Deep Speaker Representation using Orthogonal Decomposition and Recombination for Speaker Verification

Insoo Kim, Kyuhong Kim, Jiwhan Kim, and Changkyu Choi

Samsung Advanced Institute of Technology, South Korea

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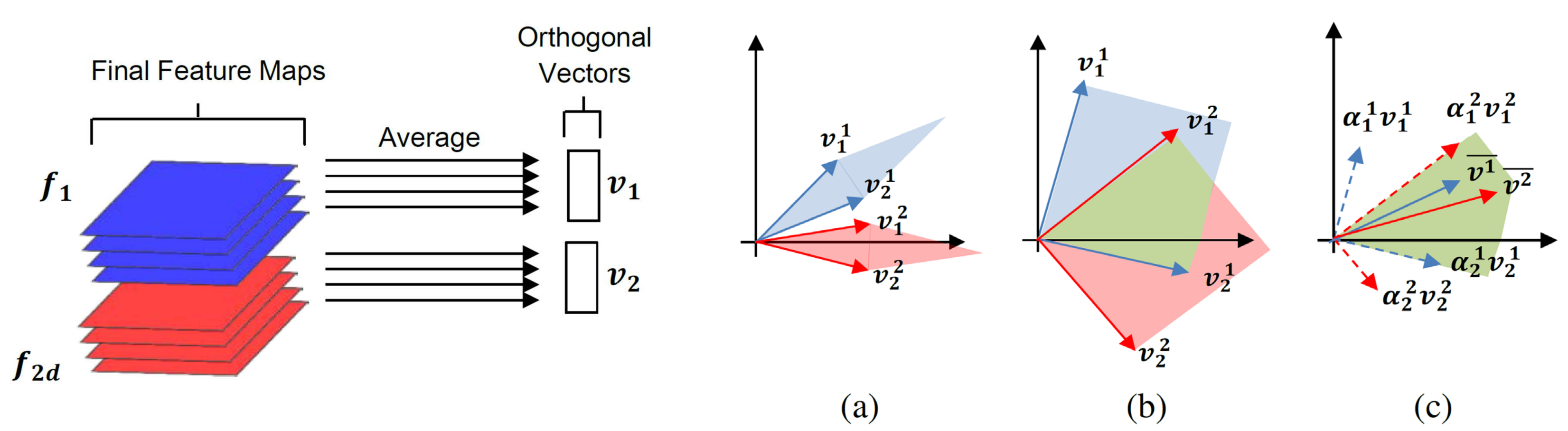
Main Idea

- The proposed method performs orthogonal decomposition and recombination to obtain the discriminative speaker representation.
- Speaker representation is generated by a linear combination of latent vectors using deep neural network.
- The proposed method can be easily applied to any deep neural network, which is connected at the end of the network.

Orthogonal Decomposition



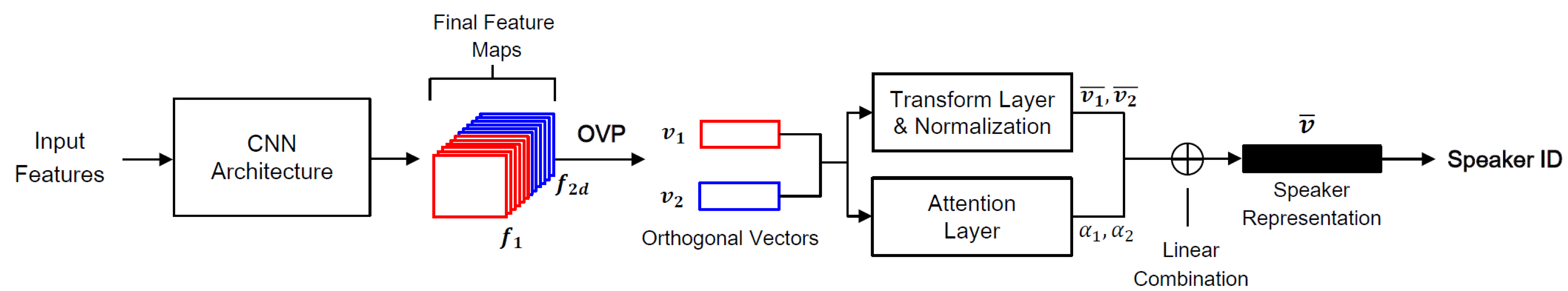
- Construct twice the number of final feature maps compared to the conventional CNN architecture in order to decompose a vector into two latent vectors.
- Orthogonal vectors can be generated by applying the following constraint.

$$L_{orthogonal} = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{\boldsymbol{v_1^n}\cdot\boldsymbol{v_2^n}}{\|\boldsymbol{v_1^n}\|_2\,\|\boldsymbol{v_2^n}\|_2}\right|$$

Why applying the orthogonal constraint ?

