Temporal Dynamic Convolutional Neural Network for Text-Independent Speaker Verification and Phonemic Analysis

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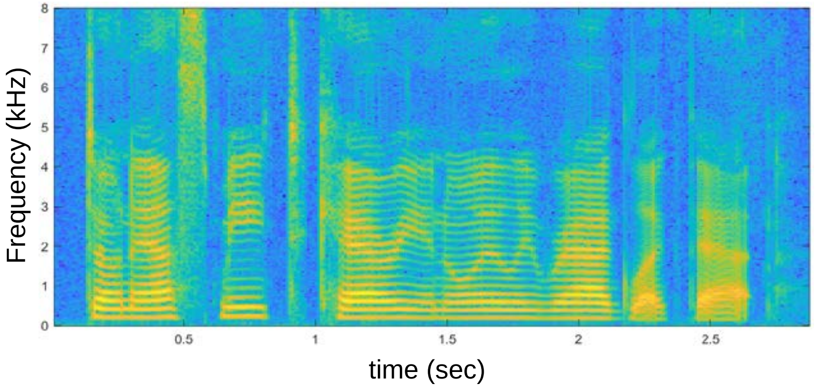
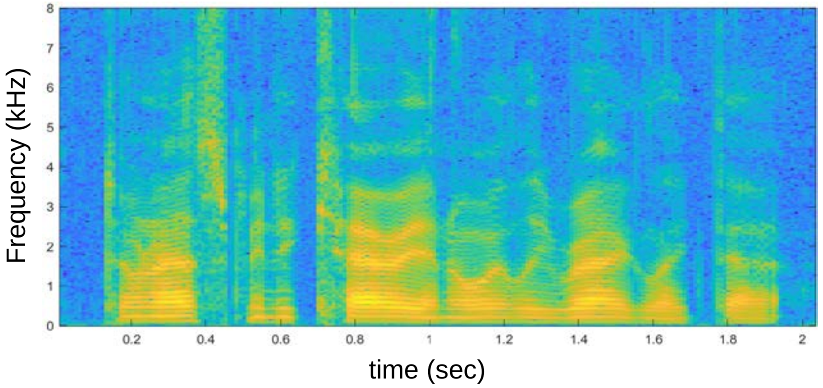
Background

- **Text-dependent speaker verification task**

SA2 utterance of Speaker FSJK1
(Don't ask me to carry an oily rag like that)



SA2 utterance of Speaker MPGH0
(Don't ask me to carry an oily rag like that)



- **Text-independent speaker verification task**

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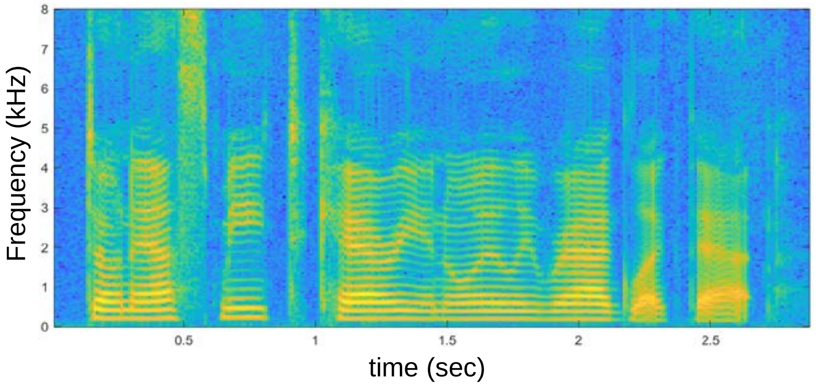
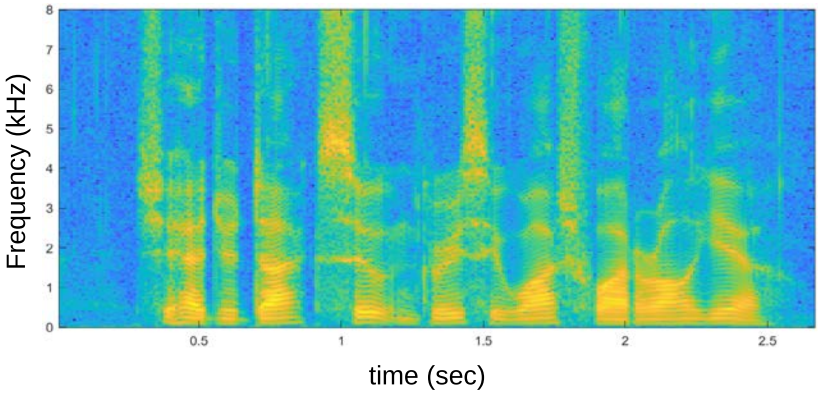


