker contiguous segments. And also by adjusting the labels within a window of three contiguous segments \(W_t = (x_{t-2}, x_{t-1}, x_t)\), it modifies the in-between segment label if the surrounding labels are equal to each other and differ from the in-between label, producing three contiguous segments with the same label.

### 3. Experiments

This section describes our experimental setup and results. We decided on a 1 s width and 0.5 s step sliding window at the speech segmentation step, discarding segments shorter than 0.5 s to ensure sufficient speaker information. Both i- and x-vectors were extracted using the Kaldi’s CALLHOME diarization recipe\(^4\). For CALLHOME x-vector experiments, a publicly available\(^5\) model and PLDA backend were used.

#### 3.1. Evaluation metrics

The system performance was evaluated in terms of Equal Error Rate (EER) and minimum Detection Cost Function (minDCF), as the key component of our tracking framework follows a speaker verification approach. In addition, we report Diarization Error Rate (DER)\(^6\) since our framework shares characteristics with the standard diarization system.

#### 3.2. Datasets

We tested our system on two standard public datasets: (1) 2000 NIST Speaker Recognition Evaluation (LDC2001S97), Disk-8, usually referred to as CALLHOME, it contains 500 utterances distributed across six languages: Arabic, English, German, Japanese, Mandarin, and Spanish. Each utterance contains up to 7 speakers; (2) DIHARD II single channel development and evaluation subsets (LDC2019E31, LDC2019E32), focused on "hard" speaker diarization, contains 5-10 minute English utterances selected from 11 conversational domains, each including approximately 2 hours of audio. Since our approach is supervised, we perform a 2-fold cross-validation on each dataset using standard partitions: callhome1 and callhome2 from Kaldi’s CALLHOME diarization recipe\(^6\), and DIHARD II single channel’s development and evaluation subsets. Then, the partitions results are combined to report the averaged DER, ERR and minDCF of each dataset.

#### 3.3. Overlap preparation

A set of our experiments is focused on speaker overlap, so it was necessary to augment the datasets, as they have a low percentage of speaker overlap (CALLHOME \(\sim 16\%\), DIHARD II single channel \(\sim 9\%\)). To perform this task the non-overlapping audio segments of each speaker are extracted using the ground-truth labels, then merged into a set of single-speaker utterances for each recording. After that, the single-speaker utterances are pairwise overlapped to create a new set of two-speaker-overlapping utterances. Finally, the new overlapping utterances are cut into segments and inserted into their original recordings at random locations. The resulting dataset contains an additional \(\sim 18\%\) of speaker overlap in CALLHOME, and \(\sim 30\%\) in DIHARD II single channel.

#### 3.4. Baseline

The baseline system follows exactly the same procedure as our proposed tracking method. The only difference is the replacement of the DNN-based speaker segment identification module with a PLDA-based one.

#### 3.5. Results

In the first set of experiments we provide an optimum set of conditions for speaker tracking, the number of tracked speakers is fixed to 2, with the input audio signal containing only speech from them, and there is no overlapped speech instances.

In Table 2 we can see that the DNN based tracking system significantly outperforms the PLDA baseline in EER and minDCF, which drops from 12.98% to 2.83% and 0.85 to 0.37, respectively in CALLHOME with the speaker models generated with 10.5 s of labeled samples. We also observe that the i-vectors provide good DER performance even when fewer labeled samples are provided. Additionally, we followed the same optimum conditions with x-vectors, the advantage of our supervised approach in EER and minDCF is consistent in both datasets. A further improvement is shown in terms of DER, which drops form 24.66% to 5.63%. It should be noted that both, DNN and PLDA systems, degrade when x-vectors are used, this is further illustrated in Figure 4 where the minDCF curves show a clear advantage of the i-vectors in our supervised system.
Table 2: DER (%), EER (%) and minDCF (0.1% target probability) on two datasets given the optimum conditions.

