The Complexity of Fitting Hearing Aids

Bert de Vries, Tjeerd M.H. Dijkstra, Alexander Ypma and Jos Leenen

GN ReSound, Algorithm R&D, Eindhoven, The Netherlands

`bdevries@gnresound.com, www.bertdv.nl`

Abstract

COMMERCIAL hearing aid (HA) algorithms contain about 140 tuning parameters (say, 15 frequency bands times 7 parameters shared by the AGC and spectral subtraction modules, plus 35 filter taps shared between the feedback cancelation and beamforming filters). If we assume that each parameter can take on 5 interesting values (very low, low, medium, high, very high), then the total number of potentially interesting algorithm configurations is 5^{140}. This is far more than 5^{115}, the number of electrons in the universe. Hence, at face value, finding the optimal parameter values for a specific patient (i.e. the fitting task) appears to be at least as complex as finding a specific electron in the universe. How can we deal with this complexity? In this presentation we report on a new fitting-engineering approach where patient measurements (audiogram, listening tests etc) are transferred without loss of information to a preference distribution for HA parameter values.

Approach

- Note that patient measurements (audiogram, listening tests etc.) say something about that patient, rather than about a HA algorithm.

$\Longrightarrow$ We use all patient measurements to train a 'patient satisfaction model' (called: utility model U), see Figure 1.

- The utility model can be updated incrementally after each single listening event, e.g. one pairwise comparison, therefore no loss of information.
- Perception involves *inference*, hence there are inherent uncertainties (e.g. finite number of subjects in trial) and inconsistencies (e.g. conflicting results from listening tests).

$\Longrightarrow$ We use a completely probabilistic (Bayesian) modeling approach to properly account for all uncertainties and inconsistencies, see Figure 2, (Heskes and De Vries, 2005).

- An important result in our framework is the probability distribution (pdf) that describes a patient's preferences for each candidate HA parameter value *relative to every other candidate value*, based on *all* observed data (auditory profiles (a) and results from listening tests (D)); this pdf is called *evidence-based* (EB) tuning distribution $p(\theta|D,a)$, which is given by

$$p(\theta|D,a) \propto \exp\left(\sqrt{\frac{K}{\sigma_u^2}}\,\mathrm{EU}\right) , \qquad (1)$$

where $\mathrm{EU} = (1/K)\sum_k p(x_k)U(x_k,\theta)$ is the *expected utility*, x_k the kth sample from a data base of K relevant sound samples and σ_u^2 the estimated variance of the utility noise (measures patient inconsistency).

- **(fitting)**: At any time, optimal HA parameters can be selected through $\hat{\theta} = \arg\max_\theta p(\theta|D,a)$. If desired, this (optimization) procedure can be executed cheaply (eg for online time-varying fitting). We put the 'complexity' in estimating a proper utility model, which leads to 'easy' fitting.

