Robust Speaker Recognition Using Speech Enhancement And Attention Model

Yanpei Shi, Qiang Huang, Thomas Hain

Speech and Hearing Research Group
Department of Computer Science, University of Sheffield
{YShi30, qiang.huang, t.hain}@sheffield.ac.uk

Abstract

In this paper, a novel architecture for speaker recognition is proposed by cascading speech enhancement and speaker processing. Its aim is to improve speaker recognition performance when speech signals are corrupted by noise. Instead of individually processing speech enhancement and speaker recognition, the two modules are integrated into one framework by a joint optimisation using deep neural networks. Furthermore, to increase robustness against noise, a multi-stage attention mechanism is employed to highlight the speaker related features learned from context information in time and frequency domain. To evaluate speaker identification and verification performance of the proposed approach, we test it on the dataset of VoxCeleb1, one of mostly used benchmark datasets. Moreover, the robustness of our proposed approach is also tested on VoxCeleb1 data when being corrupted by three types of interferences, general noise, music, and babble, at different signal-to-noise ratio (SNR) levels. The obtained results show that the proposed approach using speech enhancement and multi-stage attention models outperforms two strong baselines not using them in most acoustic conditions in our experiments.

1. Introduction

The aim of speaker recognition is to recognize speaker identities from their voice characteristics. In recent years, the use of deep learning technologies has significantly improved speaker recognition performance. Variani, et al. developed the d-vector using multiple fully-connected neural network layers, and Snyder, et al. developed X-vectors based on the Time-delayed neural networks (TDNN). However, it is still a challenging task when recognizing or verifying speakers in poor acoustic conditions.

To tackle speeches corrupted by noise signals, there have been some methods developed. Some of previous studies tended to recover original signals by removing noise. Some methods focused on feature extraction from un-corrupted speech signals, and some methods tried to estimated speech quality by computing signal-to-noise ratio (SNR).

For speech enhancement, most of previous studies are often processed individually. However, the learned features or enhanced speech signals might not be able to well match to the information required by speaker recognition and verification. It is highly desirable that both speech enhancement and speaker processing model can be optimised jointly.

In Shon et al. tried to integrated speech enhancement module and speaker processing module into one framework. In this method, the speech enhancement module tried to filter out unnecessary features corrupted by noise by generating a ratio mask and multiplying element-wise with the original spectrogram for speaker verification. However, in this framework, the speaker verification module was per-trained and fixed when training the speech enhancement. It means that the two modules are not optimised jointly although a single loss function is used.

In addition to joint optimisation, attention mechanisms has also been widely used for speaker identification and verification. This is because a neural attention mechanism has an ability to focus on a subset of its inputs by allocating different weights to different input features. This can hence highlight the relevant information and reduce the interference caused by irrelevant information. In previous studies, the use of attention models has provided benefits not only for speech processing, but also for natural language processing (NLP) and image processing.

Wang, et al. used an attentive X-vector where a self-attention layer was added before a statistics pooling layer to weight each frame. Rahman, et al. jointly used attention model and K-max pooling to selects the most relevant features. Moritz, et al. combined CTC (connectionist temporal classification) and attention model to improve the performance of end to end speech recognition. Different attention models were also designed for speech emotion recognition and phoneme recognition, respectively. In an attention model was used to allow the each time step of decoder to focus on different part of input sentence to search for most relevant words. Luong, et al. used global attention and local attention, where global attention attends to the whole input sentence and local attention only looks at a part of the input sentence.

Cheng et al. proposed self attention that relating different positions of the same sentence. Woo, et al. used combination of spatial attention and channel attention call CBAM to extract salient features from different dimension of input.

To improve the performance for speaker identification and verification, and increase the robustness against noise, in our proposed approach, the deep neural networks of the two modules, speech enhancement and speaker recognition, will be connected in a cascaded format and their parameter will be optimised jointly by a the loss function defined by the differences between the real speaker identities and predicted ones. Simultaneously, a multi-stage attention mechanism will be also taken into account in order to learn useful features from context information in time, frequency and channel dimensions of the feature map between two convolutional layers. The multi-stage attention highlights the most relevant features for identifying speaker identities in noise environment. The details of the proposed approach will be depicted in the following sections.

