ResNeXt and Res2Net Structure for Speaker Verification

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Abstract

ResNet-based architecture has been widely adopted as the speaker embedding extractor in speaker verification system. Its standard topology and modularized design ease the human efforts on hyper parameter tuning. Therefore, width and depth are left as two major dimensions to further improve ResNet’s representation power. However, simply increasing width or depth is not efficient. In this paper, we investigate the effectiveness of two new structures, i.e., ResNeXt and Res2Net, for speaker verification task. They introduce another two effective dimensions to improve model’s representation capacity, called cardinality and scale, respectively. Experimental results on VoxCeleb data demonstrated increasing these two dimensions is more efficient than going deeper or wider. Experiments on two internal test sets with mismatched acoustic conditions also proved the generalization of ResNeXt and Res2Net architecture. Particularly, with Res2Net structure, our best model achieved state-of-the-art performance on VoxCeleb1 test set by reducing the EER by 18.5% relative. In addition, our system’s modeling power for short utterances has been largely improved as a result of Res2Net module’s multi-scale feature representation ability.

Index Terms: speaker verification, ResNeXt, Res2Net

1. Introduction

Speaker verification (SV) refers to the task of verifying a person’s identity by voice. It usually requires the target speaker to enroll into the system using several recorded sentences. After receiving a test recording, SV system compares the similarity between the enrollment and test utterance to make a decision, i.e., acceptance or rejection. According to different application scenarios, SV can be categorized as text-dependent speaker verification (TDSV) and text-independent speaker verification (TISV). For TDSV, the spoken content of test utterance should also match the content in enrollment, while TISV system does not have this constraint.

In the past few years, the architecture of SV system has undergone a transformation from human designed subsystems [9, 10] to end-to-end frameworks. Many studies [9, 11-14] has demonstrated the usability and capacity of different deep neural network structures. Most recently, ResNet-based [9] convolutional network has been widely adopted as the backbone structure for SV system. It exhibits strong ability to model local time domain and frequency domain patterns. [10, 11, 12, 13, 14] all showed ResNet-based architecture is able to achieve promising results under challenging real-life conditions.

However, with the growth of training data size and mismatched acoustic environment in test conditions, there is an increased demand for SV system with stronger representation power. For ResNet structure, there are two essential dimensions controlling model’s capacity, i.e., width and depth. Nevertheless, simply going deeper or wider is not efficient. Besides, it could easily fall into overfitting due to huge amount of parameters. Researchers from visual recognition have been investigating this topic for years. They proposed several modified structures [15, 16, 17, 18] to maximize feature utilization and achieve better performance with fewer parameters.

In this paper, we intend to incorporate ResNeXt [16] and Res2Net [18] structure into our SV system given their encouraging performance on visual tasks and extensible design. ResNeXt replaces the residual block in ResNet with a multi-branch transformation, introducing many groups of convolution in one layer. Res2Net also focus on the redesign of residual block. It constructs hierarchical residual-like connections inside the residual block and provides multiple available receptive fields within one layer. Except for width and depth, ResNetXt and Res2Net expose two additional dimensions, called cardinality and scale respectively. Experimental results on VoxCeleb data show that increasing cardinality is more efficient than going deeper or wider. In addition, increasing scale is even more powerful than the other three dimensions. Experiments on our two internal test sets also proved the effectiveness of these two methods.

We further truncated the original VoxCeleb test set into 2-4s segments. Experiments show the multi-scale feature representation ability in Res2Net could largely boost the performance for short utterances. Visualization of Res2Net’s class activation mapping implies the robustness towards background noise.

The rest of this paper is organized as follows: Section 2 describes the fundamental components of our ResNet-based speaker verification baseline system. Section 3 introduces the detailed implementation of ResNeXt block and Res2Net block in our system. Experimental results are discussed in Section 4. In Section 5 we conclude this paper and present future work.

2. ResNet-based Speaker Embedding

In this section, we describe four fundamental components in our end-to-end speaker verification system. First of all, we apply an utterance-level normalization operation to input features. Then a ResNet is utilized to perceive feature patterns and generate frame-level speaker representations. In order to produce fixed length utterance-level speaker embedding from variable length observations, an attentive pooling layer is added. Lastly, a speaker-discriminative criterion is selected to guide the learning.

