Selecting an acoustic correlate for automated measurement of /x/ production in children

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² NYU Center for Promotion of Research Involving Innovative Statistical Methodology

I: Introduction

- 1: Why /1/?
- 2: Visual acoustic biofeedback
- 3: Automated scoring for /x/
- 4: Several acoustic measures to consider

II: Methods

- 1: Data collection
- 2: Measurement
- 3: Statistical modeling

III: Results and Discussion

Background

- ► Speech sound disorders (SSD) can impede academic, social, and psycho-emotional development (Hitchcock et al., 2015).
- ► For some children, errors are resolve spontaneously, but others require long-term clinical intervention (Flipsen, 2015).
 - ► May persist through adolescence and, for 1-2% of individuals, into adulthood (Culton, 1986).
- ► More than 50% of school-based speech-language pathologists (SLPs) report having discharged children with treatment-resistant errors from their caseloads (Ruscello, 1995).

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Why $/_{\rm I}/?$

- Misarticulation of American English rhotics are the most common and challenging to treat. (Shuster et al., 1995; Ruscello, 1995).
 - ► Among the latest-acquired speech sounds (Smit et al., 1990).
 - ► Articulatorily complex: simultaneous anterior and posterior lingual constrictions (Espy-Wilson, 1992) can be achieved with a variety of lingual contours (Delattre and Freeman, 1968).
- ► Despite articulatory variability, accurate /I/ has stable acoustic properties (Delattre and Freeman, 1968; Hagiwara, 1995)
 - ▶ Low third formant frequency (F3) relative to other vowels
 - ▶ Second formant frequency (F2) that is close to F3.

Retroflex





Bunched

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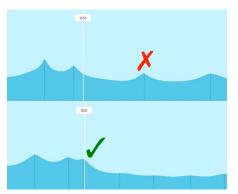
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Visual-acoustic biofeedback intervention

- ► Takes advantage of acoustic consistency of /1/.
 - Display real-time linear predictive coding spectrum representing vocal tract's resonant frequencies.
 - ▶ Display target showing correct production of sound.
 - ▶ Learner modifies output to align formants with target.
 - ► Focus is on lowering F3 to match accurate /x/ target.
- Demonstrated efficacy in single case experimental studies.

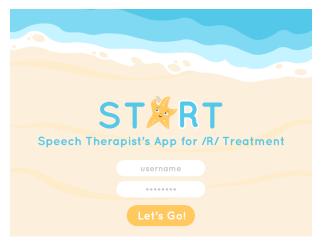
(McAllister Byun, 2017; McAllister Byun and Campbell, 2016; McAllister Byun and Hitchcock, 2012)



Visual-acoustic biofeedback intervention

App-based acoustic biofeedback

- ▶ Significant barriers to uptake of tech-based interventions:
 - ► Cost of the required technology (\$2K-\$5K).
 - Accessibility and user-friendliness of the technology.
 - ▶ Not always a quick solution; may require intensive schedule.
- ► App under development, in piloting stage (McAllister Byun et al., 2017).



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Motivation for automated scoring

- Gains in treatment do not readily generalize to contexts without biofeedback; longer treatment durations needed (Edeal and Gildersleeve-Neumann, 2011).
- Home practice may help increase the dosage of speech intervention while reducing the strain on SLP resources.
 - ► **Risk**: Without feedback from SLP, child will counterproductively reinforce incorrect speech patterns.
- Current need: Provide valid and reliable automated feedback and track progress during home practice with acoustic biofeedback.

The current study

- ▶ **Broad Goal**: Enable home practice with acoustic biofeedback through the incorporation of automated scoring.
- ► Which acoustic measure corresponds best with clinician ratings of children's /I/ productions?
- ➤ Approach: Compare models that include all possible acoustic values, with and without all possible interactions to find metric that best predicts accuracy.