SA1 utterance of Speaker MPGH0
(She had your dark suit in greasy wash water all year)



Introduction

- In text-independent speaker verification task, speech has **phoneme-varying characteristics along the time axis depending on random text,** but conventional static neural models do not reflect it.

- We propose **temporal dynamic convolutional neural network (TDY-CNN).**

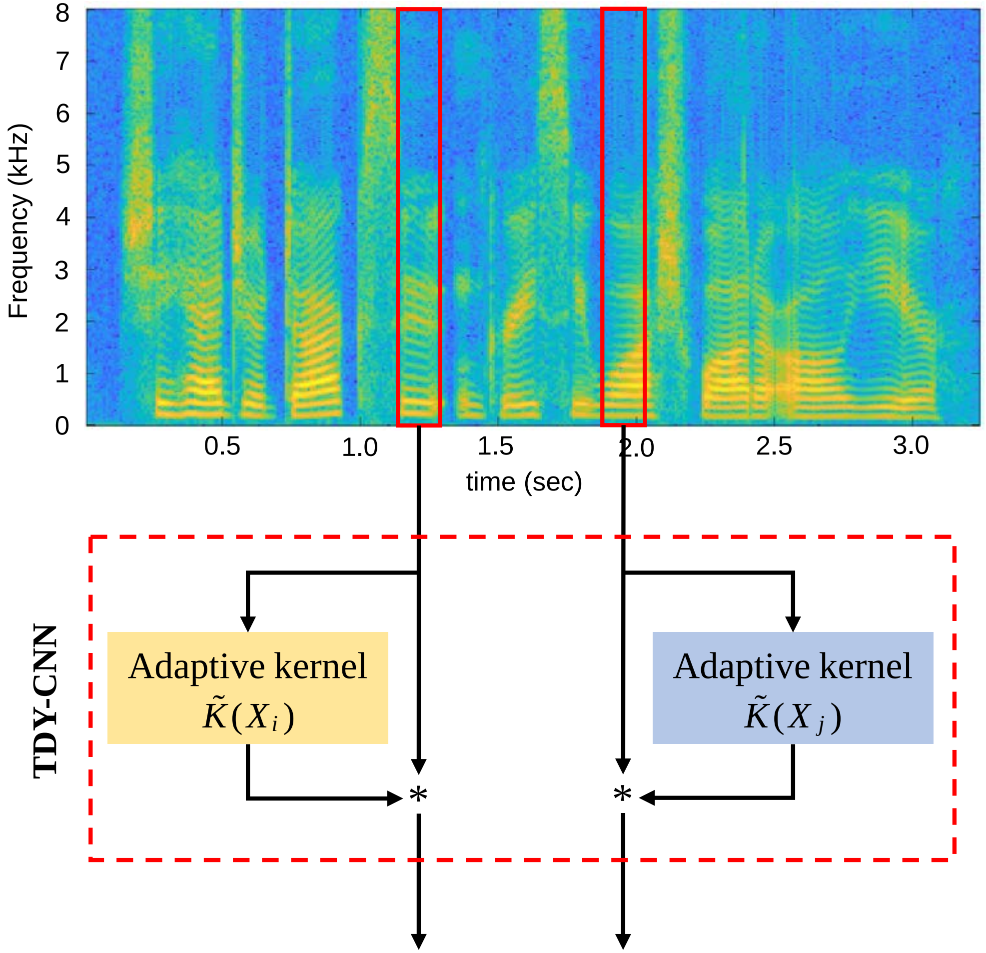
- Contributions of this paper as follows :

1. We propose **CNN kernels adaptive to each time bin** in order to effectively capture the time-varying information in utterances.