| Model time | PLDA DER | PLDA EER | DNN DER | DNN EER |
|------------|----------|----------|---------|---------|
| CALLHOME   |          |          |         |         |
| i-vector   | 3.0 s    | 6.90     | 17.40   | 5.65    |
|            | 5.5 s    | 5.41     | 14.81   | 4.93    |
|            | 10.5 s   | 4.56     | 12.98   | 4.54    |
| x-vector   | 3.0 s    | 33.95    | 41.66   | 11.53   |
|            | 5.5 s    | 28.65    | 36.68   | 7.80    |
|            | 10.5 s   | 24.66    | 32.57   | 5.63    |
| DIHARD II  |          |          |         |         |
| i-vector   | 3.0 s    | 19.01    | 36.62   | 18.44   |
|            | 5.5 s    | 16.22    | 34.73   | 13.97   |
|            | 10.5 s   | 13.29    | 33.70   | 11.03   |
| x-vector   | 3.0 s    | 28.49    | 46.58   | 12.37   |
|            | 5.5 s    | 27.61    | 41.52   | 8.13    |
|            | 10.5 s   | 22.81    | 38.06   | 6.24    |

Table 3: DER (%), EER (%) and minDCF (0.1% target probability) given the speaker verification conditions.

| Model time | PLDA DER | PLDA EER | DNN DER | DNN EER |
|------------|----------|----------|---------|---------|
| CALLHOME   |          |          |         |         |
| i-vector   | 3.0 s    | 7.37     | 22.58   | 6.25    |
|            | 5.5 s    | 5.69     | 22.52   | 4.56    |
|            | 10.5 s   | 4.53     | 22.39   | 4.43    |
| x-vector   | 3.0 s    | 32.57    | 46.58   | 12.37   |
|            | 5.5 s    | 27.61    | 41.52   | 8.13    |
|            | 10.5 s   | 22.81    | 38.06   | 6.24    |
| DIHARD II  |          |          |         |         |
| i-vector   | 5.5 s    | 16.40    | 32.86   | 15.42   |
|            | 10.5 s   | 13.05    | 32.67   | 11.44   |
| x-vector   | 5.5 s    | 29.48    | 56.65   | 16.84   |
|            | 10.5 s   | 30.04    | 59.99   | 13.77   |

Table 4: DER (%), EER (%) and minDCF (0.1% target probability) for i-vector, given the speaker overlap conditions.

| Model time | CALLHOME DER | CALLHOME EER | CALLHOME minDCF | DIHARD II DER | DIHARD II EER | DIHARD II minDCF |
|------------|--------------|--------------|-----------------|--------------|--------------|-----------------|
| 3.0 s      | 20.82        | 13.20        | 20.63           | 36.94        | 30.35        | 28.04           |
| 5.5 s      | 15.78        | 9.72         | 13.77           | 28.04        | 24.78        | 20.63           |
| 10.5 s     | 12.64        | 7.55         | 12.64           | 30.35        | 24.78        | 20.63           |

In a second set of experiments we increased the complexity of the previous conditions by mixing a set of non-target speaker segments in every recording. Such segments were built from the speaker models of other recordings within the same cross-validation fold. We are interested in the EER and minDCF results.

As shown in Table 3 the DNN-based system continues to outperform the PLDA baseline. We also observe that the performance gap between i- and x-vector disappears in the DNN system, since the i-vector error increased while the x-vector’s pretty much remained the same. We can conclude that our system is robust enough when it encounters non-target speakers along the recording.

Finally, we evaluate our proposed system considering overlapped speech, as described in Section 3.3. In this set of experiments, the number of tracked speakers is fixed to 2, with the input audio signal containing non-overlapping and overlapping speech from them. Table 4 shows promising results in both datasets, with 12% DER in CALLHOME with the additional 18% of augmented overlapped speech; and 28.04% DER in DIHARD II single channel with its 30% additional overlap.

4. Conclusions

In this paper, we propose a novel embedding-based speaker tracking DNN model focused on online tracking. We demonstrated efficiency of our approach through several experiments on two standard public datasets: CALLHOME and DIHARD II single channel. Validation results show a promising performance improvement compared to the PLDA baseline, as it drops the DER, EER and minDCF in the different experimental conditions, such as increased number of non-target speakers within a recording, and overlapping speakers.

For future research, we would like to extend our current DNN model to an online diarization and tracking system, where a recurrent neural network (RNN) will be responsible for selecting and updating the speaker models without having to resort to external sources. We expect such system to provide not only the diarization results, but also the set of speaker models that it will generate during an adaptive diarization process.

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