IMPROVING ROBUSTNESS IN SPEAKER IDENTIFICATION USING A TWO-STAGE ATTENTION MODEL

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ABSTRACT

In this paper a novel framework to tackle speaker recognition using a two-stage attention model is proposed. In recent years, the use of deep neural networks, such as time delay neural network (TDNN), and attention model have boosted speaker recognition performance. However, it is still a challenging task to tackle speaker recognition in severe acoustic environments. To build a robust speaker recognition system against noise, we employ a two-stage attention model and combine it with a TDNN model. In this framework, the attention mechanism is used in two aspects: embedding space and temporal space. The embedding attention model built in embedding space is to highlight the importance of each embedding element by weighting them using self attention. The frame attention model built in temporal space aims to find which frames are significant for speaker recognition. To evaluate the effectiveness and robustness of our approach, we use the TIMIT dataset and test our approach in the condition of five kinds of noise and different signal-noise-ratios (SNRs). In comparison with three strong baselines, CNN, TDNN and TDNN+attention, the experimental results show that the use of our approach outperforms them in different conditions. The correct recognition rate obtained using our approach can still reach 49.1%, better than any baselines, even if the noise is Gaussian white Noise and the SNR is 0dB.

Index Terms— Robust Speaker Recognition, Deep Neural Networks, Attention Mechanism, Time-Delay Neural Network, Two-Stage Attention.

1. INTRODUCTION

Speaker recognition aims to identify a person from characteristics of voices[21]. To do this, traditional i-vector method based on the GMM-UBM described in [1] was widely used to extract acoustic features for speaker recognition. However, in practical applications of speaker recognition, input audio signals are often corrupted by different types of background noise[15]. This easily interferes the extraction of some key acoustic features of speakers and thus makes speaker recognition in noise conditions a challenging task.

In recent years, due to the rapid development of deep learning technologies, recognizing speaker identities from audio signal using deep neural networks has been an active research area and different speaker modelling approaches [21, 23, 24] are proposed. Variani, et al. developed d-vector using multiple fully-connected neural network layers [23]. In [23], Snyder, et al. developed a framework called as X-vector, which is one of the popular methods for speaker recognition. It can yield a good performance using a feed-forward TDNN that computes speaker embeddings from variable-length acoustic segments.

To further tackle interferences caused by background noise, attention mechanism [8] is used as it allows the model to allocate weights on different part of data and help to search for salient features. For speaker recognition, there are some previous studies [22, 18, 27, 29] using attention model. Wang, et al. used an attentive X-vector where a self-attention layer was added before a statistics pooling layer to weight each frames [27, 18, 32]. Rahman, et al. jointly used attention model and K-max pooling to selects the most relevant features [22].

In addition to speaker recognition, the attention model has also been widely used in natural language processing [1, 13, 25, 30, 2], speech recognition [17, 15, 31, 2], and computer vision [29, 12, 28, 26, 19, 14]. In [1], Bahdanau, et al. designed an attention model to allow the each time step of decoder to pay attention to different part of input sentence. Xu et.al used an attention model in a similar way to design an encoder decoder network for image caption [29]. In [17], Moritz, et al. combined CTC (connectionist temporal classification) and attention model to improve the performance of end to end speech recognition. In [16, 31] and [2], different attention models were also designed for speech emotion recognition and phoneme recognition, respectively. To further improve the robustness of the attention model, some previous studies used two attention models within one framework. Luong, et al. used global and local attention in image processing to identify relevant features [22]. Li, et al. applied global and local attention in image processing to further improve the performance [22]. Woo, et al. used spatial attention and channel attention to extract salient features from input data [28].

Inspired by those previous studies using attention models, a two-stage framework consisting of two attention models was built to improve the robustness against background noise. The aim of this work is to use attention model not only in temporal space by computing weight on data frames, but also in embedding space by computing weight for each element of embedding vector. In this work, the two attention models are concatenated where the attention model used for data frame is followed by the attention model built on embeddings. The first attention model in our work is referred to as frame attention module and the second one is embedding attention model. The details of our approach and implementation will be presented in next sections.