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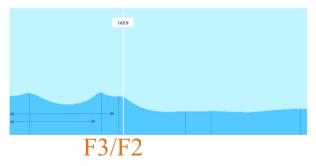
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Consider raw and derived measures for /I/

- ► F3: Primary acoustic cue to rhoticity (Espy-Wilson et al., 2000).
 - ► Low height of F3 differentiates / I/ from acoustically similar sounds such as /I/ and /w/ (Polka and Strange, 1985).
- ► F2: Secondary acoustic cue to rhoticity (Polka and Strange, 1985).
 - ► F2 in close proximity to F3.
- ▶ Derived within-subject measures reflect the influence of both raw acoustic cues simultaneously (Flipsen et al., 2001; Lee et al., 1999).
 - ► F3-F2 Distance
 - ► F3/F2 Ratio



Consider normalization relative to typical speaker data

- ▶ Raw and derived measures can be normalized relative to typical speaker data, e.g., Lee et al. (1999) for ages 5-19+.
 - ▶ Raw F2 and F3 means and SDs (Lee et al., 1999).
 - ▶ Derived F3-F2 and F3/F2 means and SDs (Flipsen et al., 2001).

		Male	s		Females				
Age	n^{b}	F3-F2°	F3/F2°	n^{b}	F3-F2°	F3/F2°			
5 years	26	797 (343)	1.47 (0.21)	20	643 (210)	1.38 (0.14)			
6 years	15	567 (152)	1.37 (0.12)	25	644 (346)	1.35 (0.19)			
7 years	19	616 (138)	1.38 (0.09)	32	749 (323)	1.44 (0.22)			
8 years	38	517 (175)	1.31 (0.12)	19	669 (497)	1.43 (0.46)			
9 years	33	527 (145)	1.34 (0.10)	37	541 (119)	1.31 (0.08)			
10 years	40	527 (169)	1.32 (0.11)	24	531 (221)	1.31 (0.13)			

Consider interactions with acoustic measures

- ▶ Listeners may bring age- and sex-based expectations to a speech rating task that have the potential to interact with the properties of the raw acoustic signal.
 - Perceived age impacts accuracy ratings (Munson et al., 2010).
 - ▶ Perceived gender impacts accuracy ratings (Dart, 1991).
- ▶ Derivation and normalization may correct for some age- and sex-related differences (Flipsen et al., 2001), but it is unknown whether there are also interactions with these factors.

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Participants

► Children receiving /x/ treatment in 3 biofeedback studies.

(McAllister Byun et al., 2014; McAllister Byun & Hitchcock, 2012; Hitchcock et al., in press)

- Normal hearing and oral structure/function.
- ► Word probes elicited throughout 8-10 weeks of intervention in a sound-shielded room with the CSL (KayPentax, Model 4150B)

Study	Children	Ages	Tokens
		(mean)	
Acoustic (2012)	11	6-11 (9;0)	2109
Ultrasound (2014)	5	6-9 (7;8)	2926
`EPG [´] (2017)	6	6-10 (8;0)	1040
Total	22		6075

▶ Varied by phonetic context: Syllabic (808), Post-vocalic (1532), Singleton onset (774), Cluster onset (2961)

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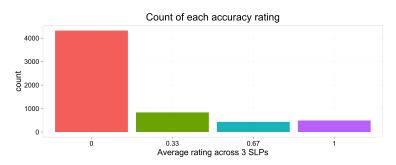
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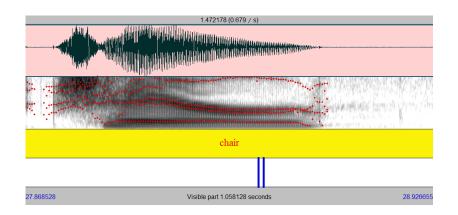
Ratings of perceptual accuracy

- ▶ Following the "industry standard" for perceptual rating in speech intervention studies (McAllister Byun et al., 2015), binary ratings were acquired in a blinded randomized fashion from 3 certified SLPs who exhibited at least 80% pairwise agreement.
 - ▶ Tokens were rated correct or incorrect.
 - Average across 3 raters was treated as an ordinal scale.
 - ▶ Ratings were unequally distributed across accuracy levels.



Acoustic measurement

► Trained graduate students measured formant frequencies from the minimum F3 in the rhotic interval of each word using Praat (Boersma and Weenink, 2014).



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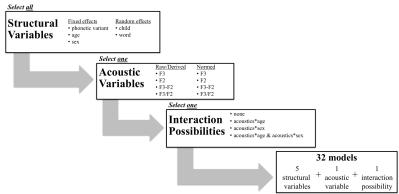
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Statistical modeling

► A series of ordinal mixed-effects regression models were fit on the aggregated data set while considering the following factors:



Model selection

- ► Akaike & Bayesian Information Criteria (AIC/BIC) were used to select the best-fitting model.
 - ▶ Both take into account the number of predictors (Cohen et al., 2013).
 - ▶ BIC penalizes for each predictor, preferring fewer predictors.
 - ▶ Select the model with the lowest AIC and BIC.
- ► All analyses were conducted in R (RStudio, 2016).
 - ▶ Data compilation using 'tidyverse' packages (Wickham, 2016).
 - Regression models were fit using the "clmm" function in the 'ordinal' package (Christensen, 2015).