2.1. Utterance-level mean normalization

According to the experimental results in [19], applying utterance-level mean normalization to input features can improve model robustness towards mismatched acoustic environment in test condition. However, variance normalization does not help. Therefore, in our system, only mean normalization is used.

Given an input sequence \{m_1, m_2, ..., m_T\}, we first calculate the mean \(\mu\) along the temporal axis, and then normalize...
the inputs as follows:

\[
\mu = \frac{1}{T} \sum_{t=1}^{T} m_t \quad (1)
\]

\[
\hat{m}_t = m_t - \mu \quad (2)
\]

where \( \hat{m}_t \) is the normalized inputs; we then feed it into the following neural network.

2.2. Network architecture

Our network structure is same with the baseline system in [14] with increased channel size. We use 80-dimensional log filter banks as input feature and the speaker embedding has a dimension of 128.

2.3. Multi-head attentive pooling

As reported in our previous work [14], attentive pooling has the potential to actively select speaker-discriminative frames. With multiple attention heads, we can further improve system performance. In this work, we still apply the multi-head attentive pooling as our aggregation approach. In consideration of the tradeoff between performance and model complexity, the number of attention heads is set to 16. Implementation and other hyper parameters stay the same with the ones in [14].

2.4. Training criterion

In order to directly compare the representation power of different model structures, we didn’t employ any modified softmax criteria or other discriminative loss functions. During the training phase, after extracting the utterance-level speaker embedding, we feed it into a classification layer and use the naive softmax loss.

3. Residual block

ResNet is a highly modularized architecture. Modules with same topology are stacked together to construct networks. In this case, less hyper parameters are exposed for tuning, potentially retain the robustness and generalization of ResNet structure. Therefore, depth and width become two major dimensions for adjusting ResNet structure to fitting a specific training set. Generally speaking, model with more parameters possesses stronger representation power. However, directly going deeper or wider is not efficient. Besides, it could easily fall into over-fitting due to huge amount of parameters. Two structures are proposed to redesign the basic blocks in ResNet.

3.1. ResNeXt block

ResNeXt [16] structure is also designed in a modular manner. The ResNeXt blocks all share same topology and can be easily stacked to construct desired network. In Figure 1(a) shows the basic block in ResNet structure and (b) shows the ResNeXt block implemented as grouped convolutions. [16] has demonstrated applying aggregating transformations to a basic block only makes it wider, which is not the nontrivial topology we want. As a result, we start with bottleneck block (depth = 3). In Figure 1(b), the second convolutional layer is a multi-branch transformation with a hyper parameter \( C \), called cardinality. It’s a new essential dimension and [16] showed increasing cardinality is more effective and efficient than going wider or deeper.

3.2. Res2Net block

Res2Net [18] architecture aims at improving multi-scale representation ability by increasing the number of available receptive fields. In order to modify the basic block in our baseline ResNet structure into Res2Net block, we keep the first \( 3 \times 3 \) layer and replace the second one with a Res2Net module, as shown in Figure 1(c). Figure 1(d) illustrates the design of Res2Net module. After going through the first \( 3 \times 3 \) layer, feature maps are evenly sliced into \( s \) subsets, denoted by \( \{ x_1, x_2, ..., x_s \} \). Each subset is then fed into a \( 3 \times 3 \) convolution (denoted by \( K_s \)), except for \( x_1 \). Starting from \( x_3 \), each output of \( K_{s-1} \) is added with \( x_2 \) before going through \( K_s \). This hierarchical residual-like connection further increases the possible receptive fields within one layer, resulting in multiple feature scales. The whole process can be formulated as

\[
y_i = \begin{cases} 
  x_i, & i = 1; \\
  K_s(x_i), & i = 2; \\
  K_s(x_i + y_{i-1}), & i = 3, 4, ..., s 
\end{cases} \quad (3)
\]

where \( \{ y_1, y_2, ..., y_s \} \) is the output of this module, they are concatenated and fed into the following \( 1 \times 1 \) convolutional layer to maintain the channel size of this residual block.

In [18], \( s \) refers to scale. Authors proved increasing this new dimension is more effective than other dimensions (width, depth and cardinality).

4. Experiments

4.1. Dataset Description

VoxCeleb: VoxCeleb [11, 12] is a public text-independent dataset with real-life conversational speech collected in unconstrained conditions. It contains diverse acoustic environments for each speaker, making it a more challenging task than telephone recordings or clean speech. All of our models are trained with 5994 speakers from VoxCeleb2-dev part, augmented by Kaldi’s simulation algorithm. The VoxCeleb1-test part is used for evaluation with 40 speakers.

