Optimizing and Evaluating Hearing-Aid Self-Fitting Methods Using Population Coverage

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OBJECTIVE

- Over-the-counter (OTC) hearing aids must allow users to self-fit their hearing aids. **An optimal self-fitting method should enable any user to find a gain-frequency configuration that balances appropriate audibility and user preference for sound quality.** The method should also make it simple for a user to find this optimal configuration. Designing a self-fitting method that serves these purposes is challenging.
- In this project, two approaches to designing optimal gain-frequency presets are considered and compared: a <u>slider-based approach</u> and a <u>collection-based</u> approach.[1,2]
- **The purpose of this project was to investigate how well each approach could optimize the trade-off between the number of presets and the population coverage, considering both audibility and preference.** Optimal gain-frequency responses based on population coverage for both methods are suggested.

1. Get the audiograms of the target population.

- Audiograms were drawn from the 1996-2016 National Health and Nutrition Examination Surveys (NHANES).
- 1,979 (1166 unilateral, 816 bilateral) audiograms were extracted representing the target population (mild-to-moderate sensorineural hearing loss) for OTC hearing aids. **Fig. 1** shows the included audiograms.

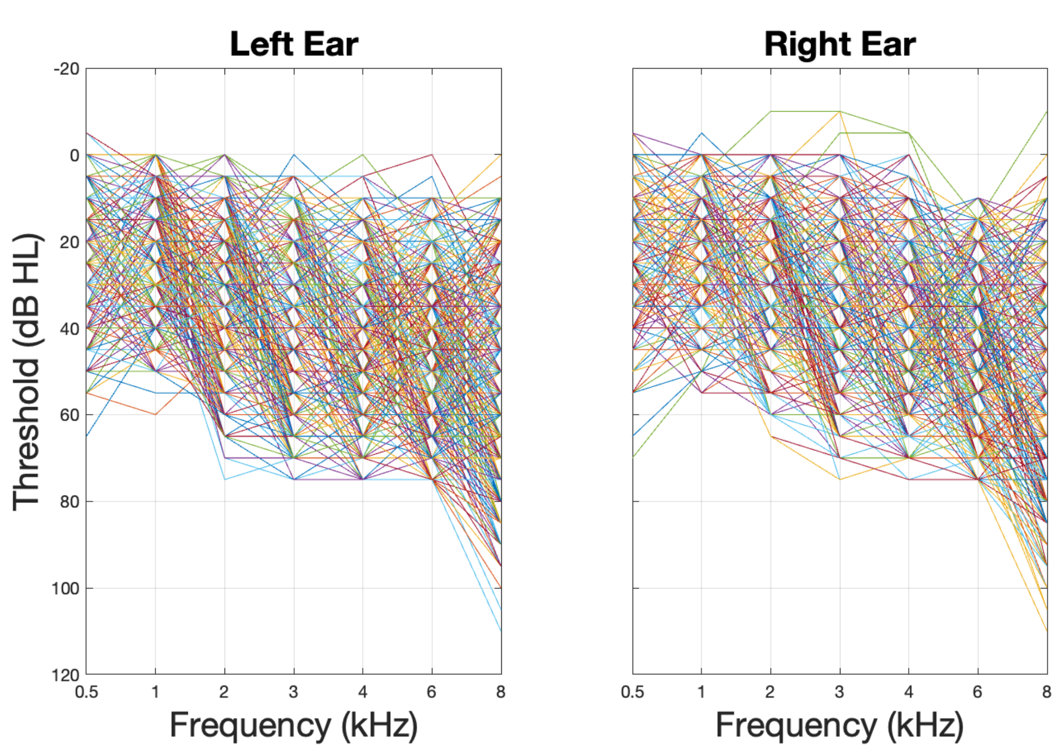

Figure 1. NHANES audiograms used in gain-frequency derivations and coverage calculations.