2. This is the **first work to perform phonemic analysis on temporal dynamic model** for text-independent speaker verification.

3. We verified that **adaptive kernels change with the acoustic characteristics of phonemes** and **extract speaker information regardless of phonemes** while static kernels do not.

'She had your dark suit in greasy wash water all year' utterance in TIMIT[1]



[1] J. S. Garofolo, L. F. Lamel, W. M. Fisher, J. G. Fiscus, and D. S. Pallett, "Darpa timit acoustic-phonetic continous speech corpus cd-rom. nist speech disc 1-1.1," NASA STI/Recon technical report n, vol. 93, p. 27403, 1993.

Temporal Dynamic CNN Module

- TDY-CNN was proposed by **referring to dynamic convolutional neural network (DY-CNN)[2]**, which generate the adaptive kernel with **weighted sum of basis kernels**.

$$y_k(f,t) = W_k * x(f,t) + b_k$$

$$y(f,t) = \sigma\left(\sum_{k=1}^{K} \pi_k(t) \cdot y_k(f,t)\right)$$

- x, y : input and output
- f, t : frequency and time features
- W_k, b_k: k-th basis kernel and bias
- K : total number of basis kerels
- $\pi_k(t)$: temporal attention weights

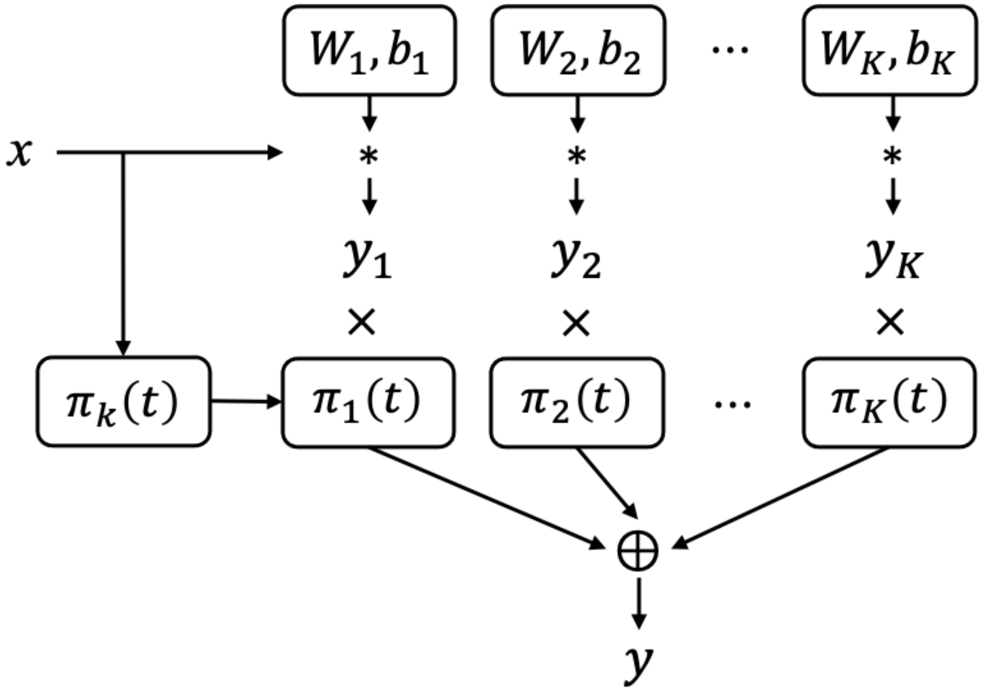


Figure 1. Structure of temporal dynamic convolutional neural network (TDY-CNN)

[2] Y. Chen, X. Dai, M. Liu, D. Chen, L. Yuan, and Z. Liu, "Dynamic convolution: Attention over convolution kernels," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 11030-11039.