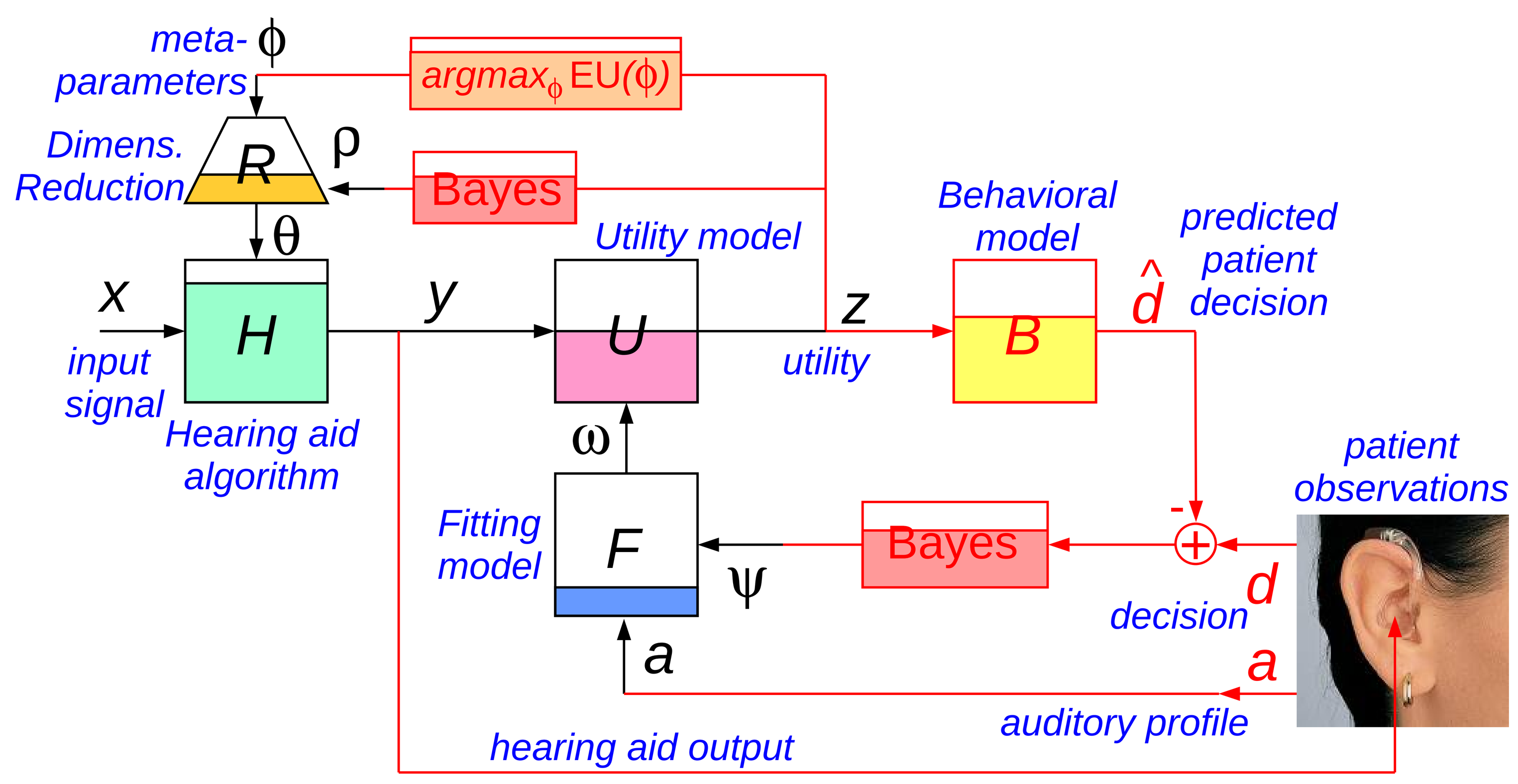

Figure 1: *Flow diagram for incremental utility elicitation.*

Properties and Benefits

- All data from patients (auditory profile, listening tests etc.) lead to updates of the patient satisfaction model U. This is in contrast to conventional fitting where direct maps from patient data to HA parameters are used (e.g audiogram-to-compression-ratio fitting rules). Some advantages of our approach:
  - A trained utility model can be used to tune many (and future) HA algorithms.
  - Multiple HA parameters can be optimized at the same time.
  - Never lose information (e.g. vs. genetic algorithm tuning which 'optimizes' well but does not really 'learn' a generative model.)
  - Bayesian approach allows to pick at any time *the* most informative next listening experiment.

$p(y|x,D,a)$ evidence-based (EB) hearing aid (HA) algorithm

$$= \sum_m p(c_m|x) \sum_j p(y|x,\theta_j)\; p(\theta_j|c_m,D,a)$$

environmental classifier — HA algorithm — HA prescription (EB tuning)

$$p(\theta_j|c_m,D,a) = \int_\Omega p(\theta_j|\omega,c_m)\; p(\omega|D,a)\; d\omega$$

tuning distribution — fitting distribution

$$p(\theta_j|\omega,c_m) = \frac{\exp(\lambda r_j(\omega,c))}{\sum_i \exp(\lambda r_i(\omega,c))} \qquad p(\omega|D,a) = \int_\Psi p(\omega|\psi,D_i,a_i)\; p(\psi|D_c,a_c)\; d\psi$$

personal fitting — communal fitting

Figure 2: *System architecture for Evidence-based HA algorithm.*

- Because of inherent uncertainties and inconsistencies, the observed data will never point to one value as the single best HA parameter value. Only relative preferences can be determined.
- The prescription $p(\theta|D,a)$ becomes more peaked (i.e. more confidence for the mostly preferred values) if the data base size K increases and/or if σ_u^2 decreases, i.e. if listening test measurements are more consistent. This behavior is correct from an information-theoretic viewpoint.
- There is no loss of information: One pairwise comparison event delivers 1 bit of information; this 1 bit is absorbed by the preference distribution $p(\theta|D,a)$, which represents everything we know (and we can possibly know) about the HA tuning parameters.