2. Derive NAL-NL2 Target REIGs.

- NAL-NL2 target real-ear insertion gains (REIG) were calculated for each audiogram for a 65 dB SPL broadband input.
- REIG configurations were calculated both unilaterally and bilaterally for bilateral hearing losses.
- Total number of REIG configurations = 4,418. **Fig. 2** shows all the REIG configurations**.**

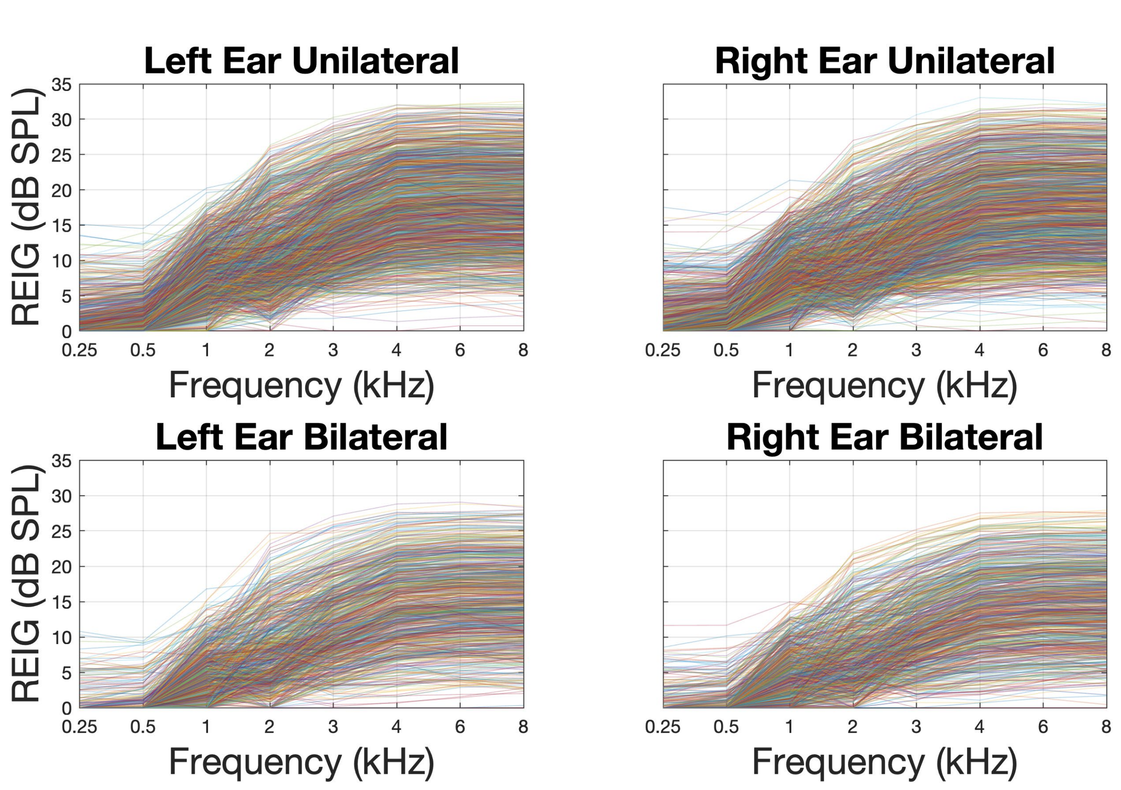

Figure 2. NAL-NL2 prescribed REIGs for the set of audiograms extracted from the NHANES database.

3. Add preference variations to NL2 REIGs.

- Hearing aid users show preference variations from NL2 targets approximately +/- 15 dB at .5 and 4 kHz.[3,4]
- Using anchor points spaced at 3.75 dB increments[5] from +15 dB to -15 dB at .5 and 4 kHz, 81 transfer functions were derived to account for a user's preferred deviation from NL2 targets. **Fig. 3a** shows the transfer functions.
- Each REIG was then superimposed on each transfer function, resulting in **<u>357,858 possible gain-frequency configurations to cover the target population.</u> Fig. 3b** shows an example of an NL2 REIG (black) and the potential preferred variations on that REIG.

