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## Rapid Speaker Adaptation Based on D-code Extracted from BLSTM-RNN in LVCSR

Shaofei Xue<sup>1</sup>, Zhijie Yan<sup>1</sup>, Zhiying huang<sup>2</sup>, Lirong Dai<sup>2</sup>

<sup>1</sup>Alibaba Inc <sup>2</sup>University of Science and Technology of China

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## Introduction





## Introduction



## < Background

Speaker code based adaptation have been applied to unsupervised speaker adaptation for NN models.

About 8%-15% relative reduction in WER/CER on different tasks.

**Two-pass decoding is needed.** 



## Introduction





**>** Obtain final results with one-pass decoding.

 $\blacktriangleright$  Improve accuracy when adaptation data is especially limited.













## A D-code extraction based BLSTM

**Classification of speakers** 



Input











## Speaker clustering BLSTM

#### Problem

- ➤ Target speakers often 100,000+ in huge task.
- Sometimes even no speaker information.
- > Implementing speaker classification with NNs often meets problem.



## Speaker clustering BLSTM



Hierarchical clustering based i-vector

- Training cluster speaker-BLSTM is fast.
- Improves ASR performance.



Input

Input

STM

STM



## D-code interpolation

#### Problem

> WER/CER increases visibly when data is extreme limited (eg. one sentence).

#### Solution

- Use D-codes of training set.
- > interpolate new speaker's D-code with N most likely D-codes from training set through

$$\overline{\boldsymbol{S}}_{\text{test}} = \frac{\alpha \boldsymbol{S}_{test} + (1-\alpha) \sum_{i=1}^{N} \beta_i \boldsymbol{S}_{traini}}{\alpha + (1-\alpha) \sum_{i=1}^{N} \beta_i}$$







## 🖄 Method







## 🝳 Experimental setup

➤ 309 hour Switchboard-I and 20 hour Call Home English training set.

≻Hub5e evaluation set.

Features: 36 dimensional FBANK features, plus their first and second derivatives.

≻A standard 8882 tri-phones GMM/HMM model for force alignment.

≻4-gram LM using training and Fisher English Part 1 transcripts.

## Baselines

➢ReLU-DNN(3x1024)

≻ReLU-DNN(6x2048)

hybrid BLSTM-RNN(3BLSTM+2ReLU-DNN)



Table1 Adaptation performance using different d-code extractions on a 3-layer ReLU-DNN.

Speaker-BLSTMs	WER(%)
baseline	15.6
BLSTM-1hid*200cell	14.2(9%)
BLSTM-1hid*400cell	14.2
BLSTM-1hid*1000cell	14.1
BLSTM-2hid*200cell	14.2
LSTM-1hid*200cell	14.8
LSTM-2hid*200cell	14.7

D-code from speaker-BLSTMs outperforms speaker-LSTMs and the size of speaker-BLSTMs has no conspicuous influence.



Table2 Training time for speaker-BLSTMs and WER(%) of adaptation with different speaker cluster number.

Number of cluster	Training time(1 epoch)	WER(%)
4803(no clustering)	1.76h	14.2
400	0.83h	14.0
800	0.9h	13.9
1200	0.96h	13.8(2.8%)
1600	1h	14.0

speaker clustering not only speeds up the training of speaker-BLSTMs (about two times) but also benefits the ASR performance.



#### Table3 WER(%) of D-code interpolation method on a 3-layer ReLU-DNN.

D-code	α				
	0	0.25	0.5	0.75	1
speaker-level	13.9	13.8	13.7	13.8	13.8
utterance-level	14.0	14.0	14.2	14.3	14.3

D-code interpolation improve the performance when data is especially limited.



## Table4 Comparison of different adaptation strategies on better baselines.

Models	Adaptation strategies	WER(%)	Decoding pass
ReLU-DNN(6x2048)	baseline	13.9	one
	d-code	12.7	one
	standard SAT-SC	12.7	two
	i-vector	13.0	one
hybrid BLSTM-RNN	baseline	13.0	one
	d-code	11.9	one
	standard SAT-SC	11.8	two
	i-vector	12.2	one













## Conclusions



 $\stackrel{\textstyle \swarrow}{\displaystyle \leftarrow}$  An effective speaker adaptation method named D-code adaptation is proposed.

Speaker clustering is introduced to accelerate training speed and improves ASR performance.

 $\stackrel{\textstyle <}{\displaystyle <}$  Interpolation method that make use of D-codes from training set is provided to improve the recognition accuracy.

## Reference



[1] Yu Zhang, et al. Highway Long Short-Term Memory RNNs for Distant Speech Recognition[J].2016.



# Thank you! Q&A

Shaofei Xue, 薛少飞 Shaofei.xsf@alibaba-inc.com