Generating segment-level foreign-accented synthetic speech with natural speech prosody

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Synopsis

- We generate foreign-accented synthetic speech audio
    - . . . with native prosody
    - . . . and finely controllable accent
    - . . . using deep learning and multilingual speech synthesis
    - . . . from non-accented speech data alone

Overview

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Studying foreign accent

What makes speech sound foreign-accented?

- A question of speech perception research
  - Empirical method: Measure how listeners respond to speech stimuli with carefully controlled differences
- Knowledge about accent perception can inform, e.g., foreign-language instruction

Cues to foreign accent

What makes speech sound foreign-accented?

- Supra-segmental properties
  - Intonation and pauses (Kang et al., 2010)
  - Nuclear stress (Hahn, 2004)
  - Duration (Tajima et al., 1997)
  - Speech rate (Munro and Derwing, 2001)
  - And more. . .
- Segmental properties
  - Pronunciation errors

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  - Speech rate (Munro and Derwing, 2001)
  - And more...
- Segmental properties
  - Pronunciation errors
    - This is often the most important aspect according to listeners! (Derwing and Munro, 1997)

Studying segmental foreign accent

- Need speech stimuli isolating and interpolating segmental effects
  - Without supra-segmental effects
  - Only specific segments should be affected

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  - Labour intensive
  - Join artefacts

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- Method 1: Record deliberate mispronunciations
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- Method 2: Cross-language splicing
  - Labour intensive
  - Join artefacts
- Method 3: Synthesise stimuli
  - Data-driven, automated approach
  - No joins

Our approach

- Methods for synthesising foreign-accented stimuli
  - Multilingual HMM-based TTS (García Lecumberri et al., 2014)
  - Multilingual deep learning (this presentation!)

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- Improvement 1: Deep learning
  - Improved signal quality (Watts et al., 2016), thus replicating more perceptual cues
  - Flexible in inputs and outputs
  - Allows easy control of the output synthesis (Watts et al., 2015; Luong et al., 2017)

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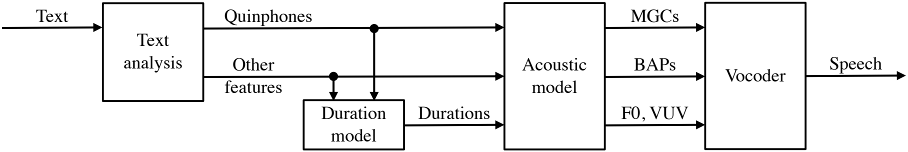
- Improvement 2: Use reference prosody (pitch and duration)
  - Can be taken from natural speech or predicted by a separate system
  - Allows us to impose native-like suprasegmental properties

Overview

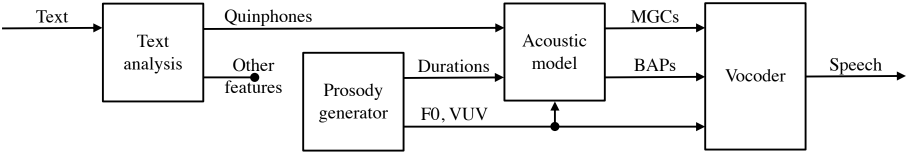
Building the synthesiser

Traditional text-to-speech:



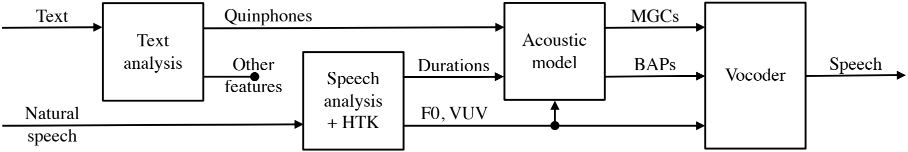
Building the synthesiser

Speech synthesis with arbitrary prosody:



Building the synthesiser

Speech synthesis with natural prosody:



"Cyborg speech"

"Cyborg speech"

- "A being with both organic and biomechatronic body parts"
  - Our acoustic parameters are a chimeric combination of man and machine

Making it foreign

- Segmental foreign accent through multilingual speech synthesis:
  - Teach a single model to synthesise several languages natively
  - Interpolate specific phones in the spoken language towards phones in the accent language
  - Maintain the same voice across languages
    - In this case by using data from a multilingually native speaker

