DYNAMIC KERNELS AND CHANNEL ATTENTION WITH MULTI-LAYER EMBEDDING AGGREGATION FOR SPEAKER VERIFICATION

Anna Ollerenshaw, Md Asif Jalal, Thomas Hain

Speech and Hearing Group, The University of Sheffield, Sheffield, UK

ABSTRACT

State-of-the-art speaker verification frameworks have typically focused on speech enhancement techniques with increasingly deeper (more layers) and wider (number of channels) models to improve their verification performance. Instead, this paper proposes an approach to increase the model resolution capability using attention-based dynamic kernels in a convolutional neural network to adapt the model parameters to be feature-conditioned. The attention weights on the kernels are further distilled by channel attention and multi-layer feature aggregation to learn global features from speech. This approach provides an efficient solution to improving representation capacity with lower data resources. This is due to the self-adaptation to inputs of the structures of the model parameters. The proposed dynamic convolutional model achieved 1.62% EER and 0.18 miniDCF on the VoxCeleb1 test set and has a 17% relative improvement compared to the ECAPA-TDNN.

Index Terms— Speaker verification, speaker identification, automatic speech recognition, x vector, convolutional neural network

1. INTRODUCTION

Speaker verification (SV) aims to identify a speaker typically from an unlabeled sample of speech. This task involves measuring the similarity between a test speaker’s acoustic embedding and the already enrolled target speaker embedding. This similarity is typically evaluated using distance metrics such as cosine distance or Probabilistic Linear Discriminant Analysis (PLDA). The main objective of an SV framework is to learn generalised global characteristics from speaker acoustics. Many current approaches use combinations of deep neural networks (DNNs) trained for utterance classification based upon learned features that correspond with the speaker’s identity. I-vectors [1] provide a fixed representation over the speaker acoustics; x-vectors [2] became the following state-of-the-art method for speaker representations, noting that the CNN-based models have typically produced better performance with fewer number of parameters than RNNs [3].

The current state-of-the-art SV architectures use Time Delay Neural Networks (TDNN) and attention mechanisms in the convolutional channel outputs, which further improved the performance results [6]. However SV is still a challenging and computationally demanding task, especially in poor acoustic conditions. Large models that have been pre-trained using huge datasets perform well [8]; however, training and serving these models is becoming increasingly computationally demanding. Work by [2] introduced the CNN-ECAPA-TDNN where the convolutional front-end allows the network to construct local, frequency invariant features to integrate frequency positional information. In order to enable the network to be invariant to small shifts in the frequency domain and to compensate for the potential intra-speaker variability, 2D convolutions are used to model at a higher resolution. However, this approach also uses large amounts of training data, where typically first a pretrained large-scale model is used to then be fine-tuned for state-of-the-art results. The ResNet-based models [3] can suffer from overfitting due to the increases in layer dimensionality and it can also take an excessive amount of time and computational resources to fine-tune the hyperparameters to improve the performance.

The general trend for CNN based architectures has been to increase the depth and complexity of the network, while simultaneously increasing training data size for improved accuracy [10][11]. However, considering the challenges for modelling speech data, it is becoming necessary to make systems that are more efficient with regard to size and training speed. The main contribution of this paper is to integrate attention-based dynamic kernels for convolutions for a speaker verification task, which has not previously been explored. The proposed approach uses parallel dynamic convolutional kernels described in [7] which are able to adjust parameters dependent upon the input attention. Dynamic kernels have shown promising potential for boosting the model representation capabilities without increasing the computational cost [12].

