Motivation & Background
Modern digital hearing aids [1] require and offer a great level of personalization. Today, this personalization is not performed based directly on what the user actually perceives. Instead, HAs are currently personalized manually by a hearing-care professional (HCP) based on the HCP’s interpretation of what the user explains about what he perceives.

It is hypothesized that hearing aid (HA) users will benefit greatly if the HAs are adjusted and personalized more intelligently based directly on how the HA processed sound is perceived, not on an oral translation thereof.

An interactive personalization system based on Gaussian process regression and active learning is proposed, which personalize HAs based directly on what the user perceives. Preliminary results demonstrate a significant difference between a truly personalized setting obtained with the proposed system compared to current practice.

Interactive Personalization System

Procedure
1) A new optimal setting, \( \hat{x}^* \), is derived based on the current model estimate of the user’s objective function.
2) The user assesses the degree of preference between the current optimal setting, \( x_{\text{max}} \), and the proposed \( \hat{x}^* \).
3) The model of the subject’s objective function is updated based on the recent assessment, \( y \).

Experimental Results

![Experimental Results](image)

Subject 2: \( p_0 < 0.001 \)
Subject 3: \( p_0 < 0.001 \)
Subject 10: \( p_0 < 0.001 \)
Subject 11: \( p_0 < 0.001 \)
Subject 12: \( p_0 < 0.001 \)
Subject 13: \( p_0 < 0.001 \)
Subject 14: \( p_0 < 0.001 \)

Paradigm & Likelihood
Pairwise comparison between input instance, \( u_k \) and \( u_{k'} \), with indication of the degree to which one is preferred over the other [2].

\[
p(y_k|f_k, \theta_c) = \text{Beta}(y_k; x^*(f_k, \sigma), \nu(1 - \langle f_k, \sigma \rangle))
\]

where \( \zeta(f_k, \sigma) = \phi \left( \frac{f(x_k^*) - f(x_k)}{\sigma} \right) \), and \( \theta_c = \{ \sigma, \nu \} \)

Bayesian Regression Framework

\[
p(\Gamma(Y, X, \theta) = \prod_{i=1}^{m} p(y_k|f_k, \theta_c)p(f(X, \theta_c))
\]

where \( f = \{ f(x_1), ..., f(x_m) \} \) and \( f(x) \sim GP(d, \theta) \) [3].

The covariance function, \( k(x, -x)_{\theta} \), is chosen as a squared exponential with ARD. The posterior, \( p(\Gamma(X, \theta)|Y, \theta) \), \( \theta = \{ \theta_1, \theta_2 \} \), and subsequent joint predictions \( p(\Gamma|X^*, \theta) = \mathcal{N}(\Gamma|\mu^*, \Sigma^*) \), are estimated based on a MAP-II approach and the Laplace approximation.

Sequential Experimental Design

A bivariate extension to standard EI [4] is proposed.

\[
x^* = \arg\max_x E[I, E(I|X)] = \sigma^2 \phi \left( \frac{\mu^2}{\sigma^2} \right) + \mu^2 \phi \left( \frac{\mu^2}{\sigma^2} \right)
\]

with \( \mu_1 = \mu^2 - \mu_{\text{max}}^2 \)

\[
\sigma^2 = \Sigma + \Sigma_{\text{max,max}} - 2 \Sigma_{\text{max}}
\]

Summary

- We have suggested a state-of-the-art machine-learning based personalization system for hearing-aid personalization which provides fast and robust optimization of HA settings.
- The system may provide a convenient fine-tuning supplement in clinics.
- Results indicate a generally consistent benefit of the obtained fine-tuned setting.
- The particular modeling approach may easily be extended to support other types of user feedback, such as rankings or absolute scores.

References