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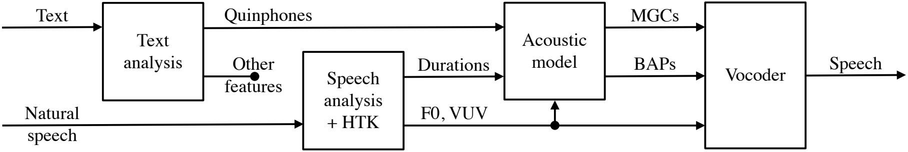
  - Maintain the same voice across languages
    - In this case by using data from a multilingually native speaker
- Running example: American English and Japanese
  - Combilex GAM (Richmond et al., 2009): 54 English phones
  - Open JTalk (Oura et al., 2010): 44 Japanese phones
  - Combined phoneset: $54 + 44 = 98$ phones

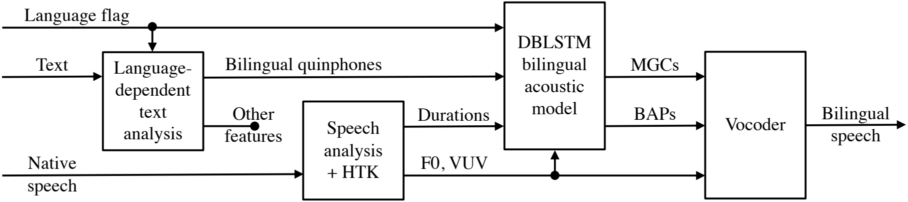
Synthesising foreign accent

Cyborg speech:



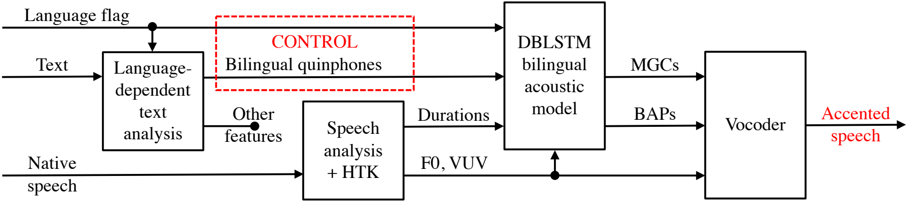
Synthesising foreign accent

Bilingual cyborg speech synthesis:



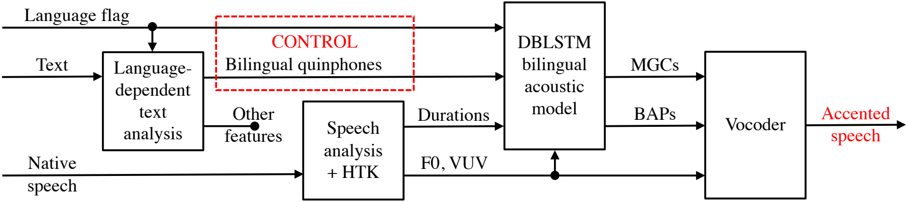
Synthesising foreign accent

Foreign-accented speech synthesis:



Synthesising foreign accent

Foreign-accented speech synthesis:



Synthetic mispronunciations through cross-language interpolation between 98-dimensional one-hot phone encodings in the quinphones

Overview

Data and processing

- Male voice talent native in both US English and Japanese
  - 2000 utterances per language
    - US English example
    - Japanese example
  - 20 pre-recorded test utterances in each language
  - 48 kHz at 16 bits

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  - 2000 utterances per language
    - US English example
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  - 20 pre-recorded test utterances in each language
  - 48 kHz at 16 bits
- WORLD vocoder for analysis and synthesis
  - GlottDNN pitch extractor (fewer VUV errors)
  - Static and dynamic features (MLPG)
- Forced alignment using monolingual HTS systems

Network and training

- Network topology
  - Same as in (Wang et al., 2017):
  - 2 logistic sigmoid feed-forward layers
  - 2 bidirectional LSTM layers

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- Network topology
  - Same as in (Wang et al., 2017):
  - 2 logistic sigmoid feed-forward layers
  - 2 bidirectional LSTM layers
- Minibatch training to minimise frame mean-square error
  - 160 epochs of raw SGD
  - $\leq$30 epochs of AdaGrad
    - Early stopping based on 5% validation utterances
  - Using the C++ framework CURRENNT (Weninger et al., 2015)

Systems

- Natural speech (NAT)
- Analysis-synthesis (VOC)
- Monolingual Japanese cyborg system (MON)
- Bilingual cyborg system (BIL)
    - Only this system can interpolate phones across languages

Cross-language substitutions

Consonant substitutions inspired by common mispronunciations among native American English speakers (L1) learning Japanese (L2):