- ► Controlling for age, sex, and phonetic context, the measure that accounted for the most variance in speech rating was F3-F2 distance normalized relative to a sample of age- and sex-matched speakers.
 - Higher normalized F3-F2 distance was associated with significantly lower accuracy ratings.
 - Best interaction possibility included acoustic variables interacting with both age and sex.
- Cluster onset tokens differed significantly from syllabic and vocalic targets.

- ▶ Process for comparing all 32 models.
 - ▶ Best models among normalized metrics.

AIC AND BIC FOR ALL 32 MODELS: LOWEST AIC AND BIC FOR EACH INTERACTION BEST MODELS SHOWN SEPARATELY FOR NORMALIZED AND NON-NORMALIZED METRICS

ACOUSTIC MEASURE INCLUDED IN MODEL	MAIN EFFECTS		Main i				MAIN EFFECTS + ACOUSTICS*AGE + ACOUSTICS*SEX	
	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC

Normalised F2								
Normalised F3				7980.7			7800.2	
Normalised F3-F2	7704.9	7778.7	7680.4	7760.9	7672.0	7752.5	7617.3*	7704.5*
Normalised F3/F2								

- Surprising that normalized version of F3-F2 performed better than non-normalized version of F3-F2.
- ▶ Limitations of normative data from Lee et al. (1999):
 - ▶ Based on 9-25 individuals in each age/sex group.
 - Speakers from a limited geographic region.
 - ▶ Only stressed vocalic /₃/ in the word "bird."

TABLE I. Distribution of subjects by age (in years) and gender.

Age	5	6	7	8	9	10	11	12	13	14	15	16	17	18	5-18	25-50
Male	19	11	11	25	23	25	24	22	16	11	11	11	10	10	229	29
Female	13	16	24	11	25	14	19	21	13	10	11	11	9	10	207	27
Total	32	27	35	36	48	39	43	43	29	21	22	22	19	20	436	56

- Process for comparing all 32 models.
 - ▶ Best models among normalized metrics.
 - ▶ Best models among non-normalized metrics.

AIC AND BIC FOR ALL 32 MODELS: LOWEST AIC AND BIC FOR EACH INTERACTION
BEST MODELS SHOWN SEPARATELY FOR NORMALIZED AND NON-NORMALIZED METRICS

ACOUSTIC MEASURE INCLUDED IN MODEL	MAIN EFFECTS			FFECTS + CICS*AGE		FFECTS +	MAIN EFFECTS + ACOUSTICS*AGE + ACOUSTICS*SEX		
	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	
F2									
F3			7871.1	7951.7			7851.6	7938.9	
F3-F2	7752.0	7825.8	7739.7	7820.2	7753.9	7834.5	7741.7	7828.9	
F3/F2									
Normalised F2									
Normalised F3			7900.2	7980.7			7800.2	7887.4	
Normalised F3-F2	7704.9	7778.7	7680.4	7760.9	7672.0	7752.5	7617.3*	7704.5*	
Normalised F3/F2									

Conclusions

- ► For future automated scoring of children's /r/ productions:
 - ▶ If normative data are appropriate, use the externally normalized F3-F2, in interaction with the child's age and sex.
 - ▶ Otherwise, we recommend the non-normalized version of F3-F2, in interaction with age only.
- ► App-based treatment with automated scoring may facilitate increases in treatment dosage by allowing home practice.



Next steps

- Collect more representative normative values, including:
 - A larger sample of children.
 - ► A more geographically diverse sample.
 - Phonetic contexts other than the syllabic rhotics.
- Improve current aggregated data set:
 - Obtain gradient ratings rather than binary ratings (McAllister Byun et al., 2016; Schellinger et al., 2016; Munson et al., 2012, 2017).
 - Obtain crowd-sourced ratings from naïve listeners (McAllister Byun et al., 2015), which may differ from SLP ratings (Klein et al., 2012).
 - ▶ Include potential control for different phonetic context: duration (Klein et al., 2012).

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Thank you!

Questions?

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