Neural Information Processing Systems Foundation

Hearing Aid Personalization

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WIDEX HIGH DEFINITION HEARING

DTU

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.

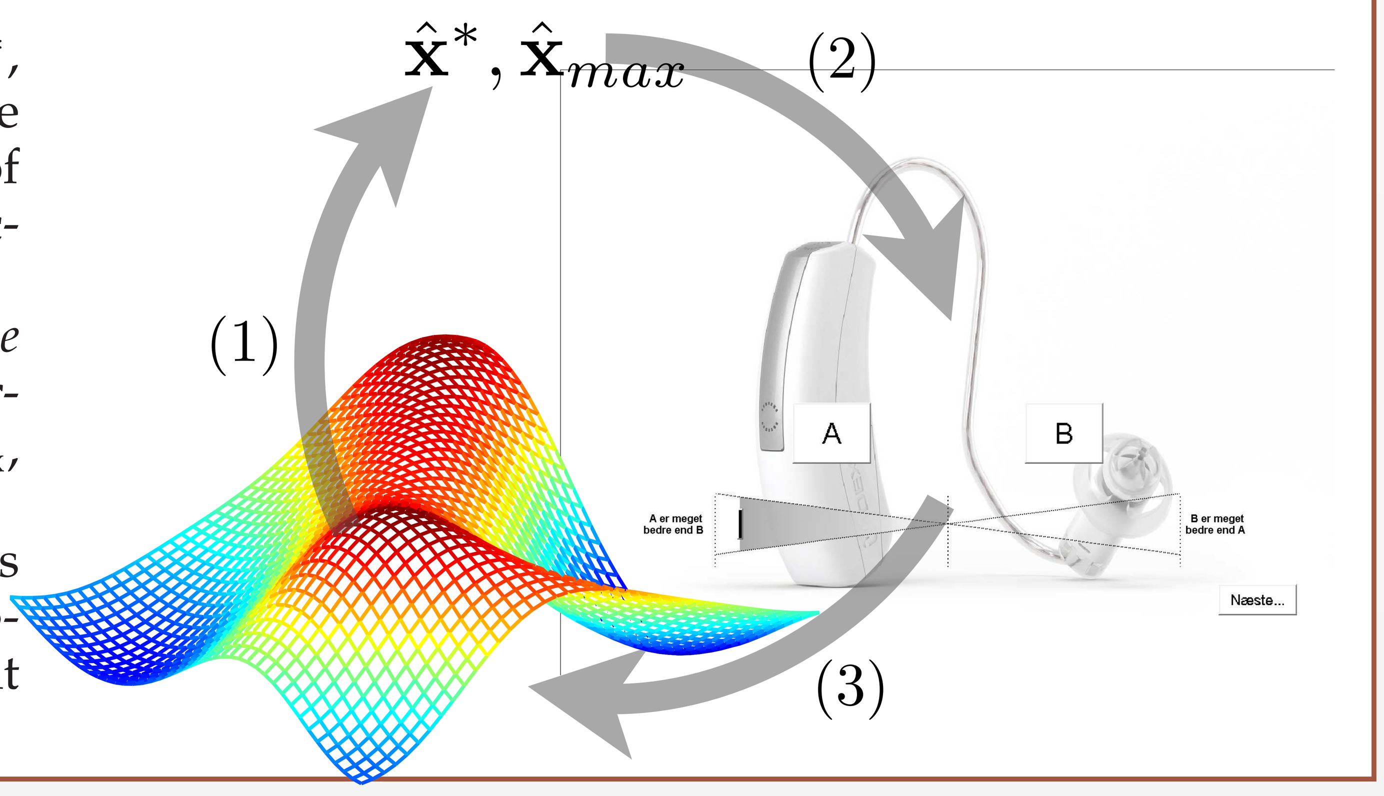
> It is hypothesized that hearing aid (HA) users will benefit greatly if the HAs are adjusted and personalized more intelligently based directly on how the HA processed sound is perceived; not on an oral translation thereof.

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, $\hat{\mathbf{x}}^*$, is determined 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, $\hat{\mathbf{x}}_{\max}$, and the proposed $\hat{\mathbf{x}}^*$.
3) The model of the subject's objective function is updated based on the recent assessment, y.



