The Learning prescription, A Neural Network Hearing Aid Core

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Abstract

The definition of a hearing aid core which is based on a prescription neural network (such as NAL-NL2) is defined here. This hearing aid core replaces a traditional compressor hearing aid core which mimics the said hearing aid prescription. Whilst the replacement of the compressors for a neural network may seem simple, the implications are vast in terms of the "learning prescription" where the topology of the neural network may be increased to make available more free parameters and allow great personalisation of the hearing aid prescription.

1 Introduction

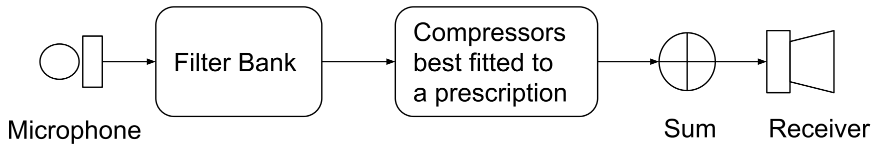
The NAL-NL2 hearing aid prescription introduced a neural network for the prescription of hearing aid gain for the first time [2] based on a desensitised speech intelligibility index (SII) designed for NAL-NL2 [1]. Concise descriptions of the NAL-NL2 hearing aid prescription are given [3, 4] which focus on the effects of the desensitised SII on gain optimisation, however the said articles gloss over the importance of the introduction of the neural network to hearing aid prescription, which overcame significant hurdles of reliable prescriptions being dispensed by NAL-NL1. The reason why arbitrary prescription is now far more accurate was the ability for the NAL-NL2 neural network to successfully interpolate between optimised prescriptions for people with unique and unseen hearing loss profiles. Prior to the introduction of the neural network in hearing aid prescription, hand crafted nonlinear equations were used to try to match the infinite possible prescriptions which can't all be optimised and thus certain patients would not receive optimal hearing aid prescriptions.

This article takes the next logical step in hearing aid development by defining for the first time the replacement of hearing aid compressors by a personal prescription neural network. This article lays the foundation for the future layering of neural network and other statistically optimised systems to greatly improve hearing aid performance. With the introduction of personal prescription neural networks this article also introduces a robust method for further personalisation away from speech intelligibility prescriptions and towards learning prescriptions.

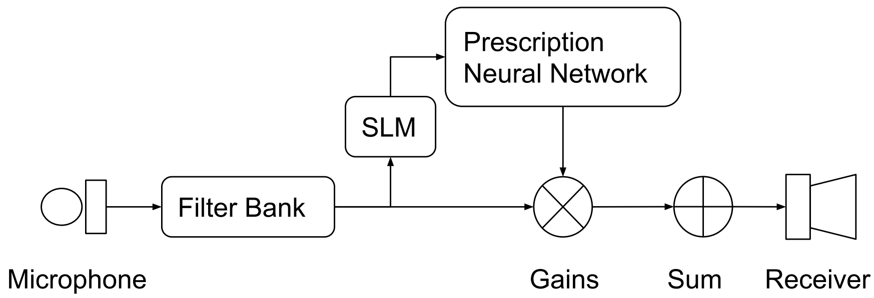
A digital hearing aid core is shown in Figure 1a where a filter bank bands the signal and pre-fit compressors implement the hearing aid prescription. The signal path is nonlinear as the sound pressure level is constantly changing and the level estimation in the compressors are constantly changing. This constantly changing level estimation generates nonlinear gain application as the compressor's operating point is slowly but constantly varying.

The hearing aid implemented with a prescription neural network core, shown in Figure 1b operates on a block of N samples of audio signal. The sound level meter (SLM) presents signal levels for the neural network to prescribe the block gain for each band of the filter bank. The gains are applied to the banded signals and summed then output to the receiver. As the gains are not varying within a signal block, the signal chain is linear. Half window overlap add techniques can be used to allow the audio blocks to vary smoothly and allow the gains to vary without output discontinuity.

This article prescribes the implementation of a hearing aid with a neural network core. Free software is also available which implements the theory in this document. The first Section 2 implements a log banded filter bank centred around the prescription frequencies (f_c). The duration of the audio in each filter is roughly eight milliseconds and after overlap add the effective hearing aid gains change at a rate of approximately four milliseconds. Rates of



(a) A digital hearing aid core. A filter bank bands a signal which is compressed, summed and output. The compressors are fitted as best as possible to the gain prescription. The signal chain is nonlinear.



(b) A neural network hearing aid core. The filter bank bands the signal and a sound level meter (SLM) drives the prescription neural network. The gains prescribed by the NN are applied to the signal which is then summed and output. The signals in this core is block linear as the gains are constant for each signal block.

Figure 1: Digital and neural network hearing aid cores.

gain change slower then three milliseconds are optimal for a prescription algorithm such as NAL-NL2 [2] as the compression ratio of the optimised prescription is not altered and thus the speech intelligibility index is maximised. The overall latencies of the filters are half the filter length as there is an overlap add framework. In operation, the first half block can be output after half the filter length is input/output and every subsequent half block is processed and output, resulting in an overall latency of half the filter length which is around 3 ms to 4 ms.

Subsequent sections 3 and 4 briefly address level metering and signal amplification. While the last section leaves the prescription neural network as an open design solution. The best neural network will start the user in a space which is optimised for SII maximisation, but allow the user to train their prescription to their own personal target. The gradual expansion of the free parameters available to the neural network will allow for the expansion in the complexity of gain prescription to the user's taste.