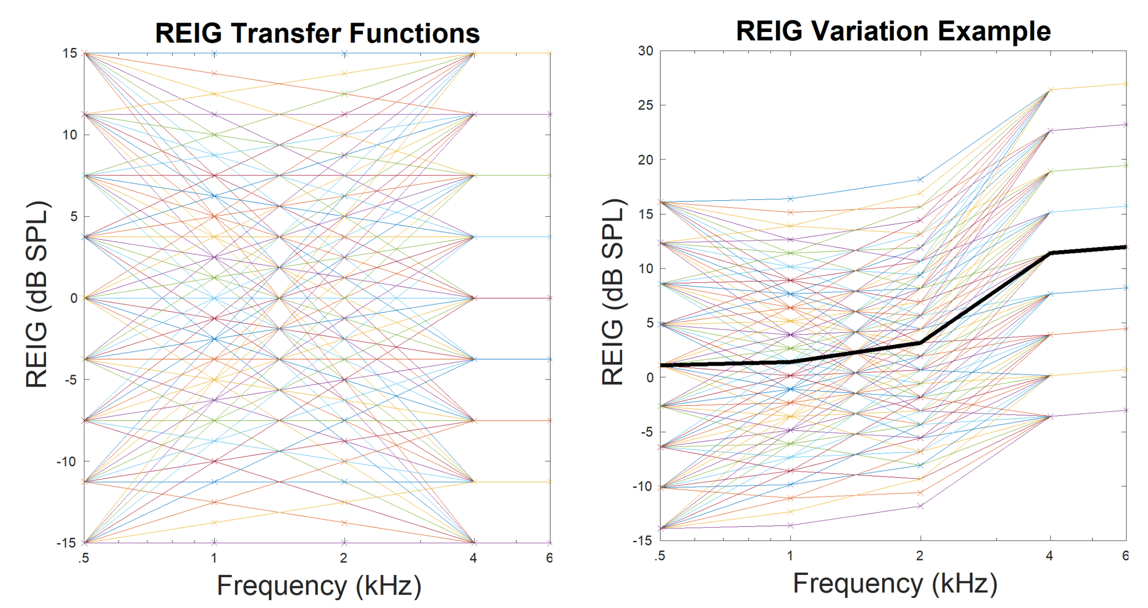

Figure 3a (left). Transfer functions for applying preference variations from NL2 targets. Figure 3b (right). Resulting REIGs after applying transfer functions to an NL2 REIG.

4. Weight the population and transfer functions.

- The coverage of a configuration depends both the <u>population weight</u> of the audiogram and the <u>transfer function weight</u> of the preference deviation from target.
- The population weight is included in the NHANES database and represents the *prevalence of the audiogram in the population*.
- The transfer function weight is determined by the Gaussian distribution of preference variations from NL2 targets and *represents the likelihood of the preference deviation.* **Fig. 4** shows the Gaussian distributions of gain preference derivations at low (.5 kHz) and high (4 kHz) frequencies based on empirical data.[3,4]

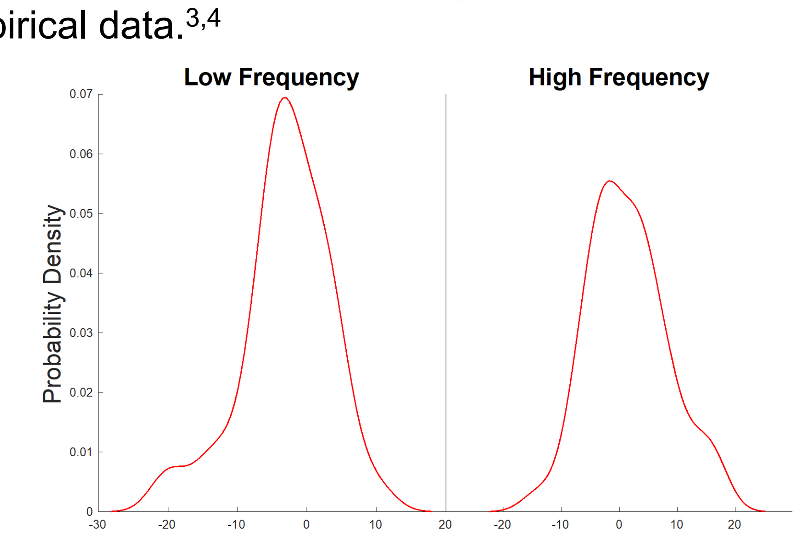

Figure 4. Gaussian distributions of gain preference variations from NL2 targets for low (left) and high (right) frequencies.