Modeling

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].

$$p(y_k|\mathbf{f}_k, \boldsymbol{\theta}_{\mathcal{L}}) = \text{Beta}\left(y_k; \nu\zeta(\mathbf{f}_k, \sigma), \nu(1-\zeta(\mathbf{f}_k,\sigma))\right),$$

$$\text{where } \zeta(\mathbf{f}_k, \sigma) = \Phi\left(\frac{f(\mathbf{x}_{v_k}) - f(\mathbf{x}_{u_k})}{\sqrt{2}\sigma}\right) \text{ and } \boldsymbol{\theta}_{\mathcal{L}} = \{\sigma, \nu\}$$

where $\mathbf{f}_k = [f(\mathbf{x}_{u_k}), f(\mathbf{x}_{v_k})]^\top$ and $f : \mathbb{R}^D \to \mathbb{R}, \mathbf{x} \mapsto f(\mathbf{x})$. The combined set of inputs and observations: $\mathcal{X} = \{\mathbf{x}_i \in \mathbb{R}^D | i = 1, ..., n\}$ and $\mathcal{Y} = \{y_k; u_k, v_k | k = 1, ..., m\}$, where $u_k \neq v_k$ and $\mathbf{x}_{u_k}, \mathbf{x}_{v_k} \in \mathcal{X}$.

Bayesian Regression Framework

$$p(\mathbf{f}|\mathcal{Y}, \mathcal{X}, \boldsymbol{\theta}) = \frac{\prod_{k=1}^{m} p(y_k|\mathbf{f}_k, \boldsymbol{\theta}_{\mathcal{L}}) p(\mathbf{f}|\mathcal{X}, \boldsymbol{\theta}_{\mathcal{C}})}{\int \prod_{k=1}^{m} p(y_k|\mathbf{f}_k, \boldsymbol{\theta}_{\mathcal{L}}) p(\mathbf{f}|\mathcal{X}, \boldsymbol{\theta}_{\mathcal{C}}) d\mathbf{f}}$$

where $\mathbf{f} = [f(\mathbf{x}_1), ..., f(\mathbf{x}_n)]^\top$ and $f(\mathbf{x}) \sim \mathcal{GP}\left(0, k(\mathbf{x}, \cdot)_{\boldsymbol{\theta}_{\mathcal{C}}}\right)$ [3].

The covariance function, $k(\mathbf{x}, \cdot)_{\boldsymbol{\theta}_{\mathcal{C}}}$, is chosen as a squared exponential with ARD. The posterior, $p(\mathbf{f}|\mathcal{Y}, \mathcal{X}, \boldsymbol{\theta})$, $\boldsymbol{\theta} = \{\boldsymbol{\theta}_{\mathcal{C}}, \boldsymbol{\theta}_{\mathcal{L}}\}$, and subsequent **joint** predictions $p(\mathbf{f}^*|\mathbf{x}_1^*, ..., \mathbf{x}_{n^*}^*) = \mathcal{N}(\mathbf{f}^*|\boldsymbol{\mu}^*, \boldsymbol{\Sigma}^*)$, are estimated based on a MAP-II approach and the Laplace approximation.

Sequential Experimental Design

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

$$\hat{\mathbf{x}}^* = \underset{\mathbf{x}_l^*}{\text{argmax}} EI, \; EI = \sigma_I \phi\left(\frac{\mu_I}{\sigma_I}\right) + \mu_I \Phi\left(\frac{\mu_I}{\sigma_I}\right), \text{with}$$

$$\mu_I = \boldsymbol{\mu}_l^* - \boldsymbol{\mu}_{\max}^*$$

$$\sigma_I^2 = \boldsymbol{\Sigma}_{l,l}^* + \boldsymbol{\Sigma}_{\max,\max}^* - 2 \cdot \boldsymbol{\Sigma}_{l,\max}^*$$

