5aPP5



Overview

- cue profile test assesses a hearing-impaired listener's use of specific speech cues • "weighting angle" quantifies how well individual listeners can use spectral & temporal cues
- previous iterations of cue profile are too time-consuming
- we created an inter-trial stability metric to determine whether early stopping was possible • testing time can be shortened significantly without much loss information • a preliminary machine learning classifier shows promise in predicting 3-way weighting angle
- class from cue profile data, while preliminary, are encouraging

Background

Pure Tone Audiograms (PTA) are inadequate to describe hearing loss

- Ability to recover speech info. is influenced by etiology and the individual [3]
- Sensitivity to pure tones is not a reliable indicator of other kinds of auditory ability [2]

Cue profile [3,4,5,6] is an alternative that provides useful information about the kinds of speech cues listeners attend to

- It can be used to compute a **cue weighting angle**, which shows whether the listener attends more to spectral information or the amplitude envelope [6] • Amount of hearing loss according to PTA is not indicative of the weighting angle
- A listener's cue profile is **reliable and repeatable** over several months [5]

Cue Profile Procedure

- familiarization, training, and test phases
- for each trial:
 - listener hears a synthesized syllable from a set of 25 where F2 & F3 transitions and amplitude envelope varied along continua
 - 2. they label the stimulus as either "BAH," "DAH," "LAH," or "WAH"

[DAH	I					LAH
	5	DAH 1 LAH 2 BAH 3	DAH 2 LAH 2	DAH 2 LAH 2	DAH 2 LAH 2	LAH 1 DAH 2 WAH 3	
	4	BAH 3 DAH 3	DAH 4 LAH 5 BAH 6	DAH 5 LAH 5	LAH 4 DAH 5 WAH 6	LAH 3 WAH 3	
Temporal	3	BAH 3 DAH 3	BAH 6 DAH 6	7	LAH 6 WAH 6	LAH 3 WAH 3	
	2	BAH 3 DAH 3	BAH 4 WAH 5 DAH 6	BAH 5 WAH 5	WAH 4 BAH 5 LAH 6	LAH 3 WAH 3	
	1	BAH 1 WAH 2 DAH 3	BAH 2 WAH 2	BAH 2 WAH 2	BAH 2 WAH 2	WAH 1 BAH 2 LAH 3	
E	BAH	1	2	3 Spectral	4	5	VAH

profile stage	# trials	stimuli	
familiarization	40	Endpoints (in pink) with correct response highlighted	Pinl stimu the in am
training	40/blk	Endpoints with correct response shown after trial, repeated until 80% accuracy attained	
test 375		All stimuli in randomized order without feedback	

nk stimuli are considered unambiguous. Blue nuli are ambiguous in a single dimension, and nner squares (orange, green, white) are more mbiguous still. The (syllable, #) text is used in classification experiments and indicates the dimension of the accuracy vector that is incremented for a given response.

A linear discriminant analysis categorizes each test (stimulus, response) pair into one of four groups using 2 discriminants. The first discriminant's coefficients are used to compute a cue weighting angle ranging 0-90°.

$$\theta = \tan^{-1} \left(\frac{\text{spectral coef}}{\text{temporal coef}} \right)$$

Listener Demographics

• 26 listeners with 375 trials, 1 listener with 360, collected in [5] and [6]

• mild to moderately-severe sensorineural hearing loss

• 63-89 years (mean 73.6)

Methods: Stability Measure

Compute rolling averages for listener's data:

- . compute angle using all trial data up to that point.
- produces a sequence of 375 predicted angles
- 2. Rolling average θ_{avg_i} over a window size w at trial *i* is calculated as

$$\theta_{avg_i} = \frac{\sum_{max(0,i-w)}^{\prime} \theta_{p_i}}{w}$$

Find **stability point**:

for divergence tolerance d, a listener is stable by trial i if, for all trials j, $i < j \le 325$

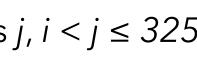
$$|\theta_{avg_i} - \theta_{avg_i}| < d.$$