MS-SV test set: This is an internal set collected for the experimental purpose of text-independent speaker verification (SV). Each participant is enrolled by reading a short paragraph
through a close microphone. Then we recorded their daily interactions in several Microsoft meeting rooms through far field microphones and post-processed as SV test set. The set contains around 150 speakers. Utterance duration ranges from 2-15s (about 4s in average). The test set is an extended version of the MS-SV test set used in [19] with more speakers and improved front-end processing.

**Cortana test set:** This is another internal set recorded for text-dependent speaker verification. Each participant is asked to read a list of commands prefixed with the 'Cortana' keyword under various environments with different recording distances. Then the utterances recorded in clean condition, 1m away from the device, are selected as the enrollment. We only keep the 'Cortana' part as our test utterance by using a CTC-based keyword detector. 'Cortana' part itself has a duration of 0.65 to 1.1 seconds. It’s cropped by shifting the CTC endpoint backward 1.5s and forward 2s, resulting in average length of 3s for processed test utterances. This set contains around 183 speakers.

### 4.2. Experiments on VoxCeleb1 test set

#### 4.2.1. Regular test set

Table 1 shows the performance of different residual blocks on VoxCeleb1 test set. \(w\) refers to the base width of each \(3 \times 3\) convolution inside ResNeXt or Res2Net module. We can adjust \(w\) to preserve model complexity when increasing cardinality or scale. In the condition of preserved complexity, ResNeXt and Res2Net have already outperformed ResNet.

Table 1: Evaluation results with different model structures. EERs are reported on VoxCeleb1-test. Notation for model: \((w: \text{base width}; c: \text{cardinality}; s: \text{scale})\)

| Complexity | Model               | Size  | EER(%) |
|------------|---------------------|-------|--------|
| Preserved  | ResNet              | 20.6M | 1.78   |
|            | ResNeXt-40w4c       | 21.4M | 1.69   |
|            | ResNeXt-26w8c       | 21.0M | 1.77   |
|            | ResNeXt-12w32c      | 23.5M | 1.69   |
|            | Res2Net-48w2s       | 22.0M | 1.75   |
|            | Res2Net-26w4s       | 22.5M | 1.68   |
|            | Res2Net-14w8s       | 22.4M | 1.60   |
| Increased  | ResNet-deep         | 29.7M | 1.77   |
|            | ResNet-wide         | 30.8M | 1.81   |
|            | ResNeXt-20w32c      | 40.7M | 1.61   |
|            | Res2Net-26w6s       | 29.8M | 1.51   |
|            | Res2Net-26w8s       | 37.1M | 1.45   |

When we increase the model complexity by 50%, comparing 'ResNet-deep', 'ResNet-wide' and 'Res2Net-26w6s', going deeper or wider with this amount of parameter boost doesn’t help. Especially for 'ResNet-wide', it shows the sign of overfitting. However, 'Res2Net-26w6s' still decreases EER. When we increase the model complexity by around 100%, 'Res2Net-26w8s' achieves even lower EER, outperforming the baseline 'ResNet' by 18.5% relative. From these experiments, we can conclude increasing cardinality is more efficient than doing deeper or wider while increasing scale is even more efficient than all of them.

Furthermore, the training accuracy of 'ResNeXt-20w32c', 'Res2Net-26w8s' and 'ResNet' are 99.11%, 99.07% and 98.41% respectively. This implies the gain is not come from better regularization, but stronger representation power.

#### 4.2.2. Truncated test set

The utterances in regular VoxCeleb1-test set have an average duration of 8s. In order to test the multi-scale feature representation ability of Res2Net structure, we keep the regular VoxCeleb1-test trial file, but truncate each test utterance into shorter segments of 2s, 3s and 4s, from the beginning of it. Table 2 shows that the performance all degrades considerably on short segments. However, ResNeXt and Res2Net still outperform ResNet in this challenging condition. Particularly, if we compare Res2Net with ResNet baseline, the EER reduction for 2s, 3s, 4s is 17.6%, 19.1%, and 13.7%, respectively. Res2Net structure exhibits great potential in representing short utterances.