The rest of the paper is organized as follow: Section presents the cascade structure of our approach and how the attention mechanism is used in these architecture. The used data set and experiment set up are introduced in Section. The obtained results and related analysis are given in Section.
finally conclusions are drawn in Section 5.

2. Model Architecture

2.1. Speech Enhancement Module

Figure 1 shows the proposed model architecture consisting of a speech enhancement module and a speaker recognition module. Suppose the input data to the enhancement module is \( X \in \mathbb{R}^{T \times F \times C} \) where \( T, F, \) and \( C \) represent the temporal dimension, frequency dimension, and channel dimension, respectively. The value of \( C \) is a variable. When \( X \) is input spectrogram, \( C \) is set to one. Besides this, the value of \( C \) equals to the number of kernels set in the convolutional neural networks.

The speech enhancement module consists of multiple Conv-MS blocks, each of which contains a dilated convolution layer followed by a multi-stage attention block. In the attention block, an attention mechanism is conducted in time, frequency, and channel domains, respectively.

The output feature map of the dilated convolutional layer is denoted as \( H_k \in \mathbb{R}^{T_k \times F_k \times C_k} \), where \( k \) means the \( k \)th CONV-MS block. The output \( H_k'' \) denotes the refined feature map of the \( k \)th Conv-MS block, and its dimension is same as \( H_k \).

The output of enhancement module is used as a ratio mask whose values are viewed as the weights corresponding to frequency bin and time frame of the spectrogram. The ratio mask multiplies with the speech spectrogram in order to reduce the interferences caused by unrelated noise signals.

2.2. Speaker Recognition Module

The speaker recognition module consists of multiple residual convolutional blocks in which a multi-stage attention block is inserted. The input of the \( k \)th residual block is denoted as \( H_k \in \mathbb{R}^{T_k \times F_k \times C_k} \), and the final refined feature map of the \( k \)th residual block is \( H_k'''' \). The last residual block is followed by fully-connected layers, by which the predictions of speaker identities are finally computed using a softmax function.

2.3. Multi-Stage Attention (MS)

Figure 2 shows the structure of a multi-stage attention block, which runs channel attention, frequency attention, and time attention sequentially. Its mathematics representation can be found in equation 1:

\[
H_k' = \alpha_{C,k} \odot H_k \\
H_k'' = \alpha_{F,k} \odot H_k' \\
H_k'''' = \alpha_{T,k} \odot H_k''
\]

where \( \alpha_{C,k}, \alpha_{F,k}, \) and \( \alpha_{T,k} \) represent the implementation of channel attention, frequency attention and time attention in the \( k \)th attention block.

2.3.1. Channel Attention

Following the principle of channel attention used in [24, 23], The working flow of channel attention is shown in Figure 2 (a) and Equation 2.

\[
H_{k,\text{max}}^C = \text{max}_{T_k \times F_k \times 1}(H_k) \\
H_{k,\text{avg}}^C = \text{avg}_{T_k \times F_k \times 1}(H_k) \\
S_{\text{max}} = \text{Relu}(H_{k,\text{max}}^C W_0 + b_0)W_1 \\
S_{\text{avg}} = \text{Relu}(H_{k,\text{avg}}^C W_0 + b_0)W_1 \\
\alpha_{C,k} = \text{Sigmoid}(S_{\text{avg}} + S_{\text{max}})
\]
where \( W_0 \in \mathbb{R}^{C_k \times 100} \), \( b_0 \in \mathbb{R}^{1 \times 100} \) and \( W_1 \in \mathbb{R}^{100 \times C_k} \) are the parameters of the \( k \)th channel attention block.