The rest of the paper is organized as follow: Section 2 presents the theoretical framework of our approach. Section 3 depicts the data we use, experimental setup, and the baselines to be compared.
2. MODEL ARCHITECTURE

Figure 1 shows the architecture of our approach, from its input to output, consisting of a time delay neural network (TDNN), a two-stage attention model, a statistics pooling layer, and two fully connected layers. The input data is \( X = \{x_1, x_2, \ldots, x_T\} \) (\( X \in \mathbb{R}^{T \times L} \)), where \( T \) represents the sequence length, \( L \) represents the dimension of each feature vector, and \( x_i \) denotes the \( i \)th acoustic feature vector converted from speech signals. The TDNN works as a frame-level feature extractor and \( H = \{h_1, h_2, \ldots, h_T\} \) (\( H \in \mathbb{R}^{T \times F} \)) denotes its output, where \( T \) is its length (same as \( X \)), \( F \) is the embedding dimension, and \( h_i \) denotes the \( i \)th embedding vector [15]. The two-stage attention model includes a frame attention model and an embedding attention model. Its output is denoted by \( H'' = \{h_1'', h_2'', \ldots, h_T''\} \), where \( H'' \) has the same dimension as \( H \).

### 2.1. Time Delay Neural Network (TDNN)

In the architecture of TDNN, the initial transforms are learnt on narrow contexts and the deeper layers process the hidden activations from a wider temporal context. Hence the higher layers have the ability to learn wider temporal relationships. Each layer in a TDNN operates at a different temporal resolution, which increases as we go to higher layers of the network [20]. Furthermore, it is more efficient than the use of RNN [6] due to its use of sub-sampling as described in [20].

In our work, a five-layer TDNN is used as a frame-level feature extractor. The first layer takes five-frame context (from \( t - 2 \) to \( t + 2 \), where \( t \in \{2, 3, \ldots, T-2\} \)) as input. The second layer takes context frames at \( t - 2 \), \( t \), and \( t + 2 \), while the next layer takes context frames at \( t - 3 \), \( t \), and \( t + 3 \). The last two layers operate on current frame \( t \), but as the previous layer has take into account context frames, so the last two TDNN layers take total 15 frames context as input [23].

### 2.2. Two-stage Attention Model

As shown in Figure 2, the two-stage attention model is a concatenating structure where the embedding attention model is followed by the frame attention model.

The embedding attention model uses a self-attention structure to allocate weights to each element of the embedding vector. The weight is computed using \( F_{embedding} \). In equation (1) the output of the embedding attention model, \( H' \) is the product of \( H \) and \( F_{embedding}(H) \):

\[
H' = F_{embedding}(H) \odot H
\]

where \( F_{embedding} \) is defined as:

\[
F_{embedding}(H) = \text{Sigmoid}(s_{\text{statistics}} + s_{\text{max}})
\]

\[
s_{\text{statistics}} = \text{Relu}(h_{\text{avg}} + h_{\text{std}})W_0^0 + b_0^0W_1^0
\]

\[
s_{\text{max}} = \text{Relu}(h_{\text{max}}W_0^1 + b_0^1W_1^1)
\]

The embedding attention model employs two different pooling mechanisms, max-pooling and statistics-pooling. The output of max-pooling \( h_{\text{max}} \in \mathbb{R}^{1 \times F} \) is used to compute \( s_{\text{max}} \) in the same way as \( s_{\text{max}} \). \( W_0^0 \in \mathbb{R}^{F \times 100}, b_0^0 \in \mathbb{R}^{1 \times 100} \) and \( W_1^0 \in \mathbb{R}^{100 \times F} \) shown in equation (2) are the parameters of linear mapping. The parameter, 100, is the number of hidden units. The weight is finally obtained using a Sigmoid function on the summation of \( s_{\text{max}} \) and \( s_{\text{statistics}} \).