Experimental Results

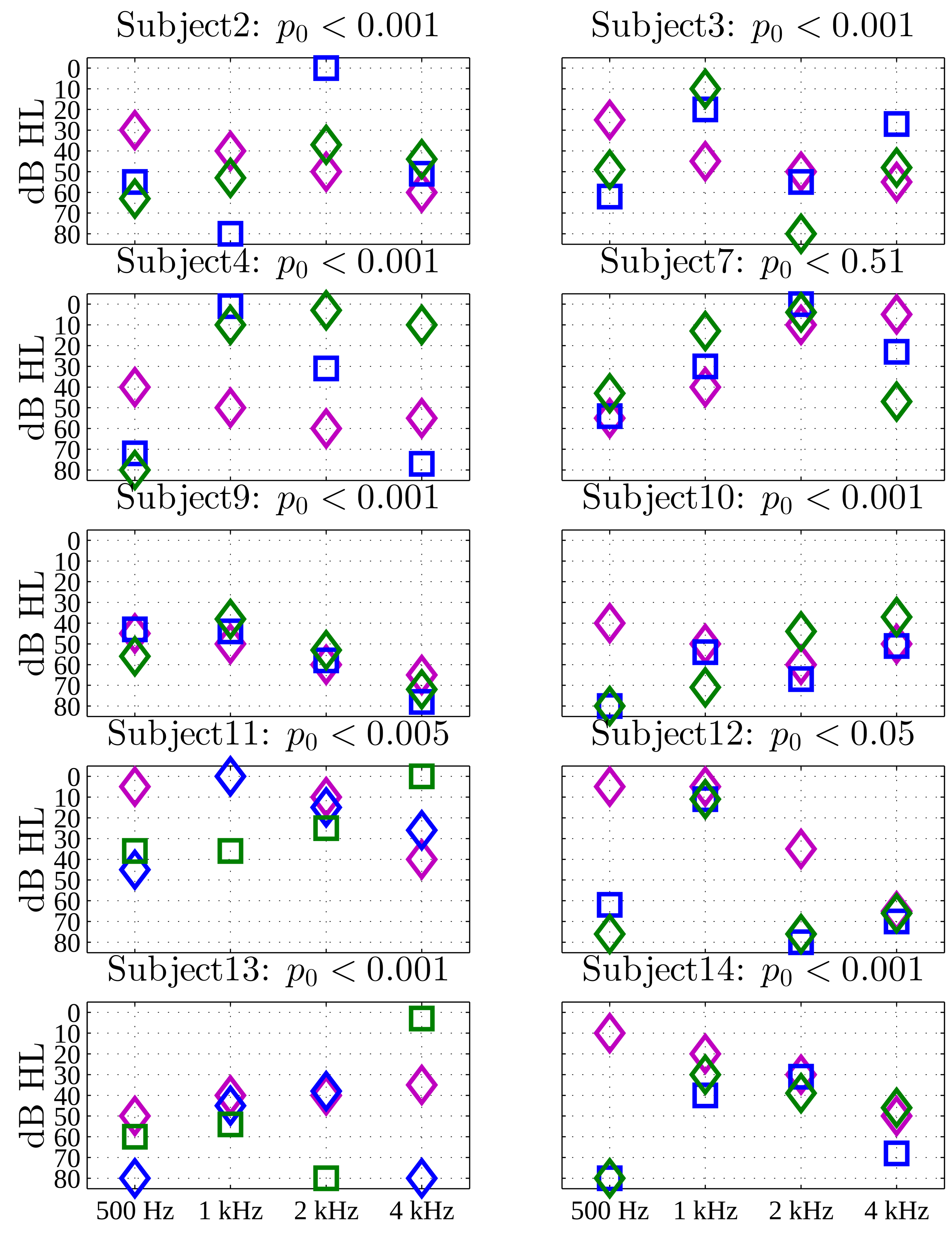


Fig. 1: *Personalized settings in two consecutive tests, Test 1 (—) and Test 2 (—), of four HA parameters effectively controlling the gain around four frequencies. The prescribed setting for each of subject is indicated by (—). p_0 indicates the significance level of the subject preferring the obtained setting marked with ◊ over the prescription ◊.*