The proposed model builds upon the original ResNet model [3], which uses a 2D CNN based approach. This method can also be integrated into other CNN-based approaches, such as the CNN-ECAPA-TDNN for further improved SV performance without the requirement for larger or pretrained models. The main motivation for using this approach is to improve representation capacity, which is shown in the following experiments to improve verification performance without increasing the computation. This is possible with the dynamic convolution approach as the kernels share the output channels, and it is observed to outperform similar models with increased layers, parameters and training data. Section [5,4] discusses the results of the experimental models with additional details regarding the average computation time of each epoch.
2. FRAMEWORK ARCHITECTURES

2.1. X-Vector and ResNet Models

The x-vector model, described in [2], was developed to replace the original text-independent i-vector method, using a fully connected DNN to capture long-term dependencies to aid speaker discrimination. The architecture uses pooling layers that aggregate over the frame-level representations. The input features are spliced across the first few layers of the DNN. As the input is variable length, statistics pooling layer computes the mean and standard deviation of the frame-level representations. A PLDA backend, separately trained, is used to compare embedded pairs.

ResNet-34 models such as [13] and [14] contain 4 residual blocks between a frame-level representation extraction module and an utterance-level aggregator. The outputs of the residual blocks are fed to attention modules which attempt to learn the channel dependencies prior to the skip connections. Frame-level speaker representations are encoded into fixed-length utterance level representations by the aggregator and classified with a softmax layer.

2.2. Dynamic Convolution Kernels

The dynamic convolution approach proposed in [15], is a technique developed to increase the model resolution capability without requirements for increasing the model depth or width to improve accuracy. Dynamic in this case refers to the combination of kernels for the changing input sequence by the application of input dependent attention weighting. This is integrated by aggregating parallel convolution kernels based on their attention weights, shown in the res_conv of Figure 1. Using a dynamic approach, models from other domains, such as image recognition, have been shown to have greater feature representation capacity for image classification and human pose estimation, while also being more computationally efficient due to the kernels sharing the output channels compared to the typical static convolutional models.

\[ y = f(\tilde{W}^T(x)x + \tilde{b}(x)) \]  

where:

\[ \tilde{W}(x) = \sum_{k=1}^{K} \alpha_k(x)\tilde{W}_k \]  

and:

\[ \tilde{b}(x) = \sum_{k=1}^{K} \alpha_k(x)\tilde{b}_k \]  

In Equations 2 and 3, \( \alpha_k \) refers to the attention weight for the \( k^{th} \) linear function where \( 0 \leq \alpha_k(x) \leq 1 \) and \( \sum_{k=1}^{K} \alpha_k(x) = 1 \).

Squeeze and excitation [16] is applied to compute the kernel attentions, where the global spatial information is squeezed by average pooling. Due to small parallel kernel sizes and shared output channels, the aggregation of convolution kernels is computationally efficient. As joint optimisation is required for all kernels and the attention model, through multiple layers; the fully connected layers have a ReLU function between them and are then normalised with a softmax function for \( K \) convolution kernels. Finally, after the attention weights are compiled, batch normalisation is conducted on the output, followed by the final ReLU function. The dynamic convolution block is denoted by the term \( \text{dconv} \) in this paper and the \( \text{dconv} \) architecture is shown in Figure 2.

2.3. Hierarchical Feature Aggregation Method for Speaker Verification

Building upon the original x-vector model, the ECAPA-TDNN [6] used hierarchically grouped convolutions rather than 1-dimensional convolutions. In this paper, embeddings from multi-layer dynamic kernel convolutions are concatenated, as shown in Figure 3. The input features are separately chunked and fed into hierarchical layers connected with skip connections before passing to the squeeze and excitation blocks. The main motivation for using a skip connection is that is a method of compensation to collect information from previous layers and thereby the features learned by the current layer. This enables the construction of models without the need to increase the model size (number of layers, dimensionality of layers) as the model should be able to learn saliency regions. The ResNet architecture proposed in [5] was inspired by VGG nets [10] and consists of multiple stacked convolutional layers with residual connections. The representation capacity of this ResNet architecture is determined by the model width and depth (number of layers).