The frame attention mode also uses a self-attention structure whose input is \( H' \) and output is \( H'' \):

\[
H'' = F_{frame}(H') \odot H'
\]

where \( F_{frame} \) is defined as:

\[
F_{frame}(H') = \alpha
\]

\[
\alpha \in \mathbb{R}^{T \times 1}
\]

is normalized score vector \( \alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_T\} \) on each frame, where \( \alpha_t \) denotes the scalar weight for each frame and is computed using Softmax [27, 32]:

\[
\alpha_t = \frac{\exp(s_t)}{\sum_{i=0}^{T} \exp(s_i)}
\]

\[
s_t = \text{Relu}(h_tW_0 + b_0)W_1
\]

where \( W_0 \in \mathbb{R}^{F \times F}, b_0 \in \mathbb{R}^{1 \times F} \) and \( W_1 \in \mathbb{R}^{F \times 1} \) are the parameters used in frame attention model.
3. EXPERIMENTS

3.1. Data

In this paper, TIMIT corpus [5] is used to evaluate the proposed approach. The TIMIT corpus of read speech is designed to provide speech data for acoustic-phonetic studies and for the development and evaluation of automatic speech recognition systems. It includes a 16-bit, 16kHz speech waveform file for each utterance. There are a total of 6300 utterances, 10 sentences spoken by each of 630 speakers from 8 major dialect regions of the United States. 70% of the speakers are male and 30% are female. As two utterances of each speaker have the same word transcriptions, they are excluded in our work to reduce possible bias. So there are finally 8 utterances spoken by each speaker. In this paper, the train and test set are re-split. Six utterances from each speaker are randomly selected for training and the rest two utterances are for testing. Hence there are 3780 utterances in the training set and 1260 utterances in the test set.

To evaluate robustness, additional noise signals are added with the TIMIT data. The noise signals are from the QUT-NOISE dataset [3], which contains five common noise scenarios with 10 unique locations. For each noise scenario, there are two different locations: in-door and out-door on cafe noise scenario; Window-down when driving and window-up when driving on car noise scenario; In a kitchen and living room on home noise scenario; Near inner-city and near outer-city on street noise scenario [3]. In this work, four scenarios, cafe, car, home and street scenarios, are used, and for each noise scenario, the locations and utterances are randomly selected. In our experiments, there are finally five types of noise: Gaussian white noise, cafe, car, home and street. The SNR values are set to be 0 dB, 5 dB, 10 dB, 15 dB, respectively.

![Illustration of data segmentation strategy.](image)

3.2. Experiment Setup

In the experiment, as shown in Figure 3, each utterance is segmented into short audio segments using a one-second sliding window with a 50-ms hop. The short audio segments are then converted into 13D MFCCs vectors. In the TDNN, the dimension of first four layers is 512, and each layer is followed by a batch normalization. The dimension of the two fully connected layers is 512, and each layer is followed by a batch normalisation and dropout layer, where dropout rate is set to 0.2. The Adam optimiser [11] is used in training, with $\beta_1$ set to 0.95, $\beta_2$ to 0.999, and $\epsilon = 10^{-8}$. The initial learning rate is $10^{-4}$.

In order to compare with the proposed approach, three baselines are built based on the methods developed in previous studies [23] [27] [2]. The first baseline (“TDNN”) is based on X-vector architecture. X-vector architecture is now widely used for speaker recognition [23]. In this baseline, it uses a TDNN, same as ours model, followed by a statistics pooling layer and a fully connected layer. The second baseline (“TDNN + Attention”) is similar to our approach, but use only frame attention model [27] [32]. The third baseline (“CNN”) is based on one-dimensional convolutional neural network [7]. It uses one-dimensional convolutional network across time axis and can yield a good performance for speaker recognition. In the first layer, there are 64 kernels and each kernel size is $1 \times L$ ($L = 13$, the dimension of MFCC vectors). The stride value of this layer is set to 1. In the following two convolutional layers, there are 128 and 256 kernels, respectively. The kernels size in the two layers is $3 \times 1$ and the stride value is 2. A fully-connected layer with 512 nodes is then used before the output of the model.

3.3. Evaluation Metric

In this paper, speaker recognition accuracy is computed over 1260 utterances collected in the test set. We initially compute the score of each segment of an utterance, and then compute the accuracy over all segments of each utterance.

