EFFICIENT **INDIVIDUALIZATION** OF HEARING AID PROCESSED SOUND

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Introduction

- Modern digital hearing aids (HAs) offer an almost infinite number of possible parameter setting combinations. The parameter setting can be adjusted to make the sound more or less comfortable, audible, intelligible etc. However, the subjective preference of the individual user is not systematically taken into account when optimizing hearing aids. Consequently, many hearing impaired (HI) users are given HAs that are merely *generalized* in contrast to *individualized*. Moreover, fine tuning of modern HAs to the individual is becoming increasingly difficult and time consuming as the palette of features continues to grow.
- In the present work, the concept of *preference-based individualization* is investigated. The concept is addressed by an interactive system (Fig. 1), where the HA setting is optimized based on a minimum of subjective preference assessments (interactions).
- The approach builds upon sophisticated state-of-the-art statistical machine learning, that potentially accounts for user inconsistency [1]. Ideally, this approach promises fast HA optimization to any individual listening strategy in a given listening situation.

Interactive Individualization Loop

- (1) Optimal Test: Sample a new test input to suggest to the user by drawing a input from

$$p(\mathbf{x}_i) \propto EI(\mathbf{x}_i, \boldsymbol{\mu}^*, \mathbf{K}^*)$$

- (2) User interaction: a 2AFC paradigm is used, where the user grades the *degree of preference* between *two settings*, while listening to the stimulus through the HAs.
- (3) Update Model: (*Internal representation of preference* (IRP))

  - Make (approximate) inference [1]:

$$p(\mathbf{f}|\mathcal{Y},\mathcal{X},\boldsymbol{\theta}) = \frac{p(\mathcal{Y}|\mathbf{f},\boldsymbol{\theta}_{\mathcal{L}})\,p(\mathbf{f}|\mathcal{X},\boldsymbol{\theta}_c)}{p(\mathcal{Y}|\boldsymbol{\theta},\mathcal{X})} \approx \mathcal{N}\left(\mathbf{f}|\hat{\mathbf{f}},(\mathbf{W}+\mathbf{K}^{-1})^{-1}\right)$$

  - Learn (hyper-)parameters [1]:

$$\boldsymbol{\theta}^{\text{MAP}} = \arg\max_{\boldsymbol{\theta}} p(\boldsymbol{\theta}|\mathcal{Y},\mathcal{X})$$

  - Make (Bayesian) predictions [1]:

$$p(\mathbf{f}^*|\boldsymbol{\mu}^*,\mathbf{K}^*), \qquad \begin{aligned}\boldsymbol{\mu}^* &= \mathbf{k}_t^{\top}\mathbf{K}^{-1}\hat{\mathbf{f}}\\ \mathbf{K}^* &= \mathbf{K}_t - \mathbf{k}_t{}^{T}(\mathbf{I}+\mathbf{W}\mathbf{K})^{-1}\mathbf{W}\,\mathbf{k}_t\end{aligned}$$

Experiments

- Five HI listeners participated in the study wearing double-domed closed earmolds. The sound stimulus was synthetic speech-in-car-noise played back over loudspeakers.
- 1. day. Subjects conducted 3 sessions of 30 assessments, each session with a particular listening strategy: preference (always the first session), perceived speech intelligibility and comfort.
- 2. day. Subjects repeated the preference session from day 1.