\( \text{dconv} \) squeeze and excitation blocks were used which adjust the context bound frame-level features per channel over time according to the global utterance properties. The following pooling layer uses...
where $\alpha_k$ refers to attention weights for the $k^{th}$ linear function. The weighted standard deviation of the channel $\tilde{C}$ is shown in Equation 4. The output of the attention pooling layer is a concatenation of the weights $\tilde{W}$ and the standard deviation.

$$\tilde{C} = \sqrt{\frac{1}{K} \sum_{k=1}^{K} \alpha_k(x) \tilde{b}_k^2 - \tilde{W}(x)^2}$$

3. EXPERIMENTS

To map the voice spectograms into compact embeddings for computation, relatively shallow dconv models were constructed. Models were built with varying layer dimensions and depth, shown in Table 1 to control the parameter computation and observe the impact upon verification performance, shown in Table 2. The training data for each model was augmented, as described in Section 3.2 as this has been shown to create sparsity and attempts to improve generalisation. The cosine distance between the vectors in the embedding space is used to measure the similarity scores.

### 3.1. Dataset

The development set and evaluation set for VoxCeleb [17] contain both monaural multi-speaker recordings taken from professionally edited Youtube videos, and general conversation. There are numerous challenging aspects that affect recognition within the dataset such as overlapping speech, background noise, music, laughter, applause and singing. The training and development set is split into 1,211 speakers and the testing set is split into 40 speakers for VoxCeleb1-O. The total number of utterances is 153,516 with 116 per speaker on average. Comparative cited research for speaker verification tasks also use the considerably larger VoxCeleb2 dataset [14] for training, which contains 6112 speakers and a total of 1,128,246 utterances, however these training and serving models with this data is computationally expensive, as explored in Section 3.4.

### 3.2. Data Augmentation

After showing promising results in [18], frequency and time domain data augmentation was performed for all models using Spectaument [19]. This was used to attempt to increase the amount of diversity in the training data and improve model generalisation. Reverberation was convoluted with the original speech using the RIRs from [20]. The augmentations were randomly chosen between babble, music, noise and reverberation.

### 3.3. Implementation Details

All models were trained with mean normalised 80-dimensional log Mel filterbank coefficients obtained with a 25ms window and 10ms frame shift. The spectograms were normalised by mean and variance on the frequency axis. Random 3 second segments were taken as mini-batches to form an input dimension of $80 \times 300$.

The models were implemented using the PyTorch-based Speechbrain framework [21] and run on 1 NVIDIA RTX3060 GPU over 10 epochs. The main model pipeline is shown in Figure 1. The details of the model compositions are described in Table 1 where variations of the dconv models were built with two size dimensions of layers; 1024 and 512 dimensions, at depths of 3, 4 and a version with 5 layers. The number of attention channels for all models remained at 128 and 192 linear neurons. Adam optimisation was used to initialise the network parameters. Each setup’s learning rate was set at $0.01 \times 10^{-6}$ with a learning decay of $2 \times 10^{-6}$ up to a value of $0.001$. The similarity scores were verified using the cosine distance metric.

### Table 1: Architecture of dconv model implementations

| Layer Name | Channels | Kernel | Dilation |
|------------|----------|--------|----------|
| Dconv-3 (small) | 512 | 5,3,1 | 1,2,1 |
| Dconv-3 | 1024 | 5,3,1 | 1,2,1 |
| Dconv-4 (small) | 512 (1024) | 5,3,3,1 | 1,2,3,1 |
| Dconv-4 | 1024 (2048) | 5,3,3,1 | 1,2,3,1 |
| Dconv-5 | 1024 (3072) | 5,3,3,3,1 | 1,2,3,4,1 |
Table 2: Experimental results tested on VoxCeleb1-O test set

| Model       | Vox1-O EER% | Training set | Vox 1 | Vox 2 | Params |
|-------------|-------------|--------------|-------|-------|--------|
| ResNet-34 22 | 10.48       | ✓            | ✓     | ✓     | 10m    |
| VGG-M 17    | 10.2        | ✓            | x     | 67m   |
| ResNet-34 14 | 5.04        | ✓            | ✓     | 63.5m |
| X-vector    | 4.33        | ✓            | x     | 8.2m  |
| ECAPA-TDNN  | 1.95        | ✓            | ✓     | 22.2m |

| Dconv-5     | 2.946       | ✓            | x     | 32m   |
| Dconv-4     | 2.926       | ✓            | x     | 21m   |
| Dconv-4 (small) | 2.935    | ✓            | x     | 6.4m  |
| Dconv-3     | 2.89       | ✓            | x     | 12.1m |
| Dconv-3 (small) | 2.941    | ✓            | x     | 3.9m  |
| Dconv-4     | 1.62        | ✓            | ✓     | 21m   |

