

Pronunciation Error Detection using DNN Articulatory Model based on Multi-lingual and Multi-task Learning

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Providing feedbacks directly related with articulation.

Challenge & Proposed method

Challenge

- Non-native corpus collection in a large scale is not easy.
- Precisely annotating non-native speech is difficult.

Proposed method

- Modeling articulatory attributes without non-native training data.
- Enhancing articulatory models with multi-task learning.
- Learning better feature representation using Multi-lingual learning .

Definition of articulatory attribute

CH (Chinese) learning by JP (Japanese) students

Manner	Phone set	Attribute		Phone set
Aspirated-stop Unaspirated-stop	CH: ptk CH: bdg		Anterior	CH:iü JP:ie
nasal	CH: mn	Backness		
Unvoiced-fricative	JP: mnN CH: fssh		Central	CH:a JP:au
	JP: s sh h		Back	CH: e u o JP: o
Unvoiced-stop	JP: ptk		11:-6	
Voiced-stop	JP: bdg		High	CH:IUU JP:IU
Place	Phone set	Height		
Retroflex	CH: zh ch sh r		Mid	CH:oe JP:eo
Bilabial	CH: bpm IP: bpm		Low	CH: a JP: a
Velar	CH: g k h	Doundodnoss	Unroundedness	CH:aie JP:aie
glottal	JP: g k JP: h	Koundeaness	Roundedness	CH:ouü JP:o

Context-dependent attribute modeling

Articulatory attribute transcription







Chinese native speech



Multi-lingual articulatory attribute modeling







Experiments Native attribute recognition (%) 4.1 Manner **Place-roundedness** 3.9 3.7 3.5 3.3 3.1 2.9 2.7 DNN ML-DNN MT-0.1 MT-0.3 MT-0.5 MT-0.7 MT-0.9 GMM DNN ML-DNN MT-0.1 MT-0.3 MT-0.5 MT-0.7 MT-0.9 GMM T2:mono-attribute T2:tri-phone T2:mono-attribute T2:tri-phone Place-height **Place-backness** 433753197 2.7 - 2.7 ML-DNN MT-0.1 MT-0.3 MT-0.5 MT-0.7 MT-0.9 GMM DNN ML-DNN MT-0.1 MT-0.3 MT-0.5 MT-0.7 MT-0.9 GMM T2:mono-attribute T2:tri-phone T2:mono-attribute T2:tri-phone

Non-native pronunciation error detection



	Data set	Amount of data
Train	Chinese native training data	42h (28males, 36females)
	Japanese native training data	42h(80males, 73females)
Test	Chinese native testing data	5.3h (5males,3females)
	Chinese non-native testing data	1896 utterances
		(7 female Japanese students)

Error type focused

Insufficient aspiration:	Insufficient aspiration when producing aspirated constants (e.g. p)
Insufficient retroflex:	Insufficient retroflex when producing retroflex constants (e.g. r)
Lip roundedness:	Vowels with spread lips have problems of rounded sound (e.g. ü)
Backness:	Inappropriate tongue position with a little back (e.g. an)

Evaluation metrics

• False Alarm Rate (FAR) : rate of correct pronunciation that are detected as pronunciation

pronunciation errors by the system.

Miss Rate (MIS) : rate of true pronunciation errors that are missed detected by system.

harmonic mean of FAR and MIS. Harmonic Mean (HM):

Conclusions

We address effective articulatory models without non-native training data.

Multi-task learning method can enhance DNN articulatory modeling.

Multi-lingual learning method is effective for modeling non-native speech.