5. Calculate the coverage of a configuration.

- The 8 dimensions of the configurations were reduced to 2 dimensions using Principal Components Analysis (PCA). <u>2-dimensional PCA accounted for 95% of the total variance.</u>
- An individual is covered if the sum of the weights of the covered potential preferred configuration exceeds 0.8 (80%). For bilateral users, this includes configurations of unilateral left or unilateral right use and bilateral use.
- The **population coverage** of a configuration is the *sum of the population weights of all the users covered by the configuration.*
- **Fig. 5** shows an example of coverage for a configuration in PCA space. The red square in the figure is a hearing aid preset. The preset covers all configurations within +/- 5 dB radius. The black dots represent the configurations covered by the preset. The grey dots are configurations not covered.

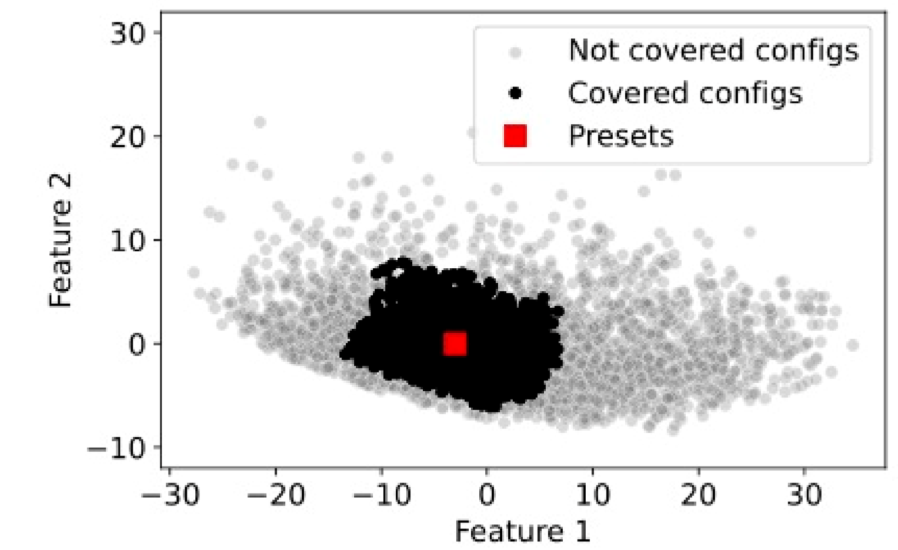

Figure 5. Example of preset coverage in the PCA space. Red dot is the preset. Black dots are configurations covered by the preset +/- 5 dB. Grey dots are not covered.

6. Derive the optimal set of presets using algorithms.

- ***Collection-based presets:* one self-fitting method is to find the presets that maximize coverage and allow the user to choose among them using pairwise comparisons, ranking, or some other selection method.**
- Collection-based presets were derived by applying different algorithms to the configurations in the PCA space: a genetic algorithm, a greedy algorithm, and k-means clustering. The algorithms were designed to find the presets that best covered the configurations in PCA space with the least number of presets.
- **Fig. 6** shows an example comparing 40 presets on the PCA space derived using the different algorithms.