Model Structure and Experiment Details

- We used 64-dimensional log Mel spectrogram as the model input.

- TDY-CNN is applied to VGG-M[3] and ResNet-34[4] with a quarter and half channel:
  VGG-M / ResNet-34 (×0.25) / DY-ResNet-34 (×0.5)

- The models were trained on Voxceleb2 development set and tested on Voxceleb1 test set.

- The models are trained using **a loss function combining the Angular Prototypical loss with the vanilla softmax loss**, which shows better performance [5].

  - optimizer : Adam
  - initial learning rate : 10^{-3}
  - learning rate decaying : 0.75 every 15 epochs
  - batch size : 800
  - data augmentation : NO

[3] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014
[4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, Conference Proceedings, pp. 770–778.
[5] J. S. Chung, J. Huh, S. Mun, M. Lee, H. S. Heo, S. Choe, C. Ham, S. Jung, B.-J. Lee, and I. Han, "In defence of metric learning for speaker recognition," arXiv preprint arXiv:2003.11982, 2020

Results and Analysis

[The number of basis convolution kernels]

- TDY-ResNet-34 (×0.25) with ***K* = 6** showed best performance for text-independent speaker verification.
- The error rate was increased when ***K* = 8** because of the **difficulty of optimization** for larger models and **overfitting**.
- We set ***K* = 6** and continued analysis.

Table 1. Text-independent speaker verification performance of temporal dynamic models

TDY-ResNet-34(×0.25)	EER (%)	MinDCF
$K = 2$	1.99	0.140
$K = 4$	1.62	0.128
$K = 6$	**1.58**	**0.116**
$K = 8$	1.69	0.133

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Results and Analysis

[Comparison of static model and utterance/frame-level dynamic model]

- Each model information :
  - **Static model** : ResNet-34 (×0.25)
  - **Utterance-level dynamic model** : DY-ResNet-34 (×0.25)
  - **Frame-level dynamic model** : TDY-ResNet-34 (×0.25)
- **TDY-CNN**, which considers frame-level speaker information, **showed the better verification performance than DY-CNN**, which considers only utterance-level speaker information.
- Thus, **TDY-CNN is suitable for text-independent speaker verification**.

Table 2. Text-independent speaker verification performances of models using dynamic convolution with frame-level and utterance level.

Network	EER (%)	MinDCF
ResNet-34(×0.25)	2.43	0.184
DY-ResNet-34(×0.25)	2.07	0.157
TDY-ResNet-34(×0.25)	**1.58**	**0.116**

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Results and Analysis

[Text-independent speaker verification results]

- **TDY-ResNet-34 (×0.5)** showed the best performance with 1.48% of EER.
- **All models to which TDY-CNN was applied show better performance** than the models using static CNN.
- The proposed models show good verification performance but lag slightly behind the state-of-the-art performance.

Table 3. Text-independent speaker verification performances of the networks without data augmentation.

Network	#Parm	EER (%)	MinDCF
VGG-M	4.16M	3.77	0.287
TDY-VGG-M	71.2M	3.04	0.237
ResNet-34(×0.25)	1.86M	2.43	0.184
TDY-ResNet-34(×0.25)	13.3M	1.58	0.116
ResNet-34(×0.5)	6.37M	1.79	0.134
TDY-ResNet-34(×0.5)	51.9M	**1.48**	**0.118**
ResNet-50 [19]	67.0M	3.95	0.429
Thin ResNet-34 [20]	12.4M	2.87	0.310
H/ASP [22]	8.00M	1.29	0.091
ECAPA-TDNN [25]	14.7M	**1.18**	**0.088**