Table 3: Average epoch computation time of models training on VoxCeleb1 using an NVIDIA RTX3060 GPU

| Layer Name       | Average computation time per epoch |
|------------------|-----------------------------------|
| X-vector         | 02:05:12                          |
| Dconv-3 (small)  | 02:46:43                          |
| Dconv-4          | 03:45:46                          |
| Dconv-4 (small)  | 03:23:27                          |
| Dconv-5          | 05:47:35                          |
| Dconv-5          | 08:33:18                          |

Fig. 4: Comparison of error rate on validation set for models of varying depth

3.4. Results and Discussion

Contrary to the typical scenario where the models are trained using large amounts of data, commonly with both VoxCeleb1 and 2, and extensive computational resources, here all except one of the dconv models were trained only using VoxCeleb1 train data and 1 GPU. The motivation for this implementation is due to computational constraints as the models trained with both datasets take over 33 hours per epoch to compute. The dconv models trained with only VoxCeleb1 achieved better performance compared to several models trained with both datasets, as shown in Table 2. The training results are also visualised in the graph in Figure 4. The x-vector model from 2 and ECAPA-TDNN from 6 were compiled in the same pipeline as observational baselines to the developed models and comprised of 4 layers at 512 dimensions. All the dynamic kernel based convolution models outperformed the x-vector and cited ResNet models despite not having hyperparameters tuned for optimum performance, as is commonplace for training ResNet-style architectures. The results also suggest that reducing the depth of the convolutions but widening the dimensionality of the layers improves the verification performance of the convolutional network as the 3 layer model with 1024 dimension layers achieved an Equal Error Rate (EER) of 2.89% with miniDCF 0.275. The dconv model trained with both VoxCeleb1 and 2 achieves an EER of 1.62% with miniDCF 0.18 which is a 17% relative improvement to the ECAPA-TDNN model.

Figure 4 displays the error rate per epoch across models with varying layers. The first observation that can be made is that the x-vector model has a worse performance despite attaining lower validation loss across epochs, suggesting there is poor generalisation capability within this model. Another key observation from the figures, is that the 3 layer and 4 layer dconv models that have a dimension of 1024 perform similarly across validation loss and error rate, which suggests that within the structure of the embeddings compiled by the dynamic kernels, critical context is learned and contained across the dimensionality of the layers rather than across the depth (number of layers) of the models. Despite the reduced parameters of the 3 layer (12 million parameters) model compared to the 4 layer (21 million parameters) model, it is possible to retain the modelling accuracy using the proposed approach by improving the embedding representation capabilities.

Table 3 displays the average computation across the dconv models and the X-vector baseline using an NVIDIA RTX3060 GPU. The average computation time for an epoch using the X-vector approach took approximately 2 hours, which is slightly faster than an epoch for the dconv models, however to achieve the EER performance of 4.33%, the number of epochs was increased to 25. The number of epochs for all dconv models was 10 to attain the results listed in Table 2 therefore while each epoch with a 3 or 4 layer dconv model may take longer to compute, the models will finish training with less overall time and with a slightly improved performance. To train the dconv model on both VoxCeleb datasets took an average of 33 hours per epoch, while the ECAPA-TDNN model took an average of 24 hours per epoch.

4. CONCLUSION

A novel approach for speaker verification has been proposed that provides improved representational capabilities while controlling network dimensionality, allowing the use of lower resources for training and computation. The dconv model can be trained to extract high resolution features while being computationally inexpensive. Several iterations of the dconv model were evaluated on VoxCeleb 1 and compared to a baseline x-vector model, which demonstrated the proposed approach’s effectiveness at lowering the EER with low resources. It was observed for the task of speaker verification, dynamic convolutional spatial dimensions (width) contribute to a slightly increased performance improvement than increasing model depth (layerwise). This work could be further extended across different variations of architectures and also for other domains such as speech recognition or diarisation.
5. REFERENCES

[1] David Snyder, Daniel Garcia-Romero, Daniel Povey, and Sanjeev Khudanpur, “Deep neural network embeddings for text-independent speaker verification,” in Interspeech, 2017, pp. 999–1003.