2 Log banded filter bank

The prescription algorithm outputs gains for the log centred frequencies (f_c in Hz) over the M=6 bands from m=0 to m=M-1

$$f_c\left(m\right) = 250\left(2^m\right)$$

Zero phase brick wall band limited filters are generated[1] where the zero phase filters ($h_{0,\,m}$) are specified in the Discrete Fourier Domain ($H_{0,\,m}$) and transformed to the time domain using the inverse Discrete Fourier Transform (DFT or $\mathcal{F}$)

$$\begin{aligned} H_{0,\,m}\left(f_i\left(m\right),\, f_a\left(m\right)\right) &= \left.1\right]_{f_i \le |f| \le f_a} \\ h_{0,\,m} &= \mathcal{F}^{-1}\left\{H_{0,\,m}\right\} \end{aligned}$$

[1]See the script gtkiostream/mFiles/ImpBandLim.m as a reference.

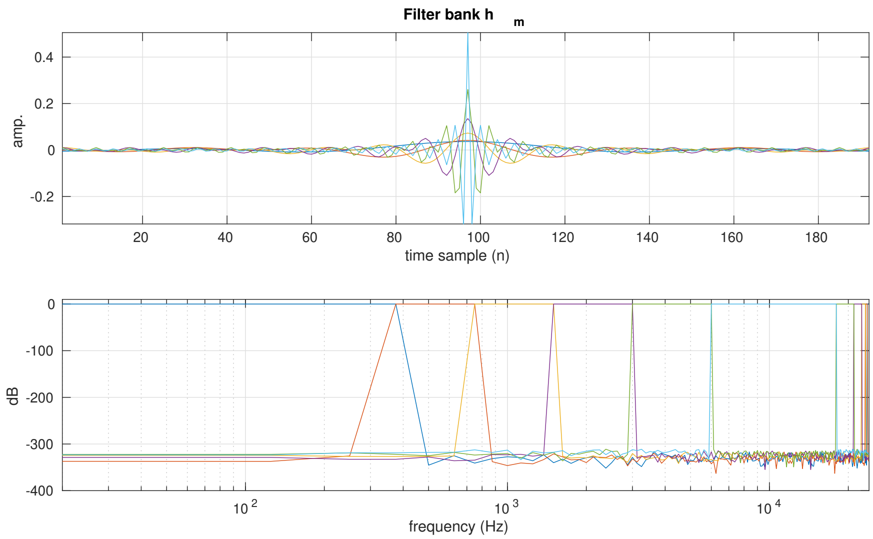


Figure 2: The hearing aid filter bank h_m.

where the minimum frequency ($f_i\,(m)$) and maximum frequency ($f_a\,(m)$) are specified per band m (see Equation 1).
These zero phase filters are circularly shifted by a constant group delay of $\frac{N}{2}$ samples to give the linear phase band limited filters (h_m)

$$h_m = h_{m,\,n} = h_m[n] = h_{0,\,m}\left[\left(n + \frac{N}{2}\right) mod\, N - 1\right]$$

The specifiaction of the band limits (in Hz) are

$$f_a\,(m) = \begin{cases} f_c\,(m) + f_t & m = 0 \\ \frac{3}{2} f_c\,(m) & m > 0 \end{cases} \tag{1}$$

$$f_i\,(m) = \begin{cases} 20 & m = 0 \\ f_a\,(m-1) & m > 0 \end{cases}$$

where f_t is the frequency stepping between Fourier bins or the DFT resolution, which is kept to a maximum value

$$f_t = \frac{f_c\,(0)}{2}$$

and this defines the number of samples (N) in the filter given a sample rate of f_s Hz

$$N = \frac{f_s}{f_t}$$

An example filter bank with a sample rate of $f_s = 24\,kHz$ is implemented in the script LogFilterBankTest.m and is shown in Figure 2.

3 The sound level meter

The SLM estimates the dB SPL level of the signal (s) for each band (l_m)

$$l_m = 20\,log10\left(\sum_{n=0}^{N-1} h_m * s + l_{t,m}\right) + l_{d,m}$$

where $*$ represents the convolution operator and the three scaling variables are defined as; l_t is a time domain DC offset which may be necessary in some systems. l_d is a gain variable which converts digital full scale levels into dB sound pressure level.

4 Audio amplification and output

The gained bands of audio are summed and output

$$y = \sum_{m=0}^{M-1} g_m h_m * s$$

At this point overlap add sums the last block of audio to the current block of audio to generate the receiver's output audio signal (r_n)

$$r_n = y_{n-N/2} * w_n + y_n * w_n$$

5 The prescription neural network

The neural network will input signal levels per band for each block of audio and output the required signal gain per band (g_m). All neural network pre and post conditioning are applied in this block of processing.

The neural network can be multi-layer and have arbitrary non-linear layer output functions. The implementation of the prescription neural network is beyond the scope of this document.

6 Conclusion

This article replaces traditional hearing aid cores which are based on compressors (see Figure 1a) with the a suitable SII maximising neural network (see Figure 1b). A traditional prescription system such as NAL-NL2 can be placed directly onto the users hearing aid in the form of a personal prescription neural network. This personal prescription neural network can then be trained to learn the user's preference in amplification. With time as the free parameters in the neural network are increased in number, more complex features and learning may be accomplished.

A suitable FIR filter for this hearing aid is defined in Section 2 which targets a half block input/output delay to allow a roughly 3 ms system latency which matches the optimal operating latency for the NAL-NL2 prescription algorithm. A simple sound level meter and amplification strategy is also defined in Sections 3 and 4.

References

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[4] Gitte Keidser, Harvey Dillon, Matthew Flax, Teresa Ching, and Scott Brewer. The nal-nl2 prescription procedure. *Audiology research*, 1(1):88–90, 2011.