Results and Analysis

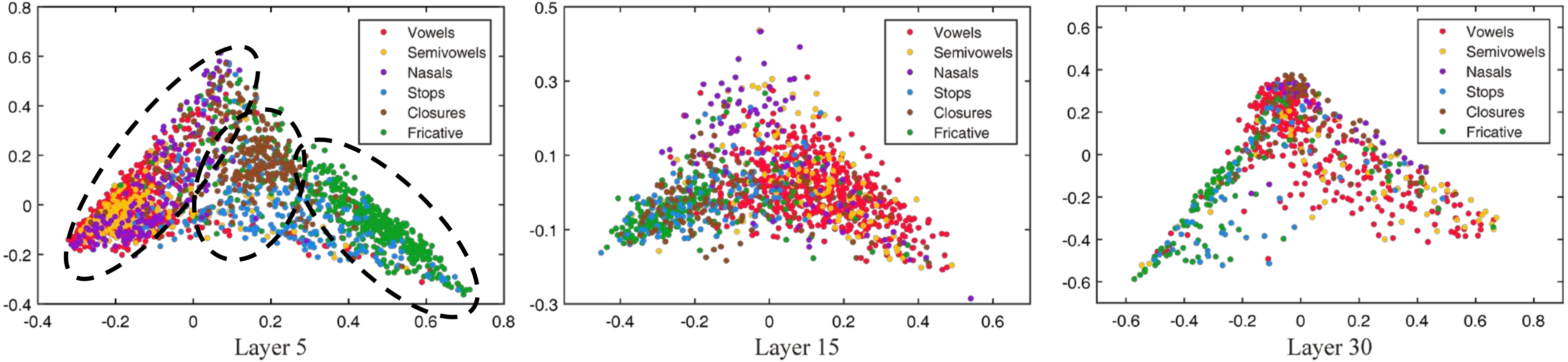
[Analysis of adaptive kernels in relation to phonemes]

- We verified how the kernels adapt to phonemes by **comparing attention weights of basis kernels depending on phonemes**.
- A total of 52 phonemes are classified into 6 categories :
  vowels / semivowels and glides / nasals / fricatives and affricates / stops / closures.
- Correlation between attention weights and phonemes was analyzed in several layers (5, 15, 30 layer) using TIMIT dataset which provides phoneme labels.
- The attention weights were extracted from trained **TDY-ResNet-34(×0.25) with K = 6** and displayed using principal component analysis (PCA).

Results and Analysis

[Analysis of adaptive kernels in relation to phonemes]

➢ **Speaker FDAS1** (the largest variance of attention weights)



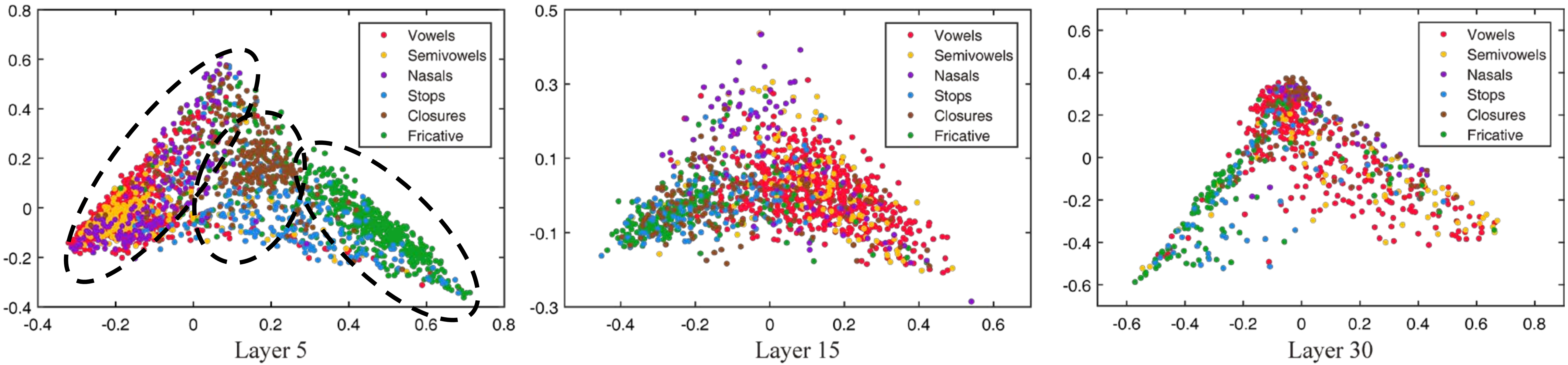
- **At layer 5**, the distribution of attention weights can be divided into three groups:
  - **voiced sounds** : vowels + semivowels + nasals
  - **stops** : stops + closures
  - **fricative-likes** : fricative

grouping with **similar acoustic characteristics and phoneme generation mechanisms!**