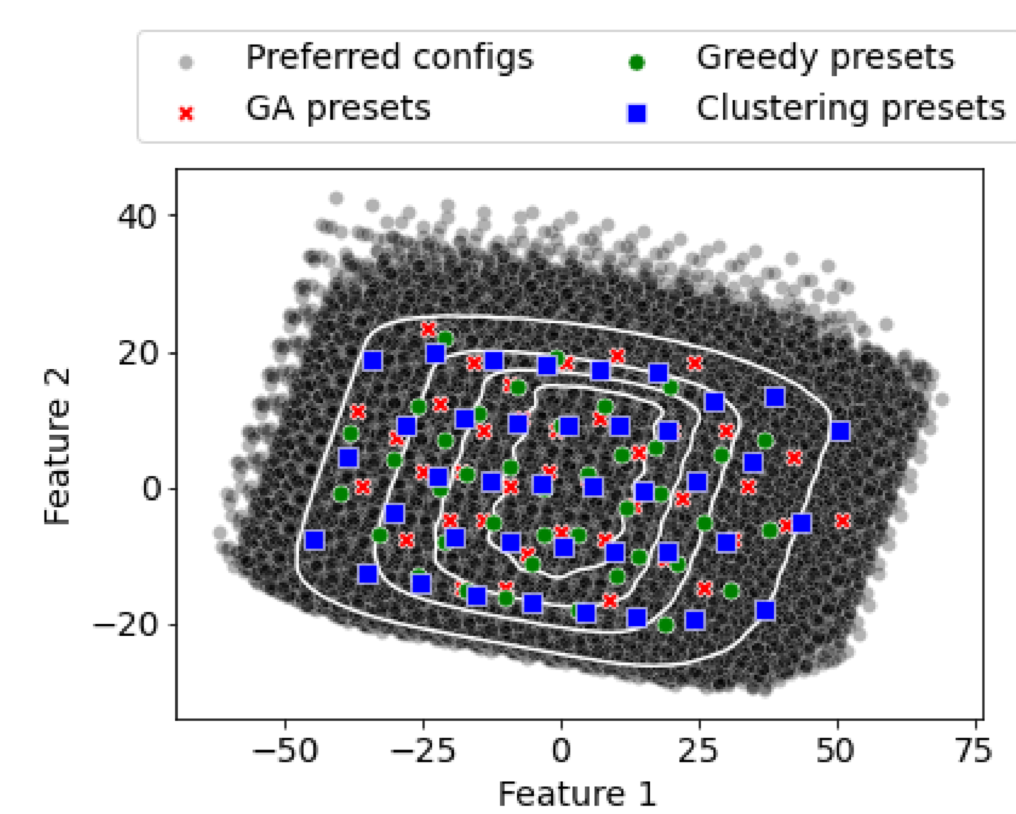

Figure 6. 40 presets derived using different algorithms shown on the configuration PCA space.

- **Fig. 7** shows the population coverage as a function of the number of presets for the 3 algorithms. As the number of presets increases, population coverage increases, but the increase in coverage over 40 presets is asymptotic. 40 presets results in approximately 85% coverage. The genetic algorithm produced the best results.