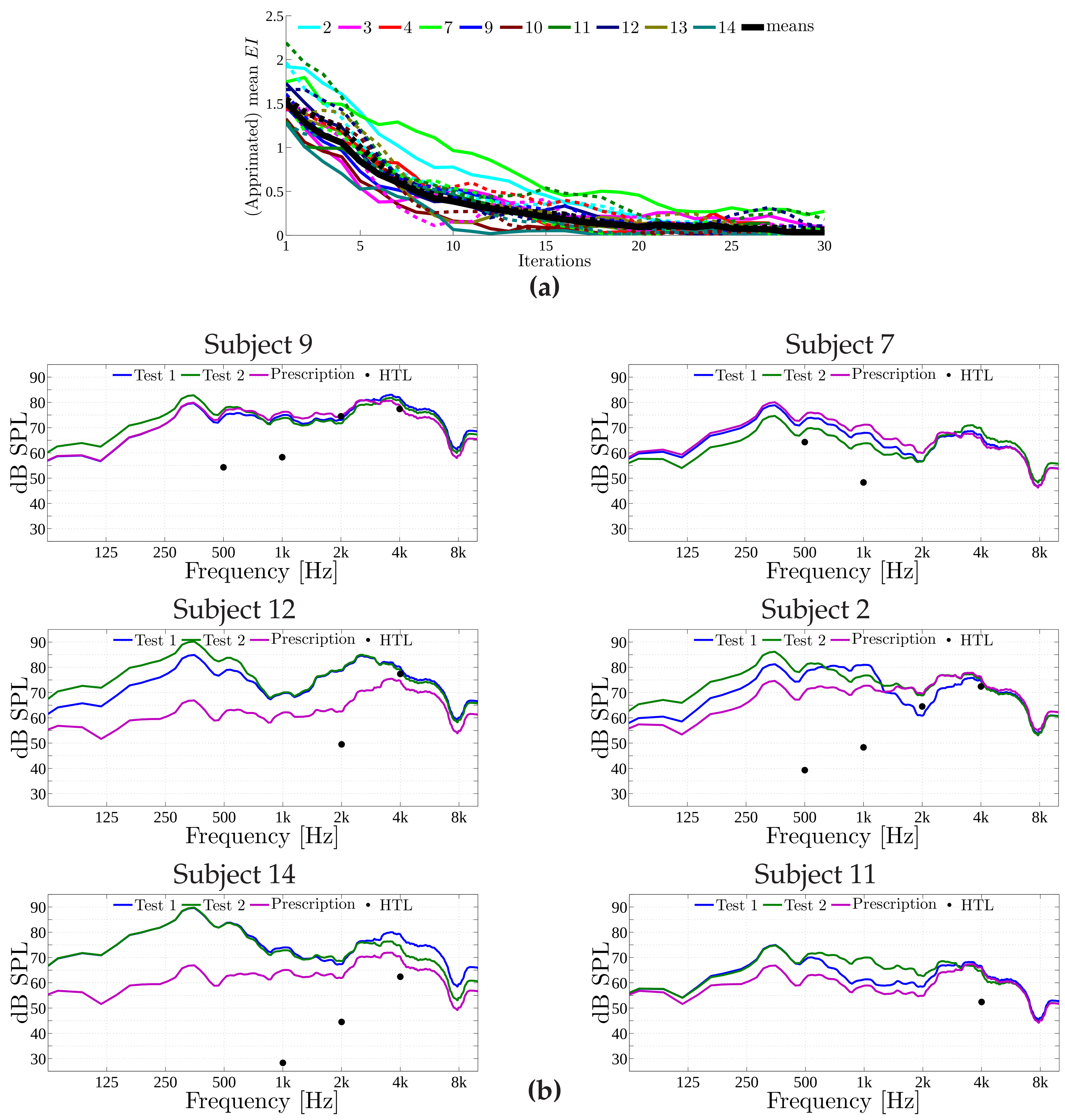


Fig. 2: *(a) Convergence plots for individual subjects in terms of average Expected Improvement (EI). (b) Long-term power spectra of the measured sound pressure level at the eardrum of a KEMAR (in a GRAS IEC711 coupler). Each subject's hearing threshold levels (HTL) at the four distinct basis frequencies are marked with black dots.*

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

[1] H. Dillon, *Hearing Aids*, Boomerang Press, 2nd edition, 2012.
[2] B. S. Jensen, J. B. Nielsen, and J. Larsen, "Efficient Preference Learning with Pairwise Continuous Observations and Gaussian Processes," *IEEE Workshop MLSP, Beijing*, September 2011.
[3] C. E. Rasmussen and C. K. I. Williams, *Gaussian Processes for Machine Learning*, MIT Press, 2006.
[4] D. R. Jones, "A Taxonomy of Global Optimization Methods Based on Response Surfaces," *Journal of Global Optimization*, vol. 21, no. 4, pp. 345–383, 2001.