In the implementation of channel attention, max pooling and average pooling are firstly applied on both time and frequency dimension of \( H_k \). Their output \( H_{k, \text{max}}^C, H_{k, \text{avg}}^C \in \mathbb{R}^{1 \times 1 \times C_k} \) and \( H_{k, \text{max}}^C, H_{k, \text{avg}}^C \in \mathbb{R}^{1 \times 1 \times C_k} \) are then used as the input of two fully connected layers sharing the same parameters and followed by \( \text{Relu} \) activation. The channel attention map \( \alpha_{k,}^C \) is finally obtained after a Sigmoid activation is applied to the summation of \( S_{\text{avg}} \) and \( S_{\text{max}} \). After broadcasting data in \( \alpha_{k,}^C \) to expand the map size same as \( H_k \), the attention map is multiplied by the original feature map \( H_k \) to generate the refined feature map \( H'_k \).

2.3.2. Frequency and Time Attention

The frequency and time attention block work similar with existing structure when processing their three dimensional input except that where an attention mechanism is applied to, frequency dimension or time dimension.

\[
\begin{align*}
H_{k, \text{max}}^F &= \max^{1 \times 1 \times 1}(H'_k) \\
H_{k, \text{avg}}^F &= \text{avg}^{1 \times 1 \times 1}(H'_k) \\
H_{k, \text{pool}}^F &= \text{Concat}(H_{k, \text{avg}}^F; H_{k, \text{max}}^F) \\
H_{k, \text{max}}^T &= \max^{T_k \times 1 \times 1}(H_{k, \text{pool}}^F) \\
H_{k, \text{avg}}^T &= \text{avg}^{T_k \times 1 \times 1}(H_{k, \text{pool}}^F) \\
H_{k, \text{pool}}^T &= \text{Concat}(H_{k, \text{avg}}^T; H_{k, \text{max}}^T) \\
\alpha_k^F &= \text{Sigmoid}(f^2 \times 7(H_{k, \text{pool}}^F))
\end{align*}
\]

Figure 2 (b) shows the working flow of the time attention block and Equation 3 shows its implementation in math format. In the \( k \)th time attention block, a max pooling and an average pooling are firstly applied to channel dimension of the input data \( H_k \), and the corresponding outputs are \( H_{k, \text{max}}^C \in \mathbb{R}^{T_k \times F_k \times 1} \) and \( H_{k, \text{avg}}^C \in \mathbb{R}^{T_k \times F_k \times 1} \) respectively. \( H_{k, \text{pool}}^C \in \mathbb{R}^{T_k \times F_k \times 2} \) is obtained by concatenating the outputs after using poolings. On time dimension, the same max pooling and average pooling steps are applied on \( H_{k, \text{pool}}^C \in \mathbb{R}^{T_k \times F_k \times 2} \) and the corresponding outputs are \( H_{k, \text{avg}}^T \in \mathbb{R}^{T_k \times F_k \times 2} \) and \( H_{k, \text{max}}^T \in \mathbb{R}^{T_k \times F_k \times 2} \). Again, the output after concatenating them on time dimension is \( H_{k, \text{pool}}^T \in \mathbb{R}^{2 \times F_k \times 2} \). The frequency attention map \( \alpha_k^F \) is computed using a convolution operation with a 2-by-7-by-2 kernel followed by a sigmoid activation. The stride value is 1 on frequency dimension during convolution. The size of \( \alpha_k^F \) is then expanded to the same as \( H'_k \) by data broadcast. The frequency refined feature map \( H_k' \) is finally obtained by the product of \( \alpha_k^F \) and \( H'_k \).

The computation of time attention is similar to frequency attention. Equation 3 and Figure 2 (c) shows the computation process. The final time refined feature map is obtained by the multiplication of the previous frequency refined feature map and the time attention weights \( \alpha_k^T \).

\[
\begin{align*}
H_{k, \text{max}}^T'' &= \max^{1 \times 1 \times F_k}(H_k^F) \\
H_{k, \text{avg}}^T &= \text{avg}^{1 \times 1 \times F_k}(H_k^F) \\
H_{k, \text{pool}}^T &= \text{Concat}(H_{k, \text{avg}}^T; H_{k, \text{max}}^T) \\
H_{k, \text{max}}^T'' &= \max^{1 \times 1 \times F_k}(H_k^F) \\
H_{k, \text{avg}}^T &= \text{avg}^{1 \times 1 \times F_k}(H_k^F) \\
H_{k, \text{pool}}^T &= \text{Concat}(H_{k, \text{avg}}^T; H_{k, \text{max}}^T) \\
\alpha_k^T &= \text{Sigmoid}(f^2 \times 2(H_k^F))
\end{align*}
\]
Table 1: The architecture of the SE-Net. SE-Net consists of 11 dilated convolution and multi-stage attention (CONV-MS) block. Within each block, a dilated convolutional process is firstly applied, then a multi-stage attention (MS) block is applied.