Results and Analysis

[Analysis of adaptive kernels in relation to phonemes]

➢ **Speaker FDAS1** (the largest variance of attention weights)



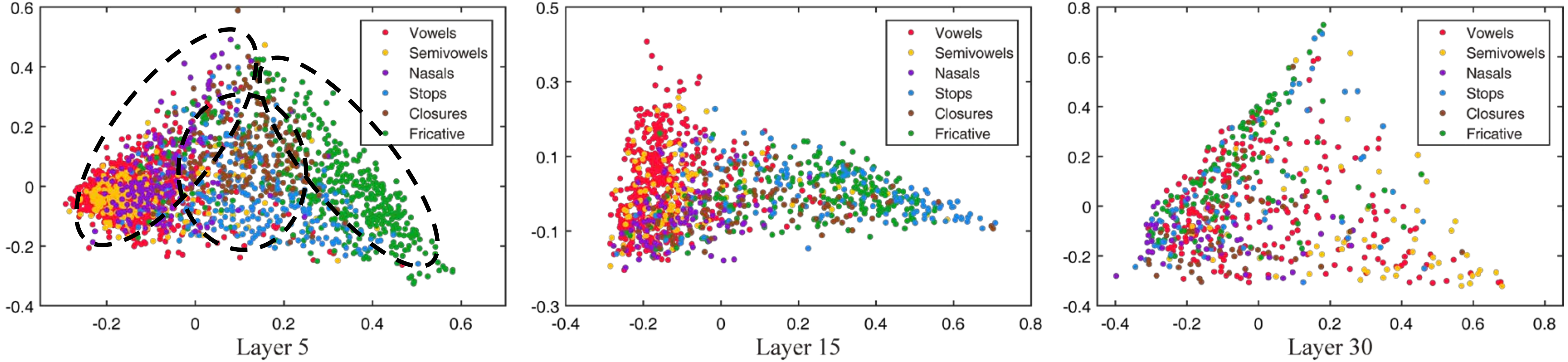
- The **boundary** between the distribution of groups starts to seem **vague at layer 15**, and the distributions completely merge and groups become **indistinguishable at layer 30**.

Attention weights are more phoneme-specific at earlier layers.
Only speaker information has been remained at later layers.

Results and Analysis

[Analysis of adaptive kernels in relation to phonemes]