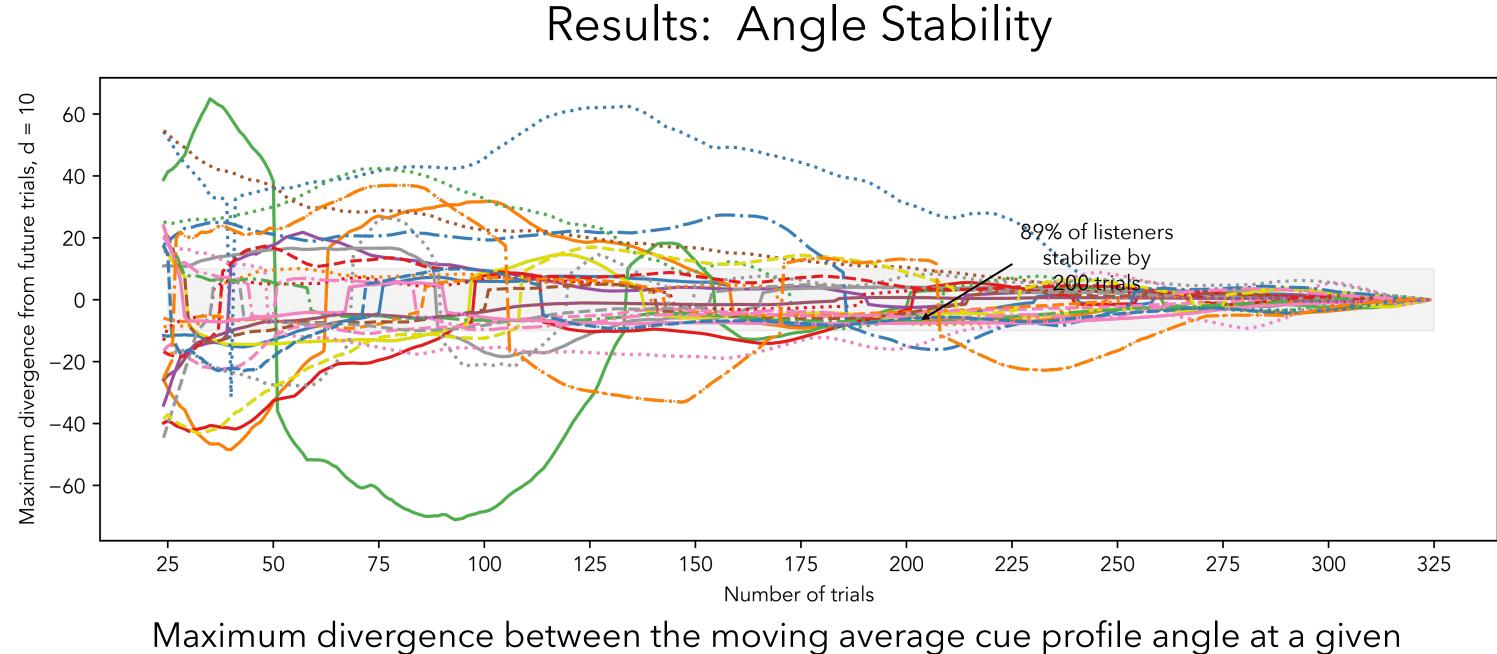
Modeling the time course of cue weighting angle calculations

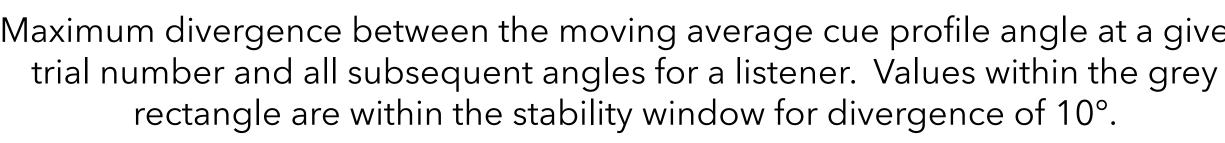
Sara Ng¹, Gregory Ellis², Pamela Souza², Frederick Gallun³, Richard Wright¹