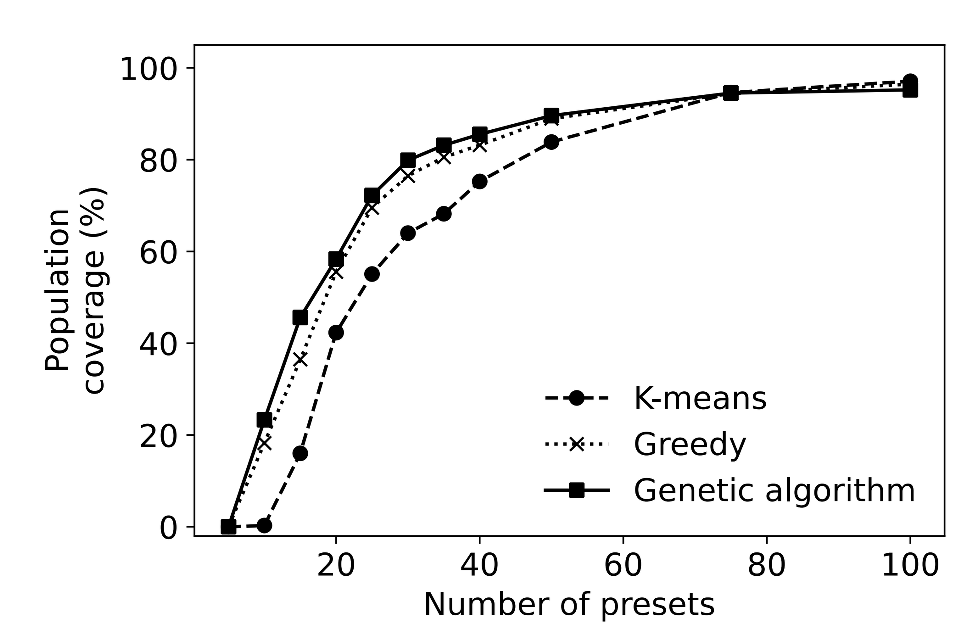

Figure 7. Population coverage as a function of number of presets derived from each algorithm.

7. Derive the optimal set of presets using sliders.

- ***Slider-based presets:* An alternative to using collection-based presets is to divide the axes of the PCA space into equally-spaced increments. The user can then choose a preset by changing coordinates in the PCA space using sliders representing the axes.**
- **Fig. 7** shows an example of sliders representing the PCA space containing the configurations.

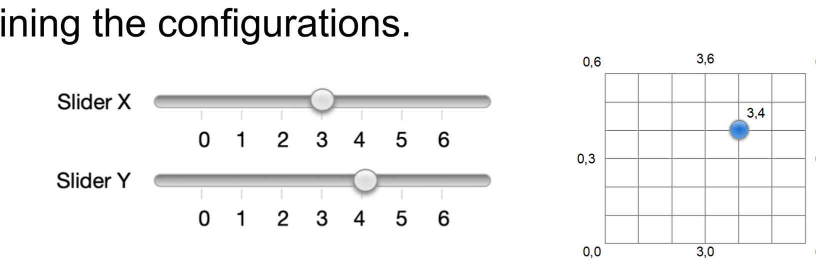

Figure 7. Example of selection sliders representing coordinates on the PCA space.

- **Fig 8** shows how coverage changes as a function of increment number of the x (left) and y (right) axes. Coverage improves a as a function of increment number, but improvement over 10 steps on either axis is asymptotic. Coverage at 10 steps (100 presets) is approximately 79%.

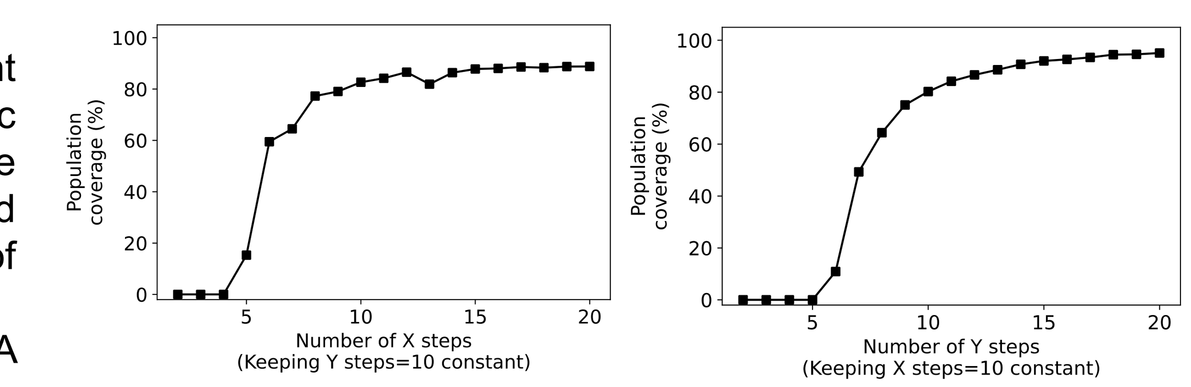

Figure 8. Population coverage as a function of the number of increments on the PCA x axis (right) and y axis (left).