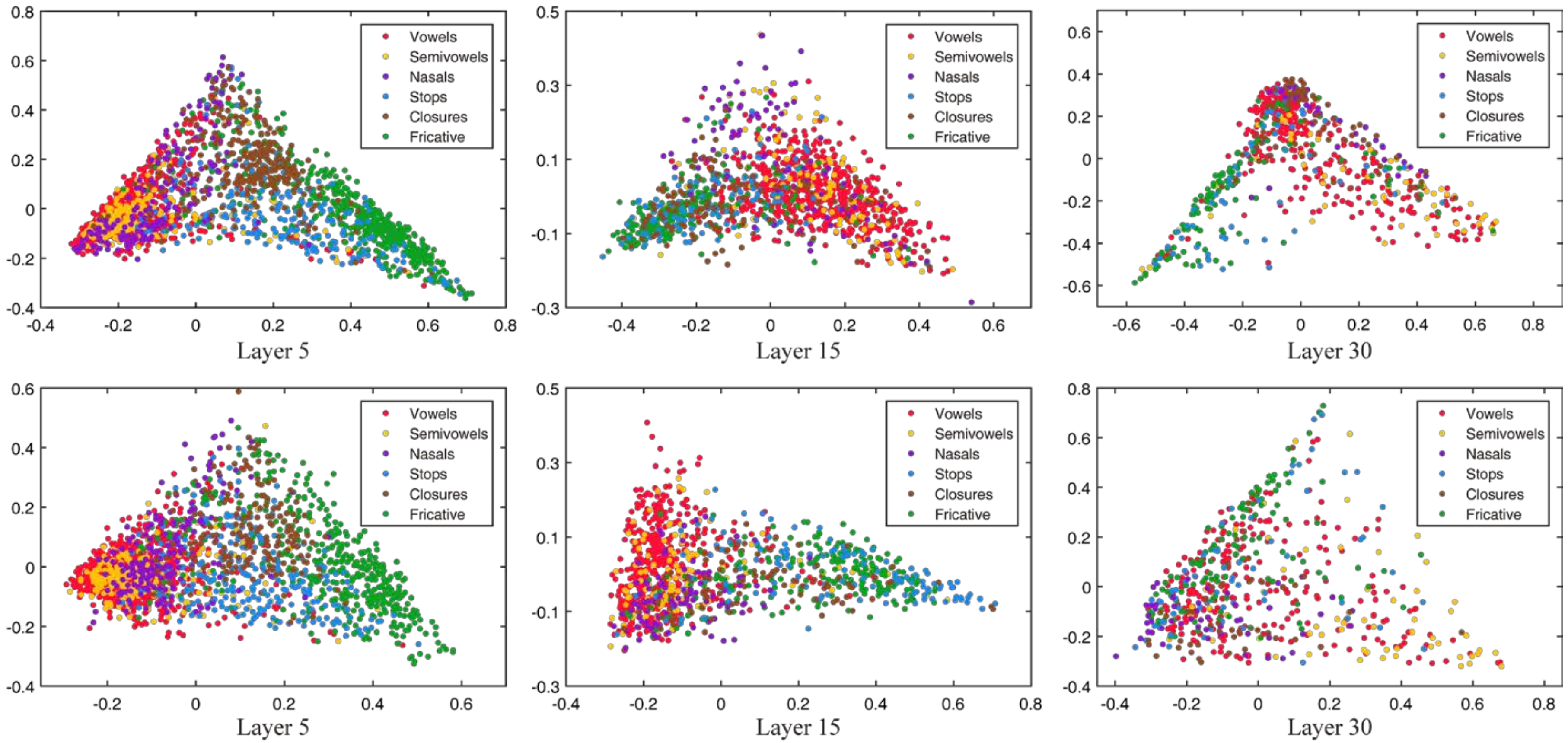
- **Speaker MHRM0** (the smallest variance of attention weights)



- **Similar results** were shown in the other speaker case.
  - The distribution of attention weights can be divided into **three groups**.
  - The distribution of groups **merge at later layers**.

Results and Analysis

[Analysis of adaptive kernels in relation to phonemes]



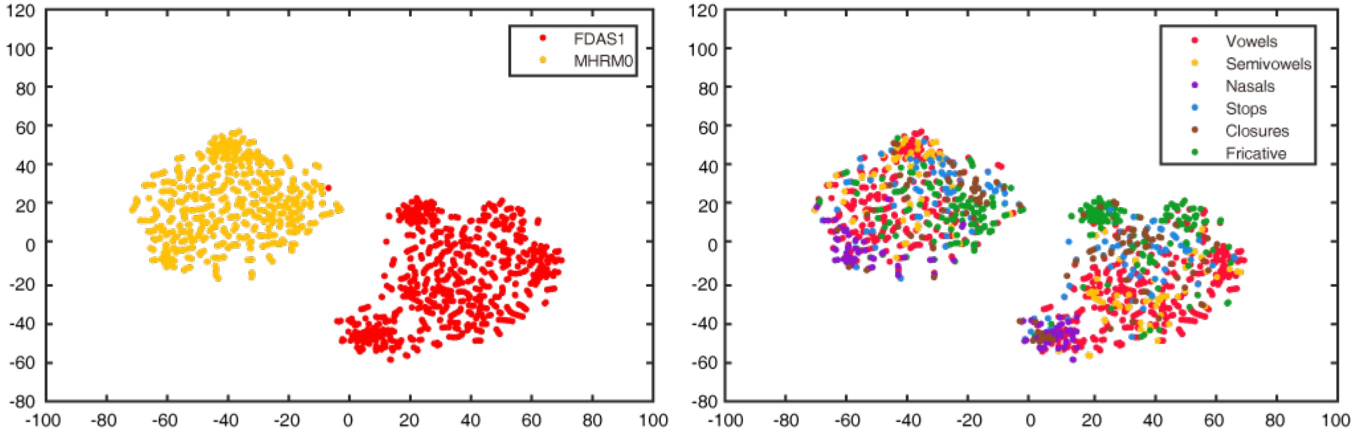
- ➢ The kernels were **adapted to phoneme groups**.
- ➢ **Only the speaker information is extracted** without phonetic information **in the speaker embeddings**.