Table 2: Evaluation results with different model structures. EER(%) is reported on VoxCeleb1-test truncated set.

| Model              | 2s  | 3s  | 4s  | Regular |
|--------------------|-----|-----|-----|---------|
| ResNet             | 6.77| 3.78| 2.49| 1.78    |
| ResNeXt-20w32c     | 6.26| 3.35| 2.35| 1.61    |
| Res2Net-26w8s      | 5.58| 3.06| 2.15| 1.45    |

#### 4.3. Experiments on text-independent MS-SV test set

In order to examine the generalization of new models, we apply the models trained with VoxCeleb data to a mismatched text-independent scenario. As shown in Table 2, we split the trials into three groups in terms of duration. Res2Net shows better generalization over ResNeXt, with 8.4% (5.28% – 4.84%) relative reduction in the overall EER over the ResNet baseline.

Table 3: Evaluation results with different model structures. EER(%) is reported on MS-SV test set.

| Model              | 1-2s | 2-4s | >4s  | Overall  |
|--------------------|------|------|------|----------|
| ResNet             | 7.66 | 3.67 | 2.11 | 5.28     |
| ResNeXt-20w32c     | 7.42 | 3.63 | 2.04 | 5.11     |
| Res2Net-26w8s      | 6.77 | 3.32 | 2.03 | 4.84     |

The results of different duration intervals are also consistent with what we have observed on VoxCeleb1 test set. A breakdown of EER by test utterance length shows that Res2Net model is capable of producing more powerful speaker representations from very short speech segments. The relative improvement over ResNet is 11.52%, 9.34%, and 3.84% for interval 1-2s, 2-4s, and >4s, respectively.

#### 4.4. Experiments on text-dependent Cortana test set

We also conduct some experiments on the text-dependent Cortana test set. For convenience, we still use the aforementioned models trained on VoxCeleb data. As a result, the spoken content between the training and test data is mismatched, but the text between the enrollment and test utterance is matched.

Table 3 shows the overall EER and a breakdown of the performance in terms of noise conditions and distance to microphones. The Res2Net outperforms the ResNet by 4.6%
Figure 2: (a) CAM of “id00018-r377L5cuPOw-00144”; (b) CAM of “id00018-r377L5cuPOw-00144-noise”.

(4.40% → 4.20) relative in the overall EER. Specifically, the Res2Net improves over the ResNet by 11.4%, 11.1% in quiet, TV conditions, respectively. ResNeXt performs worse than the ResNet. We conjecture that the ResNeXt model is less robust than Res2Net to the mismatched conditions.

Table 4: Evaluation results with different model structures. EER(%) is reported on Cortana test set

| Model         | Condition | Distance | Total  |
|---------------|-----------|----------|--------|
|               | Quiet     | TV       | 1m     | 3m     | 5m     |       |
| ResNet        | 3.26      | 5.91     | 3.11   | 4.62   | 5.51   | 4.40  |
| ResNeXt-20w32c| 3.31      | 5.80     | 2.95   | 5.11   | 5.26   | 4.61  |
| Res2Net-26w8s | 2.88      | 5.25     | 2.71   | 4.21   | 4.85   | 4.20  |

4.5. Visualization

Inspired by the class activation mapping (CAM) analysis in [18], we intend to provide some intuitive insights into the capacity of Res2Net model on speech data. We picked an utterance in clean condition as well as its simulated version with telephone ring noise. We feed two utterances into ResNet and Res2Net separately and plot the CAM using Grad-CAM [20].

As shown in Figure 2 for clean speech, Res2Net CAM is more concentrated than ResNet CAM. The latter spreads over most parts of input features, including non-speech part. For the noise-corrupted speech, Res2Net CAM shows less changes on the activation map. In addition, compared with the Res2Net CAM in clean condition, the remaining speech part is further emphasized. This example may help us understand the capacity of Res2Net structure. It might have the potential to extract more invariant feature representations and recognize speakers in adverse environments.

5. Conclusions

In this paper, we investigate the effectiveness of ResNeXt and Res2Net architecture on speaker verification task. Experimental results on VoxCeleb data demonstrate their strong representation power. As both of them outperform ResNet baseline, Res2Net exhibits even stronger capacity. It keeps improving system performance for short utterances and mismatched scenarios. Experiments on two internal test sets provide us more confidence on the generalization of Res2Net model. Future work would be incorporating ResNeXt and Res2Net structure with discriminative loss or additional phonetic information.

6. References

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