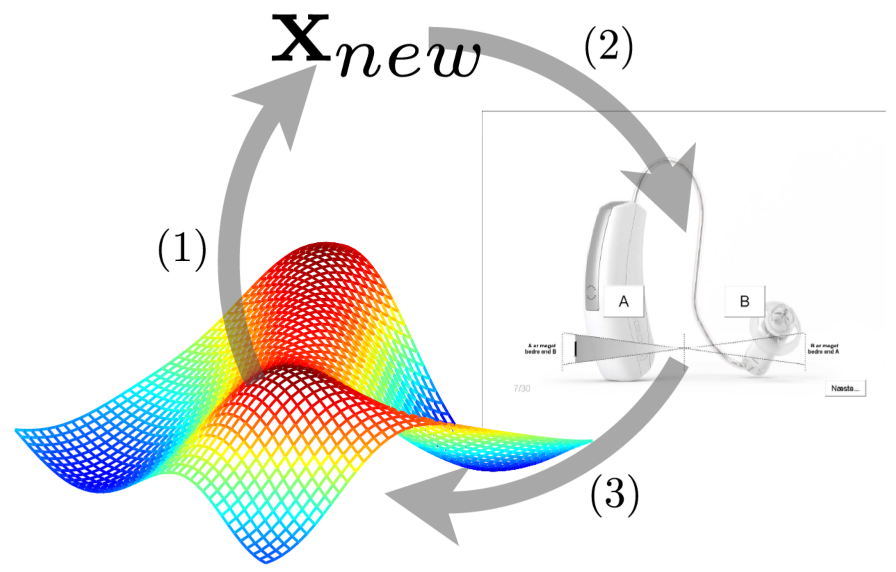

Fig. 1. Sketch of the *interactive individualization loop.*

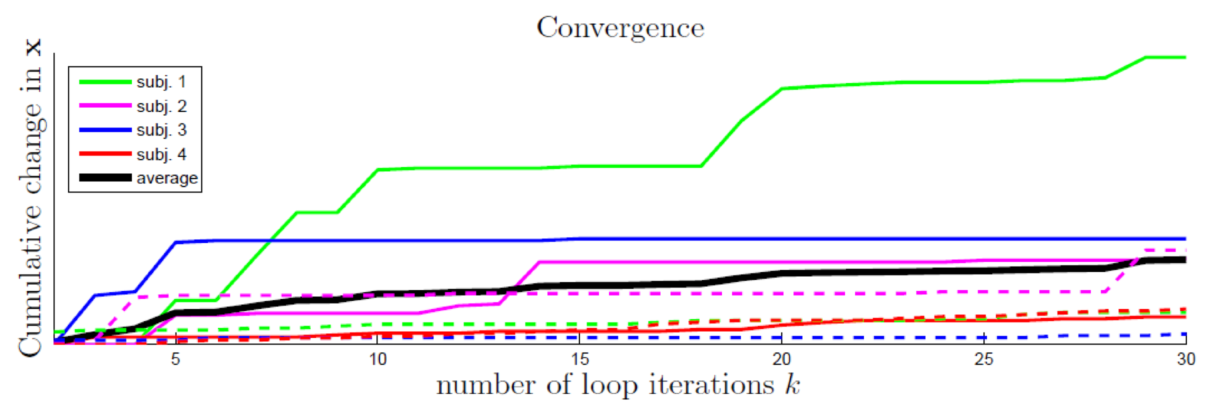

Fig. 2. Convergence of the test/retest (solid/dotted lines) preference sessions for subject 1-4. The convergence is calculated as the cumulated change in the estimated preferred setting for each of the four subjects at a given iteration. The change is defined as the distance between the current best setting and the previous best setting.