Suppose $S^j_{k,i}$ denotes the normalised value of the $j$th ($j \in \{1, 2, ..., 630\}$) speaker after using Softmax when the input is the $i$th ($i \in \{1, 2, ..., N\}$ segment of the $k$th utterance ($k \in \{1, 2, ..., 1260\}$), where $N$ is the number of segments of the $k$th utterance and is variable).

In equation (6), $Z^j_k \in R^{1 \times 630}$ denotes the score of the $k$th utterance if it is assumed to be spoken by the $j$th speaker. It is computed by logarithm average over all segments of the $k$th utterance.

$$Z^j_k = \log(\prod_{i=1}^{N} S^j_{k,i})$$ (6)

where $N$ is the number of segment of the $k$th utterance.

The most likely predicted speaker identity, $J_{predict}$, is computed by selecting the one whose score obtained using Eq. 6 is maximum

$$J_{predict} = \arg\max_j Z^j_k$$ (7)

The speaker recognition accuracy on the test set is computed by:

$$Accuracy = \frac{\#(J_{predict} = J_{True})}{\#Total\ utterances\ in\ the\ test\ set}$$ (8)

where $J_{True}$ is the ground truth of the corresponding utterance.

4. RESULTS

Table [7] shows the speaker recognition accuracy on clean speech data and data corrupted with Gaussian white noise. To evaluate the robustness of the proposed approach and compare with the three baselines, the results obtained when the SNR value varying from 0 dB to 15 dB are also shown. It is clear that the use of attention model can yield better recognition performance than the baselines without using attention model. The possible reason is that the use of attention model can highlight positive contributions from those relevant features while reduce negative impacts caused by those irrelevant ones occurring in observed acoustic information.

The use of our approach (TS-Attention) outperforms the three baselines in all SNR conditions. Even if the SNR value is 0 dB, our approach can still reach 49.1%, more than 10% relative improvement over the baseline of TDNN+Attention. This is probably because that an additional embedding attention model is used in our approach in comparison with the baseline. In the two-stage model, frame attention indicates which position is likely to be significant for speaker recognition, and the embedding attention model indicates which embedding element is important.

In addition, comparing with the other two baselines and our approach, the use of TDNN only yields relatively lower performances.
In order to further evaluate the robustness, as introduced in Section 3.1 the three baselines and the proposed approach are also tested on four types of noises (cafe, car, home, and street). Table 2 shows the speaker recognition accuracy in the four noise scenarios and with different SNRs. In the four tables, the proposed approach consistently yields better recognition performance than the three baselines in the four noise scenarios and in the condition of different SNRs. When the background noise scenario is “car”, the recognition performances obtained whether using the proposed approach or using the three baseline are better than those obtained in other noise scenarios in the condition of same SNR. Even if the SNR is 0dB, the correct recognition rate can even reach 81% when using the proposed approach in “car” noise scenario. Inversely, when background noise is Gaussian white noise, the recognition performances are relatively worse in comparison with other noise scenarios in the same conditions. This phenomena might be related to the noise distribution in time and frequency domain. For Gaussian white noise, its distributions in both time and frequency domain are relatively consistent, while the noise made by car engines are like narrow-band impulse response whose interference often covers limited frequencies and occurs discontinuously. In this paper a two-stage attention model was proposed to tackle speaker recognition in noise environment. The proposed model, containing an embedding attention model and a frame attention model, heavily depends on frame context, which is easily interfered when background noise is strong. Besides not using attention model, the input segment is randomly selected from the test data, and the model was trained in Gaussian white noise and its SNR is 0dB. In figure 4 the (a) sub-figure is the clean segment, and (b) sub-figure is the corresponding noise segment. The (c) sub-figure shows the weights generated by the embedding attention model over the the embedding whose the dimension is 1500. One could observe that some weights are quite small and some are close to 1 (due to sigmoid function). This means that some embedding elements might be more relevant to the target and some are not. The (d) sub-figure shows the weights over the frames of a one-second short audio segment generated by frame attention model. In the figure, some weights corresponding to voiced signals are different because of their different contributions to the target and much larger than the unvoiced signals. It is reasonable that the use of two attention models has the ability to help to highlight the relevant features in both frame domain and embedding domain, which is probably the key factor to yield better performances than those baselines.

