

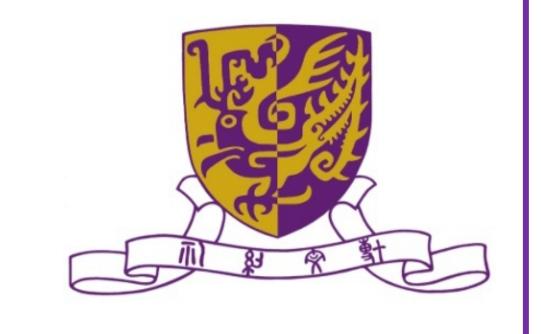
Integrating Articulatory Features into Acoustic-Phonemic Model for Mispronunciation Detection and Diagnosis in L2 English Speech

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Stage 2:

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1. Introduction

Objective

Mispronunciation detection and diagnosis (MDD) of L2 learner's speech

Challenge

- Pronunciations from L2-learners are nonstandard and unordered
- Traditional acoustic features cannot provide enough information about L2 learner's pronunciations

> Motivation

- Pronunciation is decided by production position and mechanism, i.e. articulatory features
- Employ articulatory features to boost the MDD system
- Articulatory features can help L2 learners correct their mispronunciation

Contribution

- Introduce the articulatory features to MDD in deep learning framework
- Investigate several architectures for better exploiting articulatory features

2. Articulatory Features

> Articulatory Feature Space [1]

stream	classes	cardinality
jaw	0: Nearly Closed, 1: Neutral,	4
	2: Slightly Lowered, 3: Lowered	
lip separation	0: Closed, 1: Slightly Apart,	4
	2: Apart, 3: Wide Apart	
lip rounding	0: Rounded, 1: Slightly Rounded,	4
	2: Neutral, 3: Spread	
tongue frontness	0: Back, 1: Slightly Back,	5
	2: Neutral, 3: Slightly Front, 4: Front	
tongue height	0: Low, 1: Mid, 2: Mid-High, 3: High	4
tongue tip	0: Low, 1: Neutral, 2: Dental,	5
	3: Nearly Alveolar, 4: Alveolar	
velum	0: Closed, 1: Open	2
voicing	0: Unvoiced, 1: Voiced	2

> Phoneme Manning

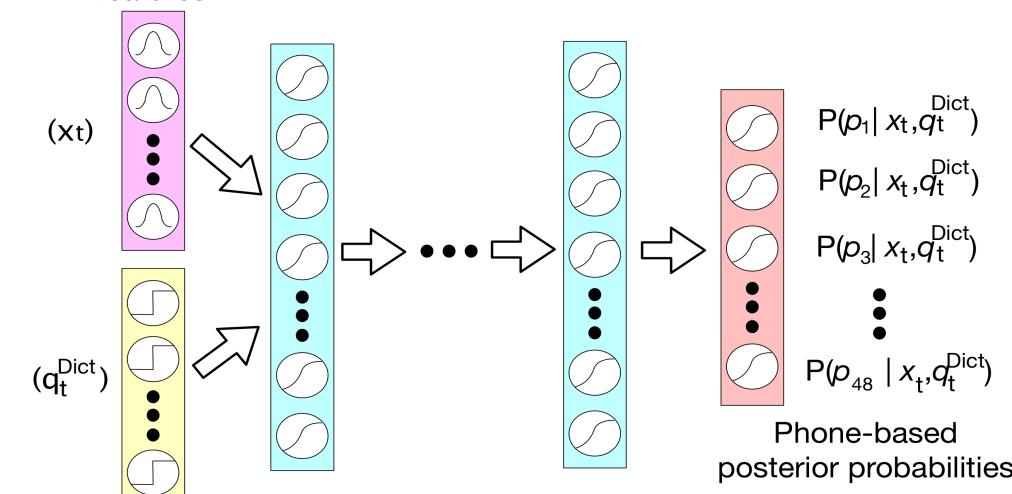
- I noncinc	i Mapping		
		<i>IPA</i>	a:
Waveform	Title title bitte i bitte i title i ti	Phoneme	aa
XX7 1		jaw	3
Words	a r t	lip	2
Phonemes	aa t	separation	
Alignment result	aa ₁ aa ₁ aa ₂ aa ₂ aa ₂ aa ₃ aa ₃ aa ₃ t ₁ t ₁ t ₁ t ₂ t ₂ t ₃ t ₃ t ₃	lip rounding	1
Jaw	3 3 3 3 3 3 3 1 1 1 1 1 1 1 1	tongue	1
Lip separation	2 2 2 2 2 2 2 1 1 1 2 2 2 2 2	frontness	1
•••	•••	tongue height	0
Tongue tip	0 0 0 0 0 0 0 0 4 4 4 4 3 3 3	tongue	0
•••	•••	<i>tip</i>	
Voicing		velum	0
voicing	1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0	voicing	1

