

domain gaps do not enhance the audibility of the signals. Such redundancies have been successfully used in the past in the area of coding and noise suppression [4].

The paper's method reduces the hearing aid gain for redundant speech components in time and frequency and keeps the prescribed gain for other components. Assuming that the models of perceptual redundancy are accurate, the changes in signal characteristics caused by reducing gain associated with those components will not be audible to the listener. Furthermore, since this process reduces the feedback components, it makes the speech more intelligible. Finally, this scheme makes the hearing aid system less prone to instability because the average open loop gain is smaller than the gain for perceptually important components, and thus reduces the build up of acoustical signal in the closed loop [5, 1].

2. AN OVERVIEW OF THE HEARING AID MODEL

The algorithm of this paper performs adaptive feedback cancellation in the frequency domain. Among various frequency domain adaptive filter algorithms available we use the frequency-domain block LMS (FBLMS) adaptive filter [2] to cancel the feedback. The notations used in this paper are as follows. Let $x(k, n)$ defined as

$$x(k, n) = x(n + k\Delta K) \quad n = 1, 2, \dots, L \quad (1)$$

represent the k^{th} frame of the input signal $x(n)$. In (1), L is the frame size in number of samples and ΔK represents the shift between successive frames. Let the discrete fourier transform (DFT) of the signal $x(k, n)$ be $X(k, m)$ where m represents the frequency bin $\omega_m = \frac{2\pi m}{L}$ radians/sample. We denote the vector of all frequency components $X(k, m)$ in frame k by $\mathbf{X}(k)$. The feedback path - the combined response of the speaker, microphone and the acoustic feedback shown in Figure 1 is modeled with an FIR filter containing N coefficients. Furthermore, signals are segmented into $L = 2N$ -points vectors with N point overlap. The FBLMS algorithm for the k^{th} block is summarized in Table 1.

In Table 1, the variables $\mathbf{W}(k)$ and $\mathbf{g}(k)$ are the vector representations of the adaptive filter coefficients and the hearing aid gain respectively in the frequency domain. $d = D/N$ is the normalized delay. For ease of implementation we chose D to be an integer multiple of N . In most implementations, the hearing aid gain is fixed and frequency dependent. However, in the experimental comparisons presented later in this paper, the maximum allowed gain was set to be the same for all frequency bins *i. e.* $\mathbf{g}(k) = G$ for the conventional method. In the system of this paper the gain $g(k, m)$ may vary for frequencies in a frame.

3. ADAPTIVE GAIN PROCESSING

The new scheme utilizes the information about masking thresholds and speech presence/excitation. A gain control scheme that results in low artifacts and low distortions in the output signals is discussed later in the section.

3.1. Calculation of Masking Thresholds and Signal Presence

In this paper, we do not consider the contribution of temporal masking because it is usually difficult to quantify [5]. Calculation of the masking thresholds $T(k, m)$ for the k^{th} frame and m^{th} frequency bin involves defining critical bands on the power spectrum $P(k, m)$ of the speech signal. The power spectrum is calculated from the spectrum of the input signal to the speaker before amplification $Q(k - d, m)$ using speech pressure level (SPL) normalization [4]. The power normalization term is fixed at 90.302 dB.

Table 1. Adaptive Feedback Cancellation with FBLMS

Initialization

$\mathbf{S}(0)$...	A vector with small positive constant
$\mathbf{W}(0)$...	A vector with all zeros
μ_0	...	Suitable adaptation constant
β	...	An averaging constant close to 1

Iterations

$$\mathbf{d}(k) = [d(kN) \quad d(kN + 1) \quad \dots \quad d((k + 2)N - 1)]$$

$$\mathbf{Y}(k) = \mathbf{W}(k) \otimes \mathbf{X}(k)$$

$\mathbf{y}(k)$ = the last N elements of IFFT($\mathbf{Y}(k)$)

$$\mathbf{e}(k) = \mathbf{d}(k) - \mathbf{y}(k)$$

$$\mathbf{E}(k) = \text{FFT} \left(\begin{bmatrix} \mathbf{0} \\ \mathbf{e}(k) \end{bmatrix} \right)$$

$$\mathbf{W}(k + 1, m) = \mathbf{W}(k, m) + \mu_0 X(k, m) E^*(k, m) / S(k, m) \quad \text{for } m = 0, \dots, 2N - 1$$

$$\mathbf{W}(k+1) = \text{FFT} \left(\begin{bmatrix} \text{the first } N \text{ elements of IFFT}(\mathbf{W}(k+1)) \\ \mathbf{0} \end{bmatrix} \right)$$

$$Q(k, m) = E(k, m) + (-1)^m E(k - 1, m) \quad \text{for } m = 0, \dots, 2N - 1$$

$$\mathbf{X}(k + 1) = \mathbf{g}(k) \mathbf{Q}(k - d)$$

$$\mathbf{S}(k + 1) = \beta \mathbf{S}(k) + (1 - \beta) \mathbf{X}(k + 1) \odot \mathbf{X}^*(k + 1)$$

- \odot denotes element-by-element multiplication
- $\mathbf{0}$ denotes column vector of length N
- \star denotes complex conjugate

Subsequently, tonal and noise maskers are identified in each critical band which are above the hearing threshold [4, 7, 5]. If two or more maskers are close to each other in a critical band, only the strongest masker is kept and others are discarded. Details of masking models and estimation of the maskers can be found in [4, 5]. After identifying the maskers, the masking effects due to these maskers in their frequency bands and their neighboring bands are calculated using the spreading function that was derived from Zwicker's data [7] as in [4]. Finally, the global masking threshold is calculated for each frequency bin by combining the individual masking thresholds of all the maskers identified in the previous steps.

