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# A Probabilistic Modeling Approach to Hearing Loss Compensation

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## 1. Introduction

Hearing loss is a serious and prevalent condition that is characterized by a frequency-dependent loss of sensitivity for acoustic stimuli. As a result, a tone that is audible for a normal-hearing person might not be audible for a hearing-impaired patient. The goal of a hearing aid device is to restore audibility by amplification and compressing the dynamic range of acoustic inputs to the remaining audible range of the patient. In practice, current hearing aids apply frequency- and intensity-dependent gains that aim to restore normal audibility levels for the impaired listener.

The hearing aid algorithm design problem is a difficult engineering issue with many trade-offs. Each patient has her own auditory loss profile and individual preferences for processed audio signals. Yet, we cannot afford to spend intensive tuning sessions with each patient. As a result, there is a need for automating algorithm design iterations based on in-situ collected patient feedback.

This short paper summarizes ongoing work on a probabilistic modeling approach to the design of personalized hearing aid algorithms (van de Laar & de Vries, 2016). In this framework, we first specify a probabilistic generative model that includes an explicit description of the hearing loss problem. Given the model, hearing aid signal processing relates to on-line Bayesian state estimation (similar to Kalman filtering). Estimation of the tuning parameters (known as the ‘fitting’ task in hearing aid parlance) corresponds to Bayesian parameter estimation. The innovative aspect of the framework is that both the signal processing and fitting tasks can be *automatically* inferred from the probabilistic model in conjunction with patient ap-

praisals (the data). The architecture of our design loop is shown in Fig. 1.

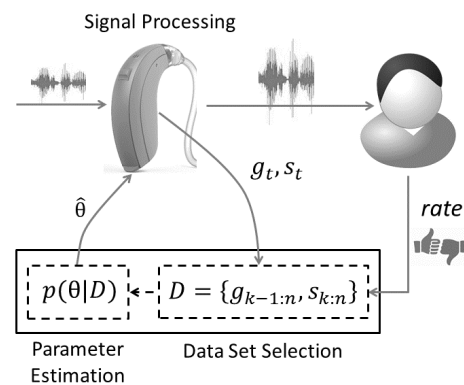


Figure 1. The iterative algorithm design loop, featuring the interplay between signal processing (Eq.5) and parameter estimation (Eq.6). Tuning parameters are designated by  $\theta$ . Figure adapted from (van de Laar & de Vries, 2016).

## 2. Model Specification

We describe the hearing loss compensation model for one frequency band. In practice, a hearing aid would apply the derived algorithms to each band independently. For a given patient wearing hearing aids, we define the received sound level as

$$r_t = L(s_t + g_t; \phi) \quad (1)$$

where  $s_t$  is the sound pressure level (in dB SPL) of the input signal that enters the hearing aid,  $g_t$  is the hearing aid gain and  $L$  is a function with tuning parameters  $\phi$  that models the patient’s hearing impairment in accordance with (Zurek & Desloge, 2007).

Hearing loss compensation balances two simultaneous constraints. First, we want restored sound levels to be approximately experienced at normal hearing levels:

$$s_t|g_t \sim \mathcal{N}(r_t, \vartheta) = \mathcal{N}(L(s_t + g_t; \phi), \vartheta) . \quad (2)$$

Secondly, in order to minimize acoustic signal distortion, the compensation gain should remain as constant as possible, which we model as

$$g_t | g_{t-1} \sim \mathcal{N}(g_{t-1}, \varsigma). \quad (3)$$

The trade-off between conditions Eqs. 2 and 3 is controlled by the noise variances  $\vartheta$  and  $\varsigma$ . The full generative model is specified by combining Eqs. 2 and 3:

$$p(g_{0:T}, s_{1:T}, \varsigma, \vartheta, \phi) = \quad (4)$$

$$p(g_0) p(\varsigma) p(\vartheta) p(\phi) \prod_{t=1}^T p(s_t | g_t, \phi, \vartheta) p(g_t | g_{t-1}, \varsigma).$$

In this model,  $s_t$  is an observed input sequence,  $g_t$  is the hidden gain signal, and  $\theta = \{\varsigma, \vartheta, \phi\}$  are tuning parameters.