|            | 0 db | 5db | 10 db | 15 db | Clean |
|------------|------|-----|-------|-------|-------|
| CNN        | 71.6 | 78.1 | 82.9  | 86.6  | 92.9  |
| TDNN       | 66.4 | 76.4 | 85.0  | 88.7  | 94.2  |
| TDNN+Attention | 72.3 | 81.7 | 86.9  | 90.0  | 95.5  |
| TS-Attention | 73.5 | 82.9 | 87.9  | 91.2  | 96.3  |

Table 1. Speaker recognition accuracy (%) on TIMIT test set in the condition of clean and different SNRs. The background noise is Gaussian white noise.

|            | 0 db | 5db | 10 db | 15 db | Clean |
|------------|------|-----|-------|-------|-------|
| CNN        | 43.2 | 58.7 | 66.1  | 76.5  | 92.9  |
| TDNN       | 34.1 | 55.2 | 69.6  | 78.2  | 94.2  |
| TDNN+Attention | 44.5 | 62.1 | 75.1  | 81.6  | 95.5  |
| TS-Attention | 49.1 | 64.4 | 78.7  | 83.7  | 96.3  |

Table 2. Speaker recognition accuracy (%) on the TIMIT test set in the condition of clean and cafe noise.

|            | 0 db | 5db | 10 db | 15 db | Clean |
|------------|------|-----|-------|-------|-------|
| CNN        | 71.3 | 78.2 | 82.5  | 84.2  | 92.9  |
| TDNN       | 68.5 | 77.6 | 82.6  | 88.4  | 94.2  |
| TDNN+Attention | 73.2 | 81.1 | 85.8  | 89.2  | 95.5  |
| TS-Attention | 76.1 | 82.2 | 86.8  | 90.4  | 96.3  |

Table 3. Speaker recognition accuracy (%) on the TIMIT test set in the condition of clean and car noise.

|            | 0 db | 5db | 10 db | 15 db | Clean |
|------------|------|-----|-------|-------|-------|
| CNN        | 78.8 | 81.5 | 84.7  | 89.9  | 92.9  |
| TDNN       | 75.2 | 82.8 | 88.3  | 91.3  | 94.2  |
| TDNN+Attention | 79.3 | 85.4 | 88.2  | 91.9  | 95.5  |
| TS-Attention | 81.0 | 86.5 | 89.0  | 92.1  | 96.3  |

Table 4. Speaker recognition accuracy (%) on the TIMIT test set in the condition of clean and home noise.

|            | 0 db | 5db | 10 db | 15 db | Clean |
|------------|------|-----|-------|-------|-------|
| CNN        | 74.4 | 81.4 | 84.4  | 88.0  | 92.9  |
| TDNN       | 70.8 | 78.4 | 85.0  | 89.5  | 94.2  |
| TDNN+Attention | 75.6 | 82.8 | 87.5  | 90.5  | 95.5  |
| TS-Attention | 77.0 | 84.6 | 88.6  | 91.2  | 96.3  |

Table 5. Speaker recognition accuracy (%) on TIMIT test set in the condition of clean and street noise.

5. CONCLUSION AND FUTURE WORK

In this paper a two-stage attention model was proposed to tackle speaker recognition in noise environment. The proposed model, containing an embedding attention model and a frame attention model, can yield better performances than the three baselines: CNN, TDNN and TDNN+attention, when speech data is corrupted by five types of noise and in the condition of different SNRs. In our future work, more data sets for speaker recognition will be tested and more complex network architecture will be investigated to further improve the robustness and effectiveness of the proposed approach.

Fig. 4. The Visualization of attention weights. (a): Clean segment; (b): Noise segment. (c): Embedding attention weights. (d): Frame attention weights. In (a) and (b), X-axis represents the sampling index and Y-axis represents the amplitude of speech signals. In (c) and (d), X-axis represents the index of embedding elements and frames respectively, Y-axis represents the attention weight value.
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