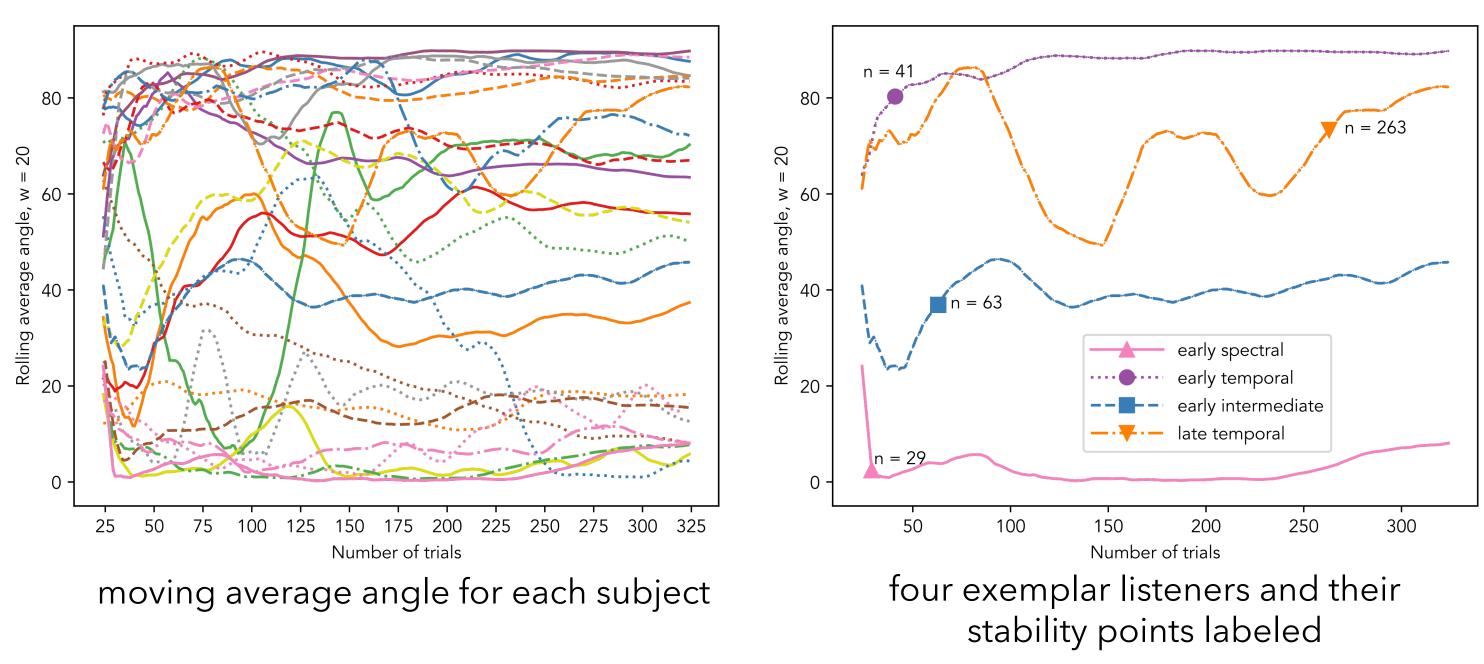
¹Linguistics, University of Washington ²Communication Sciences and Disorders, Northwestern University ³Oregon Hearing Research Center, Oregon Health and Science University









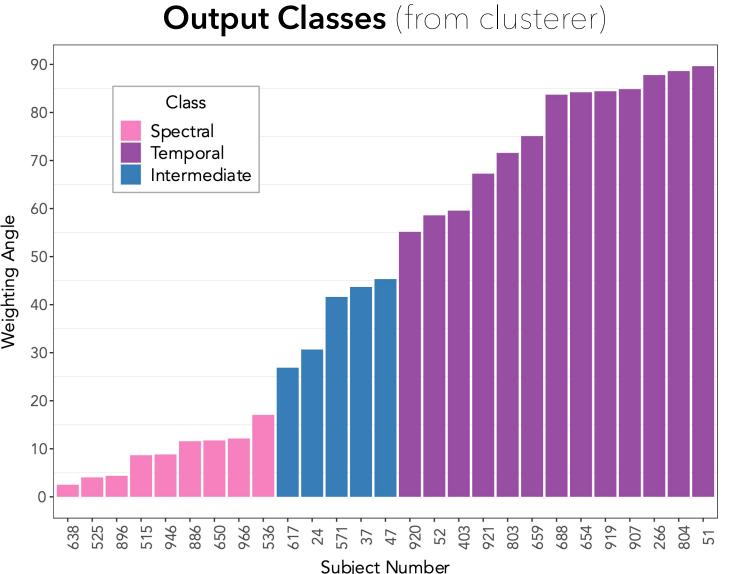


- At *t* > 325, there is **evidence of subject fatigue**, skewing angles temporally & not indicative of their actual cue preference. Because of this, we only used the first 325 trials when determining stability.
- We default to a window size *w=20* and **maximum divergence d=10°**, and compare to $d=5^{\circ}$.
- For $d=5^{\circ}$, 77% of listeners reach stability within **200 trials**.
- For $d=10^{\circ}$, 89% of listeners reach stability within the same time frame.