| Layer Name       | Structure | Dilation |
|------------------|-----------|----------|
| CONV-MS Block1   | 7x1x48    | 1x1      |
|                  | MS        |          |
| CONV-MS Block2   | 1x7x48    | 1x1      |
|                  | MS        |          |
| CONV-MS Block3   | 5x5x48    | 1x2      |
|                  | MS        |          |
| CONV-MS Block4   | 5x5x48    | 1x4      |
|                  | MS        |          |
| CONV-MS Block5   | 5x5x48    | 1x8      |
|                  | MS        |          |
| CONV-MS Block6   | 5x5x48    | 2x2      |
|                  | MS        |          |
| CONV-MS Block7   | 5x5x48    | 4x4      |
|                  | MS        |          |
| CONV-MS Block11  | 1x1x1     | 1x1      |

Table 3: The architecture of SID-Net. SID-Net consists of 8 residual convolution and multi-stage attention (RES-MS) block. Within each block, the multiple convolutional layers as firstly used on the input. Then, the output of is passed through a multi-stage attention (MS) block before residual connection.

| Block Name  | Structure | Output |
|-------------|-----------|--------|
| RES-MS Block1 | 3x3x64    | 150x129 |
|             | 3x3x64    |        |
|             | 3x3x64    |        |
|             | MS-ATT    |        |
| RES-MS Block2 | 3x3x128   | 75x65  |
|             | 3x3x128   |        |
|             | 3x3x128   |        |
|             | MS-ATT    |        |
| RES-MS Block3 | 3x3x128   | 75x65  |
|             | 3x3x128   |        |
|             | 3x3x128   |        |
|             | MS-ATT    |        |
| RES-MS Block4 | 3x3x256   | 38x33  |
|             | 3x3x256   |        |
|             | 3x3x256   |        |
|             | MS-ATT    |        |
| RES-MS Block5 | 3x3x256   | 38x33  |
|             | 3x3x256   |        |
|             | 3x3x256   |        |
|             | MS-ATT    |        |
| RES-MS Block6 | 3x3x256   | 38x33  |
|             | 3x3x256   |        |
|             | 3x3x256   |        |
|             | MS-ATT    |        |
| RES-MS Block7 | 3x3x256   | 38x33  |
|             | 3x3x256   |        |
|             | 3x3x256   |        |
|             | MS-ATT    |        |
| RES-MS Block8 | 3x3x512   | 19x17  |
|             | 3x3x512   |        |
|             | 3x3x128   |        |
|             | MS-ATT    |        |
| Pool        | 19x1      |
| FC          | 512       |

Table 2: Descriptions of five models: three baselines ([Voice Loss](#), SID, and SE+SID) and two proposed approaches (SE-MS+SID and SE+SID-MS).

| Model        | Description                                                                 |
|--------------|-----------------------------------------------------------------------------|
| Voice Loss   | baseline done by cascading speech enhancement and speaker recognition modules |
| SID          | speaker identification baseline using speaker recognition module (SID-Net)  |
| SE+SID       | joint optimisation of speech enhancement (SE-Net) and speaker recognition module (SID-Net) |
| SE-MS+SID    | proposed model using a joint optimisation and multi-stage attention (MS) models in speech enhancement module (SE-Net) |
| SE+SID-MS    | proposed model using a joint optimisation and multi-stage attention models in speaker recognition module (SID-Net) |

3. **Experiments**

3.1. **Data**

In this work, Voxceleb1 [25] dataset is used. Voxceleb1 data are extracted from Youtube videos, which contains 1251 speakers with more than 150 thousand utterances collected "in the wild". The average length of the audios in the dataset is 7.8 seconds.