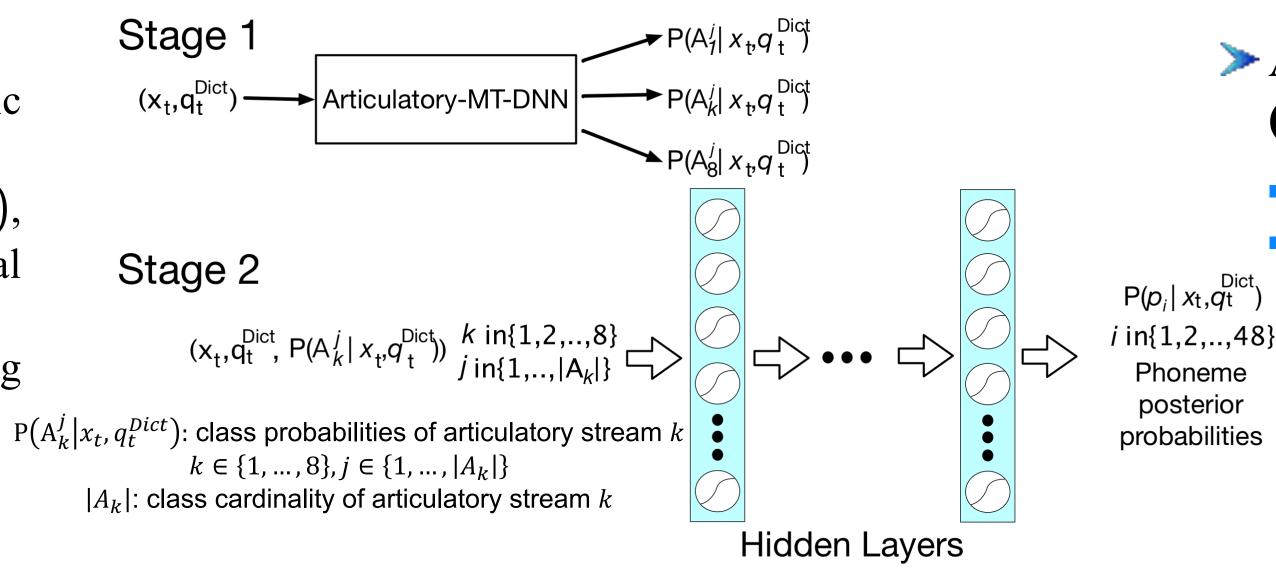
<i>IPA</i>	a:	t	
Phoneme	aa	t	
jaw	3	1	1
lip separation	2	1	2
lip rounding	1	2	2
tongue frontness	1	4	4
tongue height	0	3	2
tongue tip	0	4	3
velum	0	0	0
voicing	1	0	0

3. Acoustic-Phonemic Model with Articulatory Features

> Acoustic-Phonemic Model (APM)

- Concatenate acoustic features $(x_t, MFCC)$ and phonetic features $(q_t^{Dict}, \text{ canonical phoneme})$ as input
- Derive phoneme posterior probabilities $P(p_i|x_t,q_t^{Dict})$, $i \in [1, ..., 48]$ after several hidden layers in deep neural network (DNN)
- •Generate recognized phone sequence by a smoothing process on the frame-level recognition results