### 3. Signal Processing and Fitting as Probabilistic Inference

The signal processing and parameter estimation algorithms follow by applying Bayesian inference to the generative model. The hearing aid signal processing algorithm is defined by estimating the current gain  $g_t$  from given past observations  $s_{1:t}$  and given parameter settings  $\theta = \hat{\theta}$ . In a Bayesian framework, this amounts to computing

$$p(g_t | s_{1:t}, \hat{\theta}) = \frac{\int \dots \int p(g_{0:t}, s_{1:t}, \hat{\theta}) dg_0 \dots dg_{t-1}}{\int \dots \int p(g_{0:t}, s_{1:t}, \hat{\theta}) dg_0 \dots dg_t}. \quad (5)$$

A suitable personalized parameter setting is vital to satisfactory signal processing. Bayesian parameter estimation amounts to computing

$$p(\theta | D) = \frac{p(g_{k-1:n}, s_{k:n}, \theta)}{\int p(g_{k-1:n}, s_{k:n}, \theta) d\theta}. \quad (6)$$

In this formula, we assume availability of a training set of pairs  $D = \{(g_{k-1:n}, s_{k:n})\}$ , where  $k$  and  $n > k$  are positive indices. This training set can be obtained from in-situ collected patient appraisals on the quality of the currently selected hearing aid algorithm (Fig.1). After the user casts a positive appraisal, we collect a few seconds of both the hearing aid input signal and corresponding gain signals and add these signal pairs to the training database.

### 4. Inference Execution through Message Passing

Equations (5) and (6) are very difficult to compute directly. We have developed a software toolbox to automate these inference problems by message passing

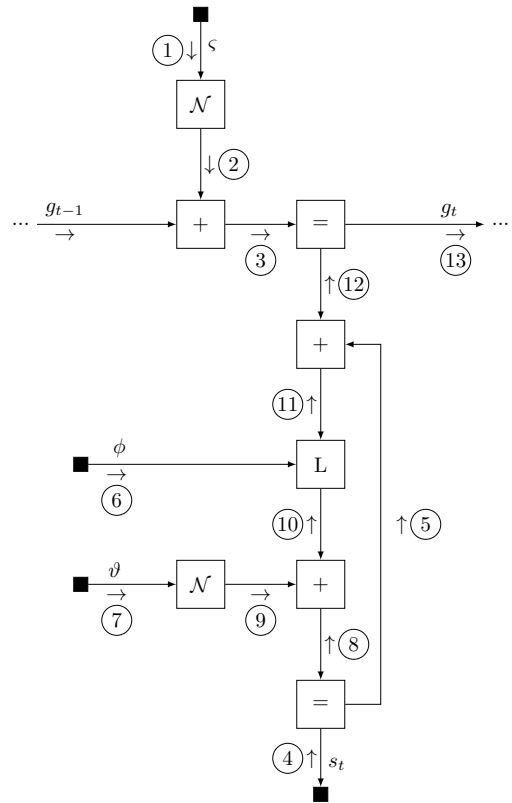


Figure 2. A Forney-style factor graph for one time step in the generative model. The small numbered arrows indicate a recursive message passing schedule for executing the signal processing task of Eq. 5. Figure adapted from (van de Laar & de Vries, 2016).

in a Forney-style Factor Graph (FFG) (Forney, 2001). In an FFG, nodes correspond to factors and edges represent variables. The FFG for the generative model of Eq. 4 is depicted in Fig. 2. The arrows indicate the message passing schedule that recursively executes the signal processing inference problem of Eq. 5. Particular message passing update rules were derived in accordance with (Loeliger, 2007) and (Dauwels, 2007).

Simulations show that the inferred signal processing algorithm exhibits compressive amplification behavior that is similar to the manually designed dynamic range compression circuits in hearing aids. Simulations also verify that the parameter estimation algorithm is able to recover preferred tuning parameters from a user-selected training example.

Crucially, our algorithms for signal processing and fitting can be automatically inferred from a given model plus in-situ collected patient appraisals. Therefore, in contrast to existing design methods, this approach allows for hearing aid personalization by a patient without need for human design experts in the loop.

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