Japanese		English		Substitutions	
IPA	Open JTalk	IPA	Combilex GAM	Max	Prompts
ɾ	`r`	ɹ	`r`	9	19
ɕ	`sh`	ʃ	`S`	8	13
dz	`z`	z	`z`	5	7
dʑ	`j`	dʒ	`dZ`	3	8
tɕ	`ch`	tʃ	`tS`	2	11

(Other substitutions allow BIL to generate Japanese-accented English)

Example stimuli

System	NAT	VOC	MON	BIL
ID 12	▶	▶	▶	▶
ID 13	▶	▶	▶	▶

System	BIL	BIL	BIL	BIL	BIL	BIL
Substitution	r	sh	z	j	ch	all
ID 12	▶	▶	▶	▶	▶	▶
ID 13	▶	▶	▶	▶	▶	▶

(How perceptible the differences are depends on your native language; they might be more obvious to non-Japanese listeners)

Overview

Listening test

- Crowdsourced listening test
  - 131 native Japanese listeners
  - Rating balanced sets of utterances
  - 599 ratings per condition (system and substitution)

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- Crowdsourced listening test
  - 131 native Japanese listeners
  - Rating balanced sets of utterances
  - 599 ratings per condition (system and substitution)
- Responses collected per stimulus presentation:
  - Speech quality: 1 (poor) to 5 (excellent)
  - Strength of foreign accent: 1 (native-like) to 7 (very strong)
  - Foreign accent classification: 5 nationalities (CHI, KOR, AUS, IDN, and USA), "none", and "unknown"

Strength of perceived foreign accent

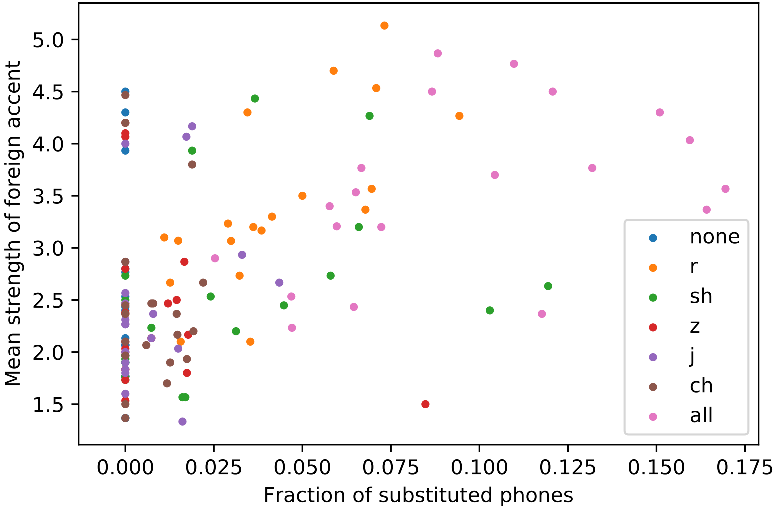
System	Substitution	Accent strength	Change
NAT	none	1.60 ± 0.046	-
VOC	none	1.73 ± 0.050	0.13 vs. NAT
MON	none	2.42 ± 0.064	0.69 vs. VOC
BIL	none	2.39 ± 0.063	-0.03 vs. MON
BIL	r	3.38 ± 0.071	0.99 vs. none
BIL	sh	2.53 ± 0.064	0.14 vs. none
BIL	z	2.42 ± 0.064	0.03 vs. none
BIL	j	2.48 ± 0.064	0.09 vs. none
BIL	ch	2.45 ± 0.062	0.06 vs. none
BIL	all	3.55 ± 0.071	1.16 vs. none

(Ranges are 95% mean accent strength confidence intervals)

Distribution of perceived accent

Condition		Accent language (%)				
System	**Substitution**	**None**	**USA**	**CHI**	**Other**	**Unk.**
NAT	none	77	5	3	4	12
VOC	none	72	8	3	4	13
MON	none	50	9	8	7	27
BIL	none	51	10	7	8	24
BIL	r	23	29	9	11	28
BIL	sh	44	10	10	9	27
BIL	z	48	11	7	7	28
BIL	j	47	11	9	8	26
BIL	ch	45	12	10	7	26
BIL	all	19	33	10	11	28

Scatterplot of BIL stimuli



(The overall Pearson correlation coefficient is 0.43)