8. Suggest optimal gain-frequency presets for collection and slider-based self-fitting methods.

- To cover approximately 80% of the target population, accounting for both NL2 targets and potential preference variations, 40 collection-based presets and 100 slider-based presets would be required.
- **Fig. 9** shows the gain-frequency configurations for the 40 presets derived using the greedy algorithm and covering 85% of the population.
- **Fig. 10** shows the gain-frequency configurations for the 100 presets derived by evenly dividing the PCA space into a 10x10 grid and covering 79% of the population.
- Both contain many presets. Whether users could find their optimal setting efficiently from this number of presets is an important future direction.

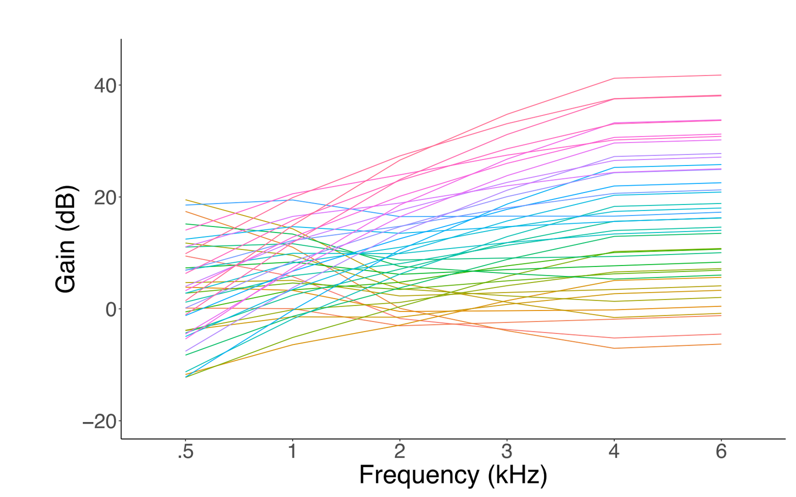

Figure 9. Gain-frequency configurations for presets derived using a genetic algorithm.

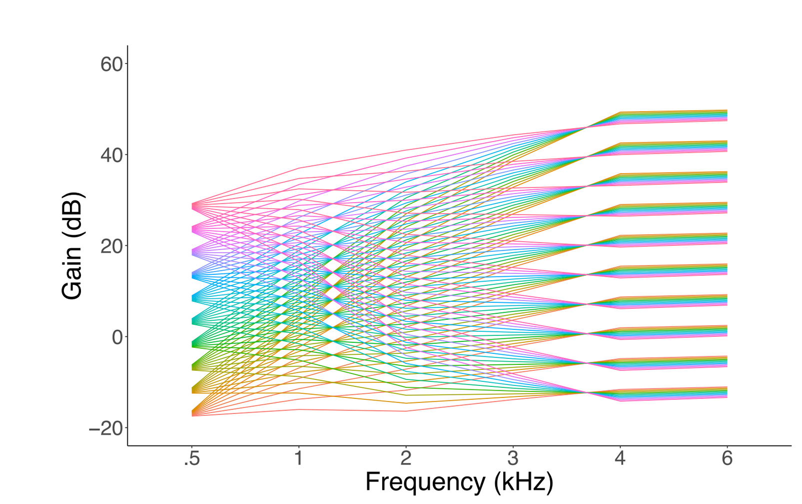

Figure 10. Gain-frequency configurations for presets derived by evenly dividing the PCA space.

References: 1. Nelson et al. 2018. TrendsHear. 22, 2331216518798264. 2. Urbanski et al. 2021. AJA. 30(1), 43–66. 3. Boothroyd et al. E&H. 2022. 43(3), 808–821. 4. Mackersie et al. TrendsHear. 2020. 24, 2331216520930545. 5. Caswell-Midwinter & Whitmer. (2019). TrendsHear. 23, 2331216518820220. **Funding**: NSF IIS-1838830 and CNS-1750155 and NIDILR 90REGE0013. **Contact:** Erik Jorgensen (erik.jorgensen@wisc.edu) or Dhruv Vyas (dhruv-vyas@uiowa.edu).