Spectrograms are used as the input feature. Spectrograms are extracted in a sliding window with 25ms window length and 10 ms hop size. 512 FFT elements are taken, results in 257 dimensional spectrogram (a DC component is concatenated). No normalization techniques are used on the input spectrogram. The time length of the spectrogram is fixed at 300 frames (3.015 seconds).

In order to test the robustness of the proposed model, additional noise from MUSAN dataset is added. MUSAN dataset contains three categories of noises: general noise, music and babble [26]. The general noise type contains 6 hours of audio, including DTMF tones, dialtones, fax machine noises et.al. The music type contains 42 hours of music recording from different categories. The babble type contains 60 hours of speech, including read speech from public domain, hearings, committees and debates et.al.

3.2. **Speaker Identification**

In VoxCeleb1 dataset, both training and test set contain the same number of speakers (1251 speakers) [25]. The training set contains 145265 utterances and the test set contains 8251 utterances. In order to reduce possible bias, the MUSAN dataset is also split into two parts for training and test. This is to ensure that the noise signals used for training will not be reused for test. Each training utterance is mixed with a type of noise at one of five SNR levels. For the test set, the same data configuration is set. To evaluate the recognition performance, Top-1 and Top-5 accuracy are employed [27].

3.3. **Speaker Verification**

There contains 148642 utterances (1211 speakers) in the VoxCeleb1 development dataset, and 4874 utterances (40 speakers) in the test dataset [25]. For the speaker verification task, there are total 37720 test pairs. The same configuration on the data
Table 4: Speaker Identification Results in different noise type (Noise, Music and Babble) at different SNR (0-20 dB), as well as the original voxceleb1 test set. Four different scenarios are tested: only use SID-Net (SID); The SE-Net and SID-Net joint system but not include multi-stage attention (SE+SID); The SE-Net and SID-Net joint system, only SE-Net use multi-stage attention (SE-MS+SID); The SE-Net and SID-Net joint system, only SID-Net use multi-stage attention (SE+SID-MS).

For speaker recognition task is also set for speaker verification. To compare with the baseline introduced in [10], the same loss function and similarity measurement (Cosine) are used. Equal Error Rate (EER) [28] and Detection Cost Function (DCF) [29] are used as evaluation metrics. DCF is computed as the average of two minimum DCF score (DCF0.01 and DCF0.001) [29, 30].

3.4. Experiment Setup

To evaluate our proposed approaches, five models including two baselines and three proposed approaches are to be tested on the data mentioned in Section 3.2 and 3.3. As listed in table 2, SID represents the baseline using the SID-Net, and Voice loss [10] represents the baseline done by cascading speech enhancement and speaker recognition. SE+SID represents the cascading structure with a joint optimisation with SE-Net and SID-Net. SE-MS+SID and SE+SID-MS are the two proposed approaches using multi-stage attention models in either the speech enhancement module (SE-Net) or the speaker recognition module (SID-Net) besides the joint optimisation used in SE+SID.

3.5. Network Structure

Table 1 and Table 3 shows the detailed structure of the speech enhancement and speaker recognition module, respectively. In the speech enhancement module, 11 dilated convolutional layers are employed. The speaker recognition module uses the Resnet-20 architecture [31], due to its effectiveness in speaker recognition [27].

For SE-MS+SID, each dilated convolutional layer in the speech enhancement module is followed by a multi-stage attention module (MS). For SE+SID-MS, the multi-stage attention module (MS) is inserted into each residual block. Each of these two models are trained independently, and are then fine-tuned by a joint optimisation. During training, Adam optimizer [32] is used with the initial learning rate being set to 1e-3 and the decay rate being set to 0.9 for each epoch.

4. Results

Table 4 shows speaker identification results obtained using the models listed in Table 2. Comparing to the SID baseline, the use of SE+SID yields better performances for speaker identification. After using the multi-stage attention models, SE+SID-MS and SE-MS+SID further improve about 2~3% on Top-1.