Results and Analysis

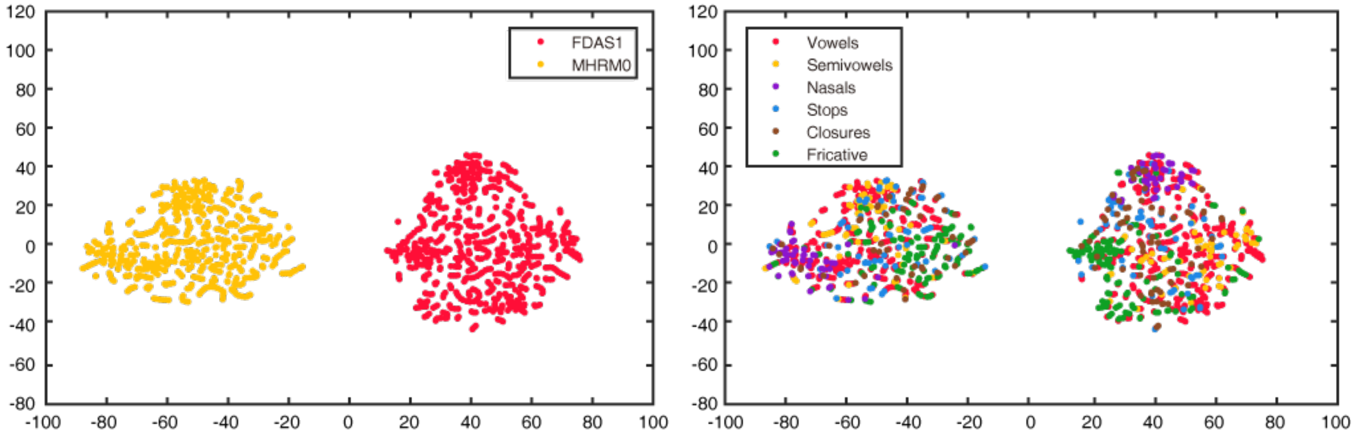
[Analysis of frame-level embeddings in relation to phonemes]

- Speaker embeddings are well gathered.
- Embeddings of nasals and fricatives within MHRM0 are far from the center of group in ResNet-34(×0.25).
- Embeddings by TDY-ResNet-34(×0.25) are closely gathered regardless of phoneme groups .
- Therefore, **TDY-CNN adapts to phonemes** and **extract consistent speaker embeddings regardless of phonemes**.

t-SNE projection of frame-level speaker embeddings



ResNet-34(×0.25)



TDY-ResNet-34(×0.25)

Conclusion

- **TDY-CNN** was proposed to **extract consistent speaker information** on **different time bins** for text-independent speaker verification.

- Models with TDY-CNN <u>**extract consistent speaker embeddings regardless of phonemes using phoneme-adaptive kernels**</u> and **improve speaker verification performance**.

- This work is the **first to analyze how temporal dynamic models work** depending on time bins and phonemes.

- The results indicate that **temporal dynamic models are suitable** and **consideration of phoneme information is crucial** in **text-independent speaker verification**.

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Thank You

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