- Prevent forming similar decomposition vectors
- Maximize the spanned subspace so that the overlapped subspace between two examples can be formed.
- The overlapped subspace enables speaker representations to be a global speaker-specific representation.

Network Architecture



Recombination Network

- Transform and normalize the decomposed vectors to control the vector magnitude

$$\boldsymbol{\bar{v}_1} = \frac{f(\boldsymbol{v_1})}{||f(\boldsymbol{v_1})||_2}, \quad \boldsymbol{\bar{v}_2} = \frac{f(\boldsymbol{v_2})}{||f(\boldsymbol{v_2})||_2}$$

- Estimate magnitude of decomposed vectors using attention layer toward minimizing intra-speaker distance and maximizing inter-speaker distance using the softmax loss

$$L_{softmax} = -\frac{1}{N}\sum_{n=1}^{N}\log\frac{\exp(\boldsymbol{w_s}\cdot\boldsymbol{\bar{v}^n}+b)}{\sum_{spk}\exp(\boldsymbol{w_{spk}}\cdot\boldsymbol{\bar{v}^n}+b)}$$

$$\alpha_1 = f_a(\boldsymbol{v_1}), \quad \alpha_2 = f_a(\boldsymbol{v_2})$$

- Be able to extract speaker-discriminative representation using a linear combination of the two normalized vectors with the estimated amplitudes

$$\boldsymbol{\bar{v}} = \alpha_1\boldsymbol{\bar{v}_1} + \alpha_2\boldsymbol{\bar{v}_2}$$

- The entire network can be learned using the following loss.

$$L_{total} = L_{softmax} + \lambda L_{orthogonal}$$

Experimental Result

- Input : logfbank features (input feature map : 64 x 100, 64 x 300)
- Text-dependent task : In-house dataset (“Hi, bixby”)
- Text-independent task : VoxCeleb dataset

Layer	ResCNN-GAP	OrthResCNN-OVP (Ours)
conv1	$[7\times 7, 64]$, stride 1	$[7\times 7, 64]$, stride 1
conv2	$[1\times 1, 64]$, stride 2 $[3\times 3, 64]\ \times 6$, stride 1	$[1\times 1, 64]$, stride 2 $[3\times 3, 64]\ \times 6$, stride 1
conv3	$[1\times 1, 128]$, stride 2 $[3\times 3, 128]\ \times 6$, stride 1	$[1\times 1, 128]$, stride 2 $[3\times 3, 128]\ \times 6$, stride 1
conv4	$[1\times 1, 256]$, stride 2 $[3\times 3, 256]\ \times 6$, stride 1	$[1\times 1, 256]$, stride 2 $[3\times 3, 256]\ \times 6$, stride 1
pooling	global average pooling (1×256)	orthogonal vector pooling $(1\times 128, 2)$, orth. loss
fc1	-	$(128\times 128, 2)$
att1	-	$(128\times 1, 2)$
fc2	(256 / 128× the number of speakers), softmax loss	

Table 1. Network Architectures

Network	Clean Condition	Real Condition
d-vector [6]	4.94	19.52
x-vector [12]	1.52	6.07
ResCNN-FCN	1.42	5.14
ResCNN-GAP	1.40	3.32
OrthResCNN-OVP	0.81	1.67

Table 2. EER (%) on text-dependent task

Network	VoxCeleb evaluation set
x-vector	8.48
ResCNN-GAP	5.39
OrthResCNN-OVP	2.85

Table 3. EER (%) on text-independent task

Conclusions

- The proposed approach outperforms the baseline systems and yields a relative EER reduction of 50-70% for text-dependent and independent tasks.
- The better performance can be achieved when we apply our method to CNN architectures.
- This method can be extended to more than two latent vectors.
- Our method can be applied to other applications, such as face verification, image classification, and sound classification.