Overview

Empirical conclusions

- Natural prosody was maintained (high correlation)
- Bilingual synthesis did not reduce speech quality
- Substituting the phone "r" (in r and all)
  - Produced foreign-accented speech
  - The accent was distinctly American
  - Was judged as somewhat lower quality (due to foreign accent?)
- Other substitutions were less noticeable
  - Also less prevalent in the test sentences
- Synthesis artefacts were perceived as an "unknown" accent

Summary of achievements

- We have generated foreign-accented synthetic speech audio
  - . . . with native prosody
  - . . . and finely controllable accent
  - . . . using deep learning and multilingual speech synthesis
  - . . . from non-accented speech data alone
  - . . . achieving a distinct and recognisable accent

Possible extensions

- Use a neural vocoder (e.g., WaveNet) to improve signal quality
  - Also consider Tacotron 2-style matched training
- Consider other phone encodings (control spaces)
  - IPA place/manner of articulation?
  - Formants frequencies?
- Apply the work in foreign-accent research
  - Currently in progress

The end

The end

Thank you for listening!

The end

Any questions?

Acknowledgement

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References I

Derwing, T. M. and Munro, M. J. (1997).
Accent, intelligibility, and comprehensibility.
Stud. Second Lang. Acq., 19(1):1–16.

García Lecumberri, M. L., Barra Chicote, R., Pérez Ramón, R., Yamagishi, J., and Cooke, M. (2014).
Generating segmental foreign accent.
In *Proc. Interspeech*, pages 1303–1306.

Hahn, L. D. (2004).
Primary stress and intelligibility: Research to motivate the teaching of suprasegmentals.
TESOL Quart., 38(2):201–223.

Kang, O., Rubin, D., and Pickering, L. (2010).
Suprasegmental measures of accentedness and judgments of language learner proficiency in oral English.
Mod. Lang. J., 94(4):554–566.

Luong, H.-T., Takaki, S., Henter, G. E., and Yamagishi, J. (2017).
Adapting and controlling DNN-based speech synthesis using input codes.
In *Proc. ICASSP*, pages 4905–4909.

References II

Munro, M. J. and Derwing, T. M. (2001).
Modeling perceptions of the accentedness and comprehensibility of L2 speech.
Stud. Second Lang. Acq., 23(4):451–468.

Oura, K., Sako, S., and Tokuda, K. (2010).
Japanese text-to-speech synthesis system: Open JTalk.
In *Proc. ASJ Spring*, pages 343–344.

Richmond, K., Clark, R. A. J., and Fitt, S. (2009).
Robust LTS rules with the Combilex speech technology lexicon.
In *Proc. Interspeech*, pages 1295–1298.

Tajima, K., Port, R., and Dalby, J. (1997).
Effects of temporal correction on intelligibility of foreign-accented English.
J. Phonetics, 25(1):1–24.

Wang, X., Takaki, S., and Yamagishi, J. (2017).
An autoregressive recurrent mixture density network for parametric speech synthesis.
In *Proc. ICASSP*, pages 4895–4899.

References III

Watts, O., Henter, G. E., Merritt, T., Wu, Z., and King, S. (2016).
From HMMs to DNNs: where do the improvements come from?
In *Proc. ICASSP*, pages 5505–5509.

Watts, O., Wu, Z., and King, S. (2015).
Sentence-level control vectors for deep neural network speech synthesis.
In *Proc. Interspeech*, pages 2217–2221.

Weninger, F., Bergmann, J., and Schuller, B. W. (2015).
Introducing CURRENNT: The Munich open-source CUDA recurrent neural network toolkit.
J. Mach. Learn. Res., 16(3):547–551.

Subjective quality

System	Substitution	Quality MOS	Change
NAT	none	4.43±0.031	-
VOC	none	3.71±0.040	−0.72 vs. NAT
MON	none	3.34±0.035	−0.37 vs. VOC
BIL	none	3.33±0.035	−0.01 vs. MON
BIL	r	3.07±0.036	−0.26 vs. none
BIL	sh	3.27±0.035	−0.06 vs. none
BIL	z	3.31±0.035	−0.02 vs. none
BIL	j	3.31±0.036	−0.02 vs. none
BIL	ch	3.28±0.035	−0.05 vs. none
BIL	all	3.01±0.037	−0.32 vs. none

(Ranges are 95% MOS confidence intervals)

Prosodic faithfulness

Correlation between NAT and test stimuli pitch (log F0):

System	Substitution?	Pearson correlation
NAT	no	1
VOC	no	0.990
MON	no	0.986
BIL	no	0.965
BIL	yes	0.961–0.965

- Note that these numbers are much higher than for standard TTS