[2] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5329–5333.

[3] 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.

[4] Hossein Zeinali, Shuai Wang, Anna Silnova, Pavel Matějka, and Oldřich Plchot, “But system description to voxceleb speaker recognition challenge 2019,” arXiv preprint arXiv:1910.12592, 2019.

[5] Yun Tang, Guohong Ding, Jing Huang, Xiaodong He, and Bowen Zhou, “Deep speech embedding learning with multi-level pooling for text-independent speaker verification,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6116–6120.

[6] Brecht Desplanques, Jenthe Thienpondt, and Kris Demuynck, “Ecapa-tdnn: Emphasized channel attention, propagation and aggregation in tdnn based speaker verification,” arXiv preprint arXiv:2005.07143, 2020.

[7] Yong Zhao, Tianyan Zhou, Zhuo Chen, and Jian Wu, “Improving deep cnn networks with long temporal context for text-independent speaker verification,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 6834–6838.

[8] Zhengyang Chen, Sanyuan Chen, Yu Wu, Yao Qian, Chengyi Wang, Shujie Liu, Yamin Qian, and Michael Zeng, “Large-scale self-supervised speech representation learning for automatic speaker verification,” in ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 6147–6151.

[9] Jenthe Thienpondt, Brecht Desplanques, and Kris Demuynck, “Integrating frequency translational invariance in tdnns and frequency positional information in 2d resnets to enhance speaker verification,” arXiv preprint arXiv:2104.02370, 2021.

[10] Karen Simonyan and Andrew Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[11] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander Alemi, “Inception-v4, inception-resnet and the impact of residual connections on learning,” in Thirty-first AAAI conference on artificial intelligence, 2017.

[12] Yizeng Han, Gao Huang, Shijii Song, Le Yang, Honghui Wang, and Yulin Wang, “Dynamic neural networks: A survey,” arXiv preprint arXiv:2102.04906, 2021.

[13] Li Zhang, Qing Wang, and Lei Xie, “Duality temporal-channel-frequency attention enhanced speaker representation learning,” in 2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). IEEE, 2021, pp. 206–213.

[14] Joon Son Chung, Arsha Nagrani, and Andrew Zisserman, “Voxceleb2: Deep speaker recognition,” arXiv preprint arXiv:1806.05622, 2018.

[15] Yinpeng Chen, Xiyang Dai, Mengchen Liu, Dongdong Chen, Lu Yuan, and Zicheng Liu, “Dynamic convolution: Attention over convolution kernels,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 11030–11039.

[16] 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.

[17] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Voxceleb: a large-scale speaker identification dataset,” arXiv preprint arXiv:1706.08612, 2017.

[18] Hitoshi Yamamoto, Kong Aik Lee, Koji Okabe, and Takafumi Koshinaka, “Speaker augmentation and bandwidth extension for deep speaker embedding,” in Interspeech, 2019, pp. 406–410.

[19] Daniel S Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D Cubuk, and Quoc V Le, “Specaugment: A simple data augmentation method for automatic speech recognition,” arXiv preprint arXiv:1904.08779, 2019.

[20] Emanuel AP Habets, “Room impulse response generator,” Technische Universität Eindhoven, Tech. Rep, vol. 2, no. 2.4, p. 1, 2006.

[21] Mirco Ravanelli, Titouan Parcollet, Peter Plantinga, Aku Rouhe, Samuele Cornell, Loren Lugosch, Cem Subakan, Naman Dawalatabad, Abdelwahab Heba, Jianyuan Zhong, et al., “Speechbrain: A general-purpose speech toolkit,” arXiv preprint arXiv:2106.04624, 2021.

[22] 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.