

Improving Hearing Aid Personalization Algorithm Efficiency with User Preference Correlations

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INTRODUCTION

- Determining the best hearing aid (HA) configuration from among all possible configurations is challenging. Prior research has proposed using machine learning algorithms to evaluate the search space of available configuration by learning from user feedback to converge on an optimal configuration.
- Our previous study evaluated several personalization algorithms and compared their accuracy, consistency, and efficiency in converging to a user's most preferred option. The results (Figure 1) indicated that although the best-performing algorithm—the Upper Confidence Bound (UCB) algorithm—could converge accurately and consistently (Figure 1), its efficiency (i.e., the total number of paired-comparisons necessary to identify the best configuration) was not good enough to be used in the real



Figure 1. Average convergence of each algorithm towards users' most preferred configuration plotted as max absolute difference* as a function timeslots (i.e., the required number of paired comparison inputs from the user).

- Max absolute difference is the maximum difference between the algorithm's current best option and the user's most preferred option at any of eight frequencies (0.25, 0.5, 1, 2, 3, 4, 6, and 8 kHz).
- The purpose of this study was to assess whether the efficiency of the UCB algorithm could be improved by incorporating correlations between patterns of preference from a group of users in addition to the feedback directly obtained from the user.

DESIGN

- Fifteen HA gain-frequency response configurations (i.e., 15 presets) were developed using audiometric data from a national health database. Speech was recorded from the output of a HA programmed with each of the 15 configurations (i.e., 15 presets) and presented to 32 older adults with hearing loss. The participants used a paired comparison paradigm to determine the order and strength of the preference for all possible combinations of configurations (105 pairwise comparisons x 4 repetitions).
- Order of preference was determined using a Borda scoring method, where a configuration's Borda score is the ratio between the number of times it was preferred and the total number of pairwise comparisons. Correlated pairs of configurations were identified by computing the Pearson correlation coefficient for all configuration pairs across all 32 users.

A positively correlated pair has a correlation coefficient greater than 0.7, and the configurations have similarly high or low Borda scores (i.e., they are both liked or both disliked out of all 105 configurations).

A negatively correlated pair has a correlation coefficient smaller than -0.7, and one configuration tends to be liked (high Borda score) while the other is disliked (low Borda score).

• Correlation results were used to determine how many paired comparisons could be removed from the search space and still yield accurate algorithm convergence. The Root Mean Square (RMS) of the NAL-NL2-based Real Ear Aided Response prescriptive targets of correlated configurations were also calculated and the differences analyzed.

Heatmap of Pearson Correlation Coefficient 15 Hearing Aid configurations														
B1 -	1	0.88	-0.43	-0.76	-0.74	0.89	0.49	0.67	-0.47	-0.22	-0.75	0.87	0.22	-0
B2 -	0.88	1	-0.53	-0.79	-0.62	0.93	0.43	0.52	-0.51	-0.34	-0.76	0.76	0.12	-0.
- B3	-0.43	-0.53	1	0.62	0.64	-0.5	0.15	-0.18	0.58	0.69	0.086	-0.34	-0.094	-0
B4	-0.76	-0.79	0.62	1	0.68	-0.79	-0.52	-0.43	0.35	0.19	0.57	-0.71	-0.14	0.
B5 -	-0.74	-0.62	0.64	0.68	1	-0.57	-0.26	-0.72	0.73	0.42	0.37	-0.75	-0.49	-0
B6 -	0.89	0.93	-0.5	-0.79	-0.57	1	0.41	0.5	-0.43	-0.28	-0.76	0.76	0.041	-0
B7 -	0.49	0.43	0.15	-0.52	-0.26	0.41	1	0.43	0.1	0.36	-0.61	0.55	0.12	-0
B8 -	0.67	0.52	-0.18	-0.43	-0.72	0.5	0.43	1	-0.45	-0.04	-0.53	0.78	0.68	-0.
69	-0.47	-0.51	0.58	0.35	0.73	-0.43	0.1	-0.45	1	0.67	0.26	-0.46	-0.36	-0
BIO	-0.22	-0.34	0.69	0.19	0.42	-0.28	0.36	-0.04	0.67	1	-0.039	-0.088	0.0075	-0
811	-0.75	-0.76	0.086	0.57	0.37	-0.76	-0.61	-0.53	0.26	-0.039	1	-0.69	-0.085	0.
B12	0.87	0.76	-0.34	-0.71	-0.75	0.76	0.55	0.78	-0.46	-0.088	-0.69	1	0.47	-0
B13 -	0.22	0.12	-0.094	-0.14	-0.49	0.041	0.12	0.68	-0.36	0.0075	-0.085	0.47	1	-0.0
B14	-0.35	-0.28	-0.45	0.17	-0.1	-0.31	-0.72	-0.31	-0.4	-0.58	0.45	-0.44	-0.094	1
B15 -	-0.65	-0.54	-0.24	0.36	0.28	-0.56	-0.68	-0.71	-0.033	-0.38	0.67	-0.7	-0.35	0.
	В1	B2	В3	Β4	B5	В6	B7	B8	В9	B10	B11	B12	B13	В