Figure 3: The Top-1 Accuracy of the linear combination of the SE-MS+SID and SE+SID-MS results when the noise is "babble". $\alpha$ denotes the combination parameter for SE-MS+SID, the combination parameter of SE+SID-MS is $1 - \alpha$. 
Table 5: Speaker Verification Results in different noise type (Noise, Music and Babble) at different SNR (0-20 dB), as well as the original voxceleb1 test set. Four different scenarios are tested: only use SID-Net (SID); The SE-Net and SID-Net joint system but not include multi-stage attention (SE+SID); The SE-Net and SID-Net joint system, only SE-Net use multi-stage attention (SE-MS+SID); The SE-Net and SID-Net joint system, only SID-Net use multi-stage attention (SE+SID-MS). The results of VoiceID Loss [10] is also listed.

| Noise Type | SNR | SID | VoiceID Loss [10] | SE+SID | SE-MS+SID | SE+SID-MS |
|------------|-----|-----|-------------------|--------|-----------|-----------|
|            |     | EER (%) | DCF | EER (%) | DCF | EER (%) | DCF | EER (%) | DCF |
| Noise      | 0   | 16.94 | 0.933 | 16.56 | 0.938 | 16.20 | 0.912 | 15.95 | 0.901 | 16.13 | 0.908 |
|            | 5   | 12.48 | 0.855 | 12.26 | 0.830 | 11.99 | 0.819 | 11.76 | 0.805 | 11.78 | 0.812 |
|            | 10  | 10.03 | 0.760 | 9.86  | 0.747 | 9.54  | 0.732 | 9.17  | 0.717 | 9.29  | 0.727 |
|            | 15  | 8.84  | 0.648 | 8.69  | 0.686 | 8.48  | 0.665 | 8.08  | 0.639 | 8.10  | 0.641 |
|            | 20  | 7.96  | 0.594 | 7.836 | 0.639 | 7.52  | 0.629 | 7.07  | 0.615 | 7.09  | 0.623 |
| Music      | 0   | 17.04 | 0.940 | 16.24 | 0.913 | 15.96 | 0.901 | 15.58 | 0.899 | 15.89 | 0.904 |
|            | 5   | 11.54 | 0.828 | 11.44 | 0.818 | 11.15 | 0.805 | 10.93 | 0.791 | 11.04 | 0.801 |
|            | 10  | 9.69  | 0.749 | 9.13  | 0.733 | 9.12  | 0.731 | 8.67  | 0.714 | 8.97  | 0.725 |
|            | 15  | 8.40  | 0.689 | 8.10  | 0.677 | 8.08  | 0.643 | 7.62  | 0.621 | 7.77  | 0.629 |
|            | 20  | 7.70  | 0.665 | 7.48  | 0.635 | 7.39  | 0.619 | 7.13  | 0.607 | 7.26  | 0.614 |
| Babble     | 0   | 38.90 | 1.000 | 37.96 | 1.000 | 37.53 | 0.999 | 37.55 | 0.999 | 37.46 | 0.998 |
|            | 5   | 28.04 | 0.998 | 27.12 | 0.996 | 26.97 | 0.979 | 26.42 | 0.981 | 26.35 | 0.977 |
|            | 10  | 17.34 | 0.917 | 16.66 | 0.926 | 16.44 | 0.911 | 16.30 | 0.907 | 16.36 | 0.911 |
|            | 15  | 11.31 | 0.795 | 11.25 | 0.807 | 11.24 | 0.801 | 10.89 | 0.795 | 10.94 | 0.801 |
|            | 20  | 9.12  | 0.720 | 8.99  | 0.705 | 8.77  | 0.695 | 8.39  | 0.677 | 8.51  | 0.688 |
| Original   | 6.92 | 0.565 | 6.79  | 0.574 | 6.41  | 0.541 | 6.18  | 0.528 | 6.26  | 0.535 |

The SE-Net and SID-Net joint system, only SID-Net use multi-stage attention (SE+SID-MS). The results of VoiceID Loss [10] is also listed.