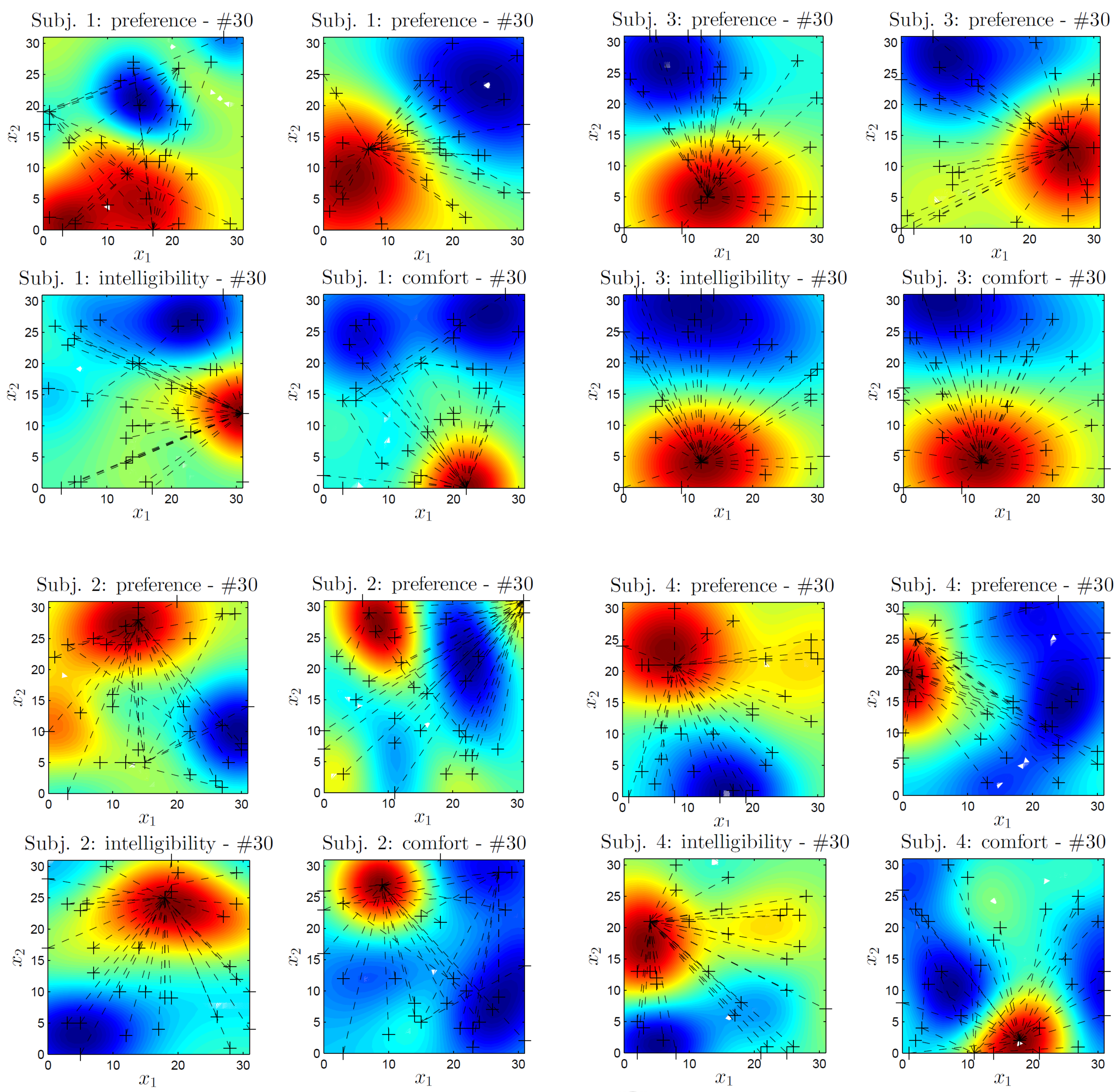

Fig. 3. Estimates of the *Internal representations* after 30 pairwise comparisons for subject 1-4. For each subject the four estimates from the four sessions are shown in a 2-by-2 group. The two top plots in each group are the preference test/re-test estimates, and the bottom two plots are the perceived speech intelligibility and comfort test estimates, respectively.

Red indicates high-preference regions and blue indicates low-preference regions over the two HA parameters x_1 and x_2. Note, that the representations are unit-free.

'+'s indicate settings and the dotted lines between settings indicate which pairs of settings that have been compared.

Results and Discussion

- The estimates of the internal representations for subject 1-4 are shown in Fig. 3. As subject 5 could not hear any differences between the different settings, the corresponding pattern has been excluded.
- Test/retests estimates for the preference strategy (the pairs of top plots in Fig. 3) generally end up in similar patterns (and maxima) for the four subjects, but a Binomial test only showed significance for subject 3.
- It is speculated that this is due to the sample size in the Binomial test, but this has to be verified in the future.
- Subject 2 and 4 reported that they thought their preference where identical with the perceived speech intelligibility strategy, which is also indicated in the estimated internal representations.
- Subject 3 behaved in the same manner for all three listening strategies, which is consistent with the internal representations.
- Subjects commented that the preference sessions were easier to conduct, because they were allowed to choose their own strategy, whereas especially the comfort strategy was difficult due to ambiguity in relation to the perceived sensation.
- Subjects reported that they experienced a learning effect—both over the 3 sessions on the first day and from the first day to the second day.
- An expression of the convergence is presented in Fig. 2. Generally, all estimates converge prior to the 30'th iteration.

Future work

- The change in the HA sound over the two parameters was quite subtle as reported by the subjects and, more importantly, the effort of the subjects does therefore not match the experienced gain. Instead, parameters for which adjustments are easier distinguished by the user will be used in the future.
- Next, Experiments in which more parameters (>2) are optimized with the interactive system will be conducted in the future.
- Better convergence criteria based on the statistics from the modeling framework alone, will be investigate in the future. One solution could be the average EI over the input space.
- Future results will prove significance for an preferred *individualized* solution compared to baseline and not-preferred solutions.

References

[1] B. S. Jensen, J. B. Nielsen, J. Larsen: *Efficient Preference Learning with Pairwise Continuous Observations and Gaussian Processes*, IEEE International Workshop on Machine Learning for Signal Processing, 2011

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