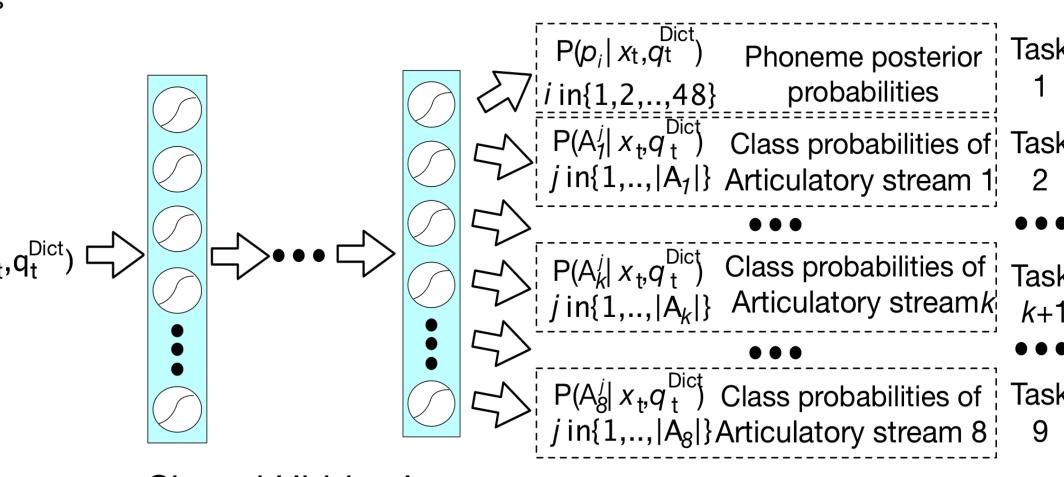


> Articulatory-Acoustic-Phonemic Model (AAPM)

- Stage 1: ☐ Train an articulatory multi-task DNN to predict articulatory features
- ☐ Embed the predicted articulatory features into input features
- Derive phoneme posterior probabilities with the concatenation of x_t , q_t^{Dict} and the predicted articulatory features

> Articulatory Multi-Task Acoustic-Phonemic Model (A-MT-APM)

- Incorporate the multi-task learning technique into APM
- Train the phoneme recognizer and articulatory stream $P(p_i|x_t,q_t^{Dict})$ classifiers together



Shared Hidden Layers

4. Experiments & Conclusions

Corpus: CU-CHLOE (Chinese University Chinese Learners of English)

> Experimental Setup

- AVERAGE ACCURACY

Comparing models :

canonical

phones

- 1) State-based APM; 2) Phoneme-based APM; 3) AAPM;
- 4) Bottleneck-AAPM; 5)A-MT-APM

ACCURACY OF EACH ARTICULATORY FEATURE

Fig. The accuracy of articulatory feature prediction

- Acoustic features (x_t) : 11 frames (5 before, 1 current and 5 after) of MFCC
- Phonemic features (q_t^{Dict}) : 7 canonical phones (3 before, 1 current and 3 after)

> Evaluation Metrics and Experimental Results $Precision = \frac{TR}{TR + FR}$, $Recall = \frac{TR}{TR + FA}$

$$F - measure = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$Detection\ Accuracy = \frac{TA + TR}{TA + TR}$$

$$Diagnostic\ Accuracy = \frac{CD}{CD + DE}$$

Table.1 The definitions in hierarchical evaluation

		Recognition Result		
		C.P.	M.P.	
Manually Transcribed	C.P.	TA	FR	
Phonetic Unit	M.P.	FA	TR (CD/DE)	

C.P.: Correct pronunciation; M.P.: Mispronunciation.

Table.2 Experimental results of MDD with different metrics

Table:2 Experimental results of With afficient metrics					
	Performance of Mispronunciation Detection and Diagnosis				
Method	Precision	Recall	F1-measure	Detection Accuracy	Diagnosis Accuracy
State-based APM	63.4%	83.7%	72.1%	89.0%	68.4%
Phoneme-based APM	71.8%	80.2%	75.7%	92.1%	77.3%
AAPM	72.9%	80.9%	76.7%	92.5%	77.4%
Bottleneck-AAPM	79.8%	77.9%	78.8%	93.7%	80.4%
A-MT-APM	86.5%	76.7%	81.3%	94.6%	84.3%

Conclusions:

- Reliable articulatory features can be predicted with acoustic and phonemic inputs
- APM with articulatory features greatly improves the MDD performance, especially when the phoneme recognizer are jointly trained with articulatory stream classifiers

5. Acknowledgment

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- The research was conducted while the first author was an intern at CUHK.
- [1] J. Tepperman and S. Narayanan. "Using articulatory representations to detect segmental errors in nonnative pronunciation." IEEE TASLP, 16(1): 8-22, 2008.