

DEEP CNN BASED FEATURE EXTRACTION FOR TEXT-PROMPTED SPEAKER RECOGNITION



MaxPool1

MFM1

Conv1

Speaker

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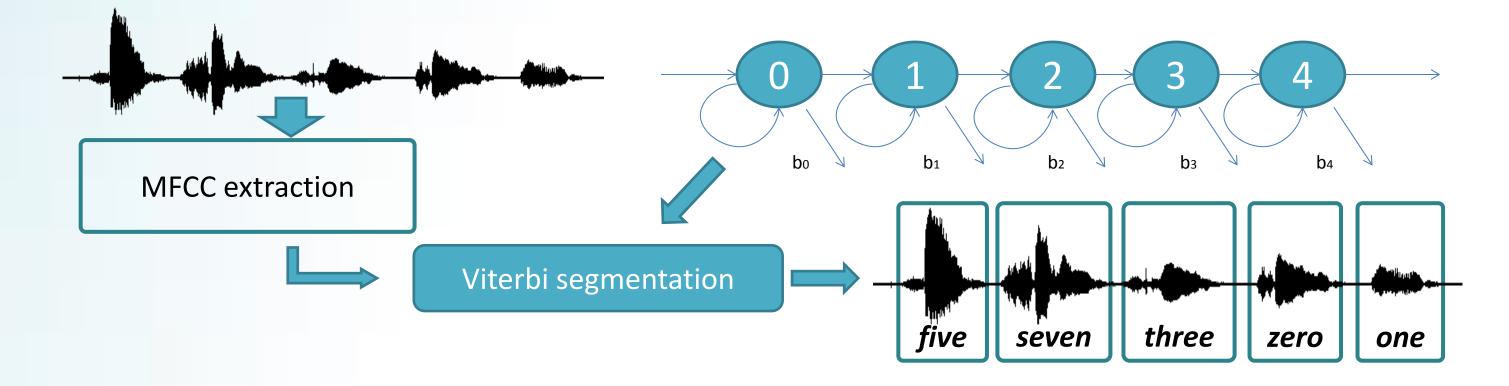
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Introduction

- **Text-dependent** speaker recognition task [1,2,3,4] is studied
- Deep convolutional neural network based speaker specific features extractor in the text-prompted speaker verification task is presented
- The prompted passphrase is segmented into word states i.e. digits to test each digit utterance separately
- A single high-level feature extractor for all states is used and cosine similarity metric is applied for scoring
- Multitask learning scheme is used to train the high-level feature extractor

Features

Viterbi segmentation to word states



Input features for the CNN are $64 \times 96 \log \text{ mel power spectra}$:

- 64 frequency bands
- 96 frames (longest single digit utterance)
- Voice activity detector removes non-speech frames

Experiments

We explored 5-digit password verification scenario when the speaker pronounces the correct passphrase. Training/evaluation bases consist of short digit passphrases

Training Datasets:

- RSR2015 [1] Part 3 train set: 194 speakers (94 Female + 100 Male) $RSR2015_{tr}$
- Wells Fargo Bank set: 300 speakers (150 Female + 150 Male) WF
- STC-Russian-digits train set: 786 speakers (263 Female + 523 Male) $STCRus_{tr}$

Evaluation Datasets:

- **RSR2015 Part 3 eval set**: 106 speakers (49 Female + 57 Male) $RSR2015_{ev}$
- STC-Russian-digits eval set: 92 speakers (42 Female + 50 Male) $STCRus_{ev}$

Results

Table 1. EER [%] and minDCF ($C_{miss}=10$, $C_{fa}=1$, $P_{tar}=10^{-2}$) for 5-digit password verification

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System	Multi-Task	Training data	Evaluation	EER (%)	Min DCF
	mode		data		
Baseline State-GMM- SVM ^[2]	None	$RSR2015_{tr} + WF$	$RSR2015_{ev}$	3.11	0.14
State-CNN	None	$RSR2015_{tr}$		7.83	0.39
	Speaker & Digits			5.12	0.25
		$RSR2015_{tr} + WF$		4.27	0.2
		$STCRus_{tr}$	$STCRus_{ev}$	5.86	0.29
	Speaker & Digits & Language	$RSR2015_{tr} + WF + STCRus_{tr}$	$RSR2015_{ev}$	2.85	0.13
			$STCRus_{ev}$	4.24	20.45

Fusion results

Systems description:

State-GMM-SVM [2]:

Viterbi segmentation, state supervector extraction, state SVM based scoring, S-norm

State-GMM-PLDA [3]:

Viterbi segmentation, state supervector extraction, state TV space transform, state PLDA scoring **State-CNN:**

Viterbi segmentation, state CNN deep speaker embedding extraction, cosine based scoring

Table 2. Fusion. EER [%] and minDCF for 5-digit password verification

System	EER	Min	
	(%)	DCF	
State-CNN +	2.09	0.1	
StatePLDA			
State-CNN +	1.63	0.07	
State-GMM-SVM	1.00	3.07	
State-CNN +	1.57	0.08	
State-GMM-SVM	1.07	0.00	
All	1.43	0.07	

Convolutional Neural Network

SoftMax Input features are processed with a CNN embedding extractor FC2 speaker embedding -> MFM6 **Max Feature** FC1 MaxPool4 Mapping MFM5b Conv5b MFM5a Conv5a MFM4b Conv4b MFM4a Max Feature Mapping Conv2D MaxPoo Features Conv4a MaxPool4 $\frac{H}{2} \times \frac{W}{2} \times \frac{N}{2}$ $H \times W \times \frac{N}{2}$ MFM3b $H \times W \times N$ Conv3b MFM3a Conv3a MaxPool2 $H \times W \times \frac{1}{2}$ MFM2b Conv2b MFM2a Max Feature Mapping (MFM) reduces dimensionality and selects features Conv2a

- Pre-softmax layer produces speaker embeddings
- Last dense layers are included only during training

Speaker embedding Speaker classes Speaker embedding

Speaker Speaker Speaker

Input Digit

Features

speakers

Single-task

Extractor is trained to discriminate

Learning mode

 $N_{speakers}$ neurons at softmax layer

Multi-task

- Extractor is trained to discriminate speakers and word states
- $N_{speakers} \times N_{digits}$ neurons at softmax layer

Conclusions

- A deep CNN based speaker feature extractor for speech digits is presented
- Multitask learning mode allows to train effective high-level speaker embeddings extractor for all states (digits)
- Discriminatively trained deep CNN based solution is able to surpass the classic baseline systems in terms of quality
- No complex trainable backend is needed for scoring. Speaker embeddings can be compared simply with cosine similarity metric
- CNN-based method fuses well with our previous methods [2,3]

References

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