Table 6: Speaker Identification and Verification results of SE-MS+SID-MS.

| Noise Type | SNR | SE-MS+SID-MS |
|------------|-----|--------------|
|            |     | Top-1 (%) | Top-5 (%) | EER (%) | DCF |
| Noise      | 0   | 79.2      | 91.0      | 15.62   | 0.899 |
|            | 5   | 84.2      | 92.7      | 11.61   | 0.798 |
|            | 10  | 88.2      | 96.2      | 9.05    | 0.707 |
|            | 15  | 90.1      | 96.9      | 8.01    | 0.621 |
|            | 20  | 91.4      | 97.5      | 6.98    | 0.604 |
| Music      | 0   | 71.7      | 86.0      | 15.35   | 0.881 |
|            | 5   | 82.3      | 92.2      | 10.64   | 0.780 |
|            | 10  | 87.2      | 96.1      | 8.77    | 0.709 |
|            | 15  | 90.0      | 97.2      | 7.55    | 0.615 |
|            | 20  | 90.8      | 97.6      | 7.09    | 0.601 |
| Babble     | 0   | 68.6      | 85.1      | 37.44   | 0.998 |
|            | 5   | 81.8      | 90.4      | 26.28   | 0.996 |
|            | 10  | 87.4      | 95.2      | 16.25   | 0.899 |
|            | 15  | 89.1      | 95.5      | 10.74   | 0.784 |
|            | 20  | 89.7      | 96.1      | 8.23    | 0.662 |
| Original   | 92.3 | 98.0      | 6.12      | 0.511   |

Table 6: Speaker Identification and Verification results of SE-MS+SID-MS.

The nomenclature shows the contribution of SE-MS+SID is bigger than SE-SID+MS to the final accuracy. The MS module added in SE module obtains better recognition results.
5. Conclusion and Future Work

In this paper, a joint optimisation by cascading the speech enhancement network and speaker recognition network was implemented in order to improve speaker identification and verification performance in different poor acoustic environments. Furthermore, a multi-stage attention model also used in either the speech enhancement or speaker recognition module to highlight speaker relevant information. It is clear that the use of speech enhancement can yield better performances than the only use of speaker identification model. Moreover, joint optimisation and the use of attention model can further increase the robustness of our system against the interferences caused by different types of noise.

In the future work, Different order of the channel, frequency and time attentions in MS module will be investigated. More advanced speech enhancement technologies and training strategy such as adversarial training will be investigated. Post-processing techniques for speaker embeddings such as PLDA back-end will also be taken into account.

6. References

[1] Arnab Poddar, Md Sahidullah, and Goutam Saha, “Speaker verification with short utterances: a review of challenges, trends and opportunities,” IET Biometrics, 2017.

[2] Ehsan Variani, Xin Lei, Erik McDermott, Ignacio Lopez Moreno, and Javier Gonzalez-Dominguez, “Deep neural networks for small footprint text-dependent speaker verification,” in ICASSP. IEEE, 2014.

[3] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition,” in ICASSP. IEEE, 2018.

[4] Simon Leglaive, Umut Şimşekli, Antoine Liutkus, Laurent Girin, and Radu Horaud, “Speech enhancement with variational autoencoders and alpha-stable distributions,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 541–545.

[5] Mostafa Sadeghi, Simon Leglaive, Xavier Alameda-Pineda, Laurent Girin, and Radu Horaud, “Audio-visual speech enhancement using conditional variational auto-encoder,” arXiv preprint arXiv:1908.02590, 2019.

[6] Insoo Jang, ChungHyun Ahn, Jeongil Seo, and Younson Jeong, “Enhanced feature extraction for speech detection in media audio,” in INTERSPEECH, 2017, pp. 479–483.

[7] Gholamreza Farahani, Seyed Mohammad Ahadi, and Mohammad Mehdi Homayounpour, “Robust feature extraction of speech via noise reduction in autocorrelation domain,” in International Workshop on Multimedia Content Representation, Classification and Security. Springer, 2006, pp. 466–473.

[8] Lara Nahma, Pei Chee Yong, Hai Huyen Dam, and Sven Nordholm, “An adaptive a priori snr estimator for perceptual speech enhancement,” EURASIP Journal on Audio, Speech, and Music Processing, vol. 2019, no. 1, pp. 7, 2019.