Validation Experiment

We computed $p(G_{min}|U=Q3)$ for a noise suppression algorithm, with utility model CSII-Q3 (Kates and Arehart, 2004) on TIMIT speech database, dialect DR1, 8 speakers, 10 sentences/spk, plus (white, babble or factory) noise from NOISEX92, over the range $SNR = [-6, 20]$ dB.

- All candidate values for the G_{min} parameter have > 0 preference probability.
- Observe that confidence about optimal minimal gain increases when the calculation is based on more sound samples.
- SNR seems to be an interesting candidate for steering the G_{min} parameter.

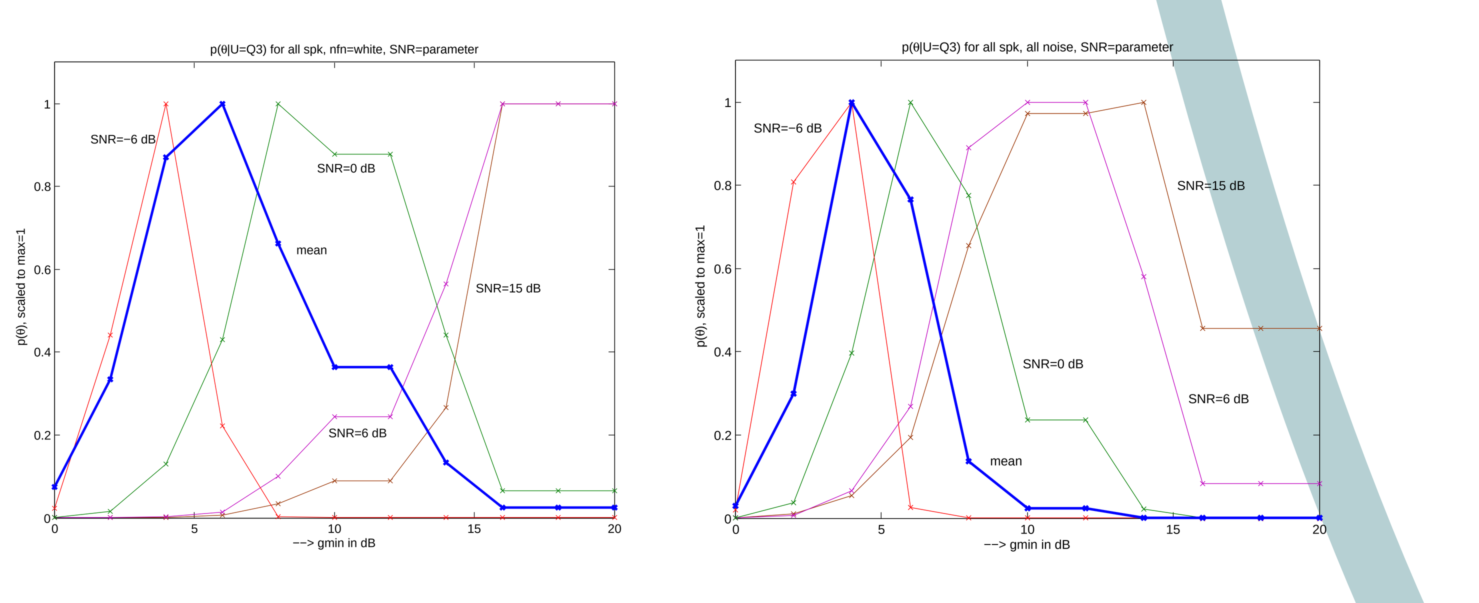

Figure 3: $p(G_{min}|U=Q3)$ *for a noise suppression algo, with* θ *is minimal gain parameter, and CSII-Q3 utility model, TIMIT plus NOISEX-92 database. (a) for white noise, (b) average over three noise sources.*

References

Tom Heskes and Bert de Vries, Incremental Utility Elicitation for Adaptive Personalization, *BNAIC*, Brussels, 2005-10.

James M. Kates and Kathryn H. Arehart, A metric for evaluating speech intelligibility and quality in hearing aids, *JASA*, 2004-10, pp. 2536-2537.

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