Methods: Clustering and Classification

Step 1) with coarse-angle categorization as a clinical motivation, we use an automatic **clusterer** to define the boundaries between spectral, temporal, and balanced cue weighting.

Step 2) train an LSTM, a neural network that handles sequential information, to predict the angle class using the cue profile and demographic data



nonsequential sequential real of the sequential real of the sequential sequential real of the sequential real of the sequence of the sequence

Subject Number

Input Features	(for LSTM)
----------------	------------

		,
aining data type	dim.	values
unning angle: predicted sing trials up to <i>t=i</i>	1	0 - 90
imulus type and response	25	1 - 4
rid accuracy	7	0 - # trials
uickSIN	1	float
TA score, per ear, 500 000 and 2000 Hz	6	int
ge	1	int 63-89
ex	1	M or F

UNIVERSITY of WASHINGTON

W

Train and Eval pipeline:

- step size of 5
- feature to the previous best combination

model type	input features used	test acc.
random forest	stimulus type & resp. + grid accuracy	0.57
	ΡΤΑ	0.83
	PTA + Running angle	0.73
	PTA + Running angle + Age	0.83
LSTM	PTA + Running angle + Age + Gender	0.81
	PTA + Running angle + Age + Gender + QuickSIN	0.83
	PTA + Running angle + Age + Gender + QuickSIN + stimulus & resp.	0.73

The cue profile can be simplified.

• for many listeners, testing during the cue profile **could be shortened by 175 trials** (46%) with reasonable fidelity Simplifications should consider individual differences.

- stabilize very quickly

This work was funded by NIH NIDCD R01 DC006014 (PS) and R01 DC 015051 (FJG). The views expressed are those of the authors and do not represent the views of the NIH or the Department of Veterans Affairs. We would like to thank Lauren Balmert (Northwestern) and Mari Ostendorf (University of Washington) for their guidance in developing the stability metric. Thanks to Agatha Downey (University of Washington) for her help debugging the LSTM.

[1] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-

[2] Musiek, F. E., Shinn, J., Chermak, G. D., & Bamiou, D. E. (2017). Perspectives on the puretone audiogram. Journal of the American Academy of Audiology, 28(07), 655-671. [3] Souza, P. E., Ellis, G., Marks, K., Wright, R., & Gallun, F. (2021). Does the Speech Cue Profile Affect Response to Amplitude Envelope Distortion?. *Journal of Speech, Language, and Hearing*

Research, 64(6), 2053-2069. [4] Souza, P., Gallun, F., & Wright, R. (2020). Contributions to speech-cue weighting in older adults with impaired hearing. Journal of Speech, Language, and Hearing Research, 63(1), 334-344. [5] Souza, P., Wright, R., Gallun, F., & Reinhart, P. (2018). Reliability and repeatability of the speech cue profile. Journal of Speech, Language, and Hearing Research, 61(8), 2126-2137.

[6] Souza, P. E., Wright, R. A., Blackburn, M. C., Tatman, R., & Gallun, F. J. (2015). Individual sensitivity to spectral and temporal cues in listeners with hearing impairment. Journal of Speech, Language,

and Hearing Research, 58, 520-534.







Northwestern University

Results: Machine Learning Classification

Augment training data by creating copies of each listener with first *n* trials, using

2. Configure network with 2 LSTM^[1] layers, hidden dimension 32, dropout rate 0.1 3. Select input features for model, with each subsequent models adding one

4. Train each model using 3 random seeds for 100 epochs with early stopping 5. For each input configuration, report the seed which gave best test performance

Discussion

listeners with strongly spectral or strongly temporal angles often

• listeners with medial angles can stabilize quickly, but it's less common • depending on parameters selected, some listeners require the full cue profile test, or may not stabilize at all

Machine learning shows promise as a mechanism to shorten the cue profile • a simple neural network can fit well to observed input features

naïve data augmentation strategies improve performance

• generalization to unseen data is less reliable

• cause is likely the small dataset size

Acknowledgments

References



get this poster and more info about the project 🔮