[9] Rui Yao, ZeQing Zeng, and Ping Zhu, “A priori snr estimation and noise estimation for speech enhancement,” EURASIP journal on advances in signal processing, vol. 2016, no. 1, pp. 101, 2016.

[10] Suwon Shon, Hao Tang, and James Glass, “Voiceid loss: Speech enhancement for speaker verification,” arXiv preprint arXiv:1904.03601, 2019.

[11] FA Rezaur rahman Chowdhury, Quan Wang, Ignacio Lopez Moreno, and Li Wan, “Attention-based models for text-dependent speaker verification,” in ICASSP. IEEE, 2018.

[12] Yingke Zhu, Tom Ko, David Snyder, Brian Mak, and Daniel Povey, “Self-attentive speaker embeddings for text-independent speaker verification,” in Interspeech, 2018.

[13] Miquel India, Pooyan Safari, and Javier Hernandez, “Self multi-head attention for speaker recognition,” arXiv preprint arXiv:1906.09890, 2019.

[14] Nguyen Nang An, Nguyen Quang Thanh, and Yanbing Liu, “Deep cnns with self-attention for speaker identification,” IEEE Access, 2019.

[15] Qiongqiong Wang, Koji Okabe, Hong Aik Lee, Hitoshi Yamamoto, and Takafumi Koshinaka, “Attention mechanism in speaker recognition: What does it learn in deep speaker embedding?” in 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018.

[16] Niko Moritz, Takaaki Hori, and Jonathan Le Roux, “Triggered attention for end-to-end speech recognition,” in ICASSP. IEEE, 2019.

[17] Seyedmahdad Mirsamadi, Emad Barsoum, and Cha Zhang, “Automatic speech emotion recognition using recurrent neural networks with local attention,” in ICASSP. IEEE, 2017.

[18] Yuanzhuang Zhang, Jun Du, Zirui Wang, Jianshu Zhang, and Yanhui Tu, “Attention based fully convolutional network for speech emotion recognition,” in APSIPA ASC. IEEE, 2018.

[19] Jan K Chorowski, Dzmitry Bahdanau, Dmitriy Serdyuk, Kyunghyun Cho, and Yoshua Bengio, “Attention-based models for speech recognition,” in Advances in neural information processing systems, 2015.

[20] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio, “Neural machine translation by jointly learning to align and translate,” arXiv:1409.0473, 2014.

[21] Minh-Thang Luong, Hieu Pham, and Christopher D Manning, “Effective approaches to attention-based neural machine translation,” arXiv:1508.04025, 2015.

[22] Jianpeng Cheng, Li Dong, and Mirella Lapata, “Long short-term memory-networks for machine reading,” in Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, 2016, pp. 551–561.

[23] Sanghyun Woo, Jongchan Park, Joon-Young Lee, and Seokhun Cho, “Cham: Convolutional block attention module,” in ECCV, 2018.

[24] Jie Hu, Li Shen, and Gang Sun, “Squeeze-and-excitation networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 7132–7141.

[25] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Voxceleb: a large-scale speaker identification dataset,” arXiv preprint arXiv:1706.08612, 2017.
[26] David Snyder, Guoguo Chen, and Daniel Povey, “Musan: A music, speech, and noise corpus,” arXiv preprint arXiv:1510.08484, 2015.

[27] Mahdi Hajibabaei and Dengxin Dai, “Unified hypersphere embedding for speaker recognition,” arXiv preprint arXiv:1807.08312, 2018.

[28] Jyh-Min Cheng and Hsiao-Chuan Wang, “A method of estimating the equal error rate for automatic speaker verification,” in 2004 International Symposium on Chinese Spoken Language Processing. IEEE, 2004, pp. 285–288.

[29] David A Van Leeuwen and Niko Brümmer, “An introduction to application-independent evaluation of speaker recognition systems,” in Speaker classification I, pp. 330–353. Springer, 2007.

[30] Weidi Xie, Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Utterance-level aggregation for speaker recognition in the wild,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 5791–5795.

[31] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[32] Diederik P Kingma and Jimmy Lei Ba, “Adam: A method for stochastic optimization,” .