Figure 2. Heatmap of Pearson correlation coefficients for the Borda scores all pairs of 15 hearing aid configuration pairs across all 32 users. Positively correlated pairs have a correlation coefficient of 0.7 or greater. Negatively correlated pairs have a correlation coefficient of less than or equal to -0.7.

BORDA SCORING & UCB SELECTION ALGORITHM

Borda Scoring:

configuration winning a pairwise comparison with another preset beating *j*th preset in a pairwise comparison:

Borda Scoring Conceptual Diagram $B_i = \frac{1}{(n-1)} \sum_{i \neq j} P_{ij}$ $1 \quad 2 \quad 3 \quad \longrightarrow \quad 2 \quad Or \quad 3 \quad \longrightarrow \quad 3 \quad$ Pool of Configurations

Upper Confidence Bound (UCB) algorithm: Tracks probability of win plus number of times a given option is presented to the user. If difference in score of top two is more than the confidence bound, the top choice is declared the overall winner.



• Negatively correlated configurations had an average RMS Figure 4. RMS difference in dB between the NAL-NL2 based prescriptive REAR targets of positively correlated difference of 9.47 dB, with differences spread across all (blue) and negatively correlated (red) hearing aid frequencies. configuration pairs.

Borda score of a preset *i* is defined as the probability of that configuration chosen at random. It is calculated via the following equation, where n = total no of presets and $P_{ii} = \text{Probability}$ of *i*th



- convergence rate.

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Jensen et al. AJA 2020. Jensen et al. AAS 2020. National Health and Nutrition Examination Survey 2009-2012. Retrieved from: https://www.cdc.gov/nchs/nhanes/index.htm. Arabie, et al. 1996. Clustering and Classification, pp. 65-121. Lai and Robbins. 1985. Science Direct, 6(1), 4-22.



Comparison of Real Ear Aided Response targets for Correlated Configuration Pairs



Figure 3. Comparison of the Rear Ear Aided Response NAL-NL2 targets for 65 dB SPL input level for two positively correlated HA configuration pairs (left) and two negatively correlated HA configuration pairs (right). The maximum absolute difference and the RMS difference between the NAL-NL2 prescriptive targets of the two positively correlated pairs is 7 dB and 3.67 dB, respectively.

> • Among the 105 possible pairwise comparisons, 33 correlated pairs of configurations were identified, meaning that the outcome of one trial could yield multiple conclusions about the outcomes of other pairwise trials.

> • The correct order of a given user's preferences can be determined with only 72 comparison trials compared to the 105 total possible combinations, a reduction of 32%.

> • Positively correlated configurations had an average RMS difference of 4.52 dB, with differences driven by mid-tohigh frequency bands (1 - 6 kHz).

DISCUSSION

• Incorporating correlations between user preferences across a larger group of users can reduce the search space for an optimal configuration for a single user because the results of a non-queried trial can be assumed based on correlations with a queried trial. This reduction in search space can be as much as 32%, an estimation based on the preference selections of a group of 32 older adults. Additional human subject research is needed to confirm if this 32% improvement is the case.

• Reducing the search space can translate to a more efficient convergence of the selection algorithm. Additional research is needed to assess the degree to which the reduced search space improves the algorithm's

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