Many methods to improve speech processing algorithms using the notion of temporal and spectral gaps in speech signals are available in the literature [6]. The simplest method to find such gaps uses an energy-based detector. Average energies $P_Q(k, m)$ and $P_{Q, \min}(k, m)$ at each frequency bin are calculated with a single pole IIR filter

$$P_Q(k, m) = \gamma_1 P_Q(k - 1, m) + (1 - \gamma_1) |Q(k - d, m)|^2$$

$$P_{Q, \min}(k, m) = \gamma_2 P_{Q, \min}(k - 1, m) + (1 - \gamma_2) |Q(k - d, m)|^2$$

respectively. The averaging constants γ_1 and γ_2 are such that $0 < \gamma_1 < \gamma_2 < 1$. Consequently, the average energy $P_Q(k, m)$ is effectively based on fewer samples than $P_{Q, \min}(k, m)$. If $P_Q(k, m)$ is sufficiently smaller (with the help of the parameter

δ) than $P_{Q,min}(k, m)$, we consider the frequency bin m to be not excited. Otherwise, the m^{th} frequency bin is assumed to be excited. The algorithm employs a smaller gain at unexcited frequencies than for excited frequency components. In all our work so far we have used $\delta = 0.8$. We use a variable $S_{AVL}(k, m)$ to indicate whether the m^{th} frequency bin of the k^{th} block is excited. For some δ , we define the parameter as

$$S_{AVL}(k, m) = \begin{cases} 0 & \text{if } P_Q(k, m) < \delta P_{Q,min}(k, m) \\ 1 & \text{if } P_Q(k, m) > \delta P_{Q,min}(k, m) \end{cases} \quad (2)$$

3.2. Gain Adjustment with $T(k, m)$ and $S_{AVL}(k, m)$

The adaptive gain processing algorithm reduces the hearing aid gain at frequencies where the instantaneous signal energy ($|Q(k-d, m)|^2$) is below the global masking threshold $T(k, m)$ or when the signal is determined to be unexcited at a frequency bin *i.e.* $S_{AVL}(k, m) = 0$. However, a large reduction in the gain may produce artifacts due to aliasing [2]. Consequently, the algorithm reduces the gain by no more than some preselected fraction η , where $0 < \eta < 1$ from frame to frame. Similarly, we also limit the minimum gain at a frequency to avoid unnatural artifacts in the output.

The algorithm for varying the gain $g(k, m)$ is summarized in Table 2 where G_{min} is the minimum permissible gain at any frequency.

Table 2. Adaptive Gain Processing

$$pr(k, m) = \begin{cases} 0 & \text{if } S_{AVL}(k, m) = 0 \text{ or } |Q(k-d, m)|^2 < T(k, m) \\ 1 & \text{else} \end{cases}$$

$$g(k, m) = pr(k, m)G + (1 - pr(k, m))\eta g(k-1, m)$$

$$g(k, m) = \max[g(k, m), G_{min}]$$

4. RESULTS AND DISCUSSION

This section presents the results from MATLAB simulations and real time implementations of the hearing aid algorithms to demonstrate the performance of the paper's approach and a classical scheme. A subjective evaluation of the output sound of the two methods from real time implementation is also be presented in this section.

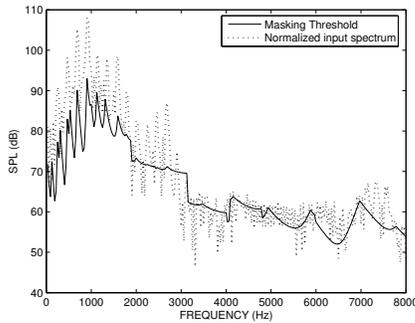


Fig. 2. Masking thresholds at various frequencies

In the first experiment, adaptive feedback cancellation was performed in MATLAB with an FBLMS algorithm with fixed gain and the method of this paper. The feedback path used in simulations was modeled with a 128-tap FIR filter. In addition, a random perturbation was added to the feedback coefficients to simulate real time changes. The random perturbation was such that the mean values of the coefficients do not change over time and the variance of the perturbation

was 10^{-4} for each coefficient. The critical gain of the feedback path was approximately 11 dB. A delay of one block ($D = 8$ ms) at 16 KHz was used in the simulations. Other parameters employed were $N = 128$, $\mu_0 = 0.02$, $\beta = 0.99$, $\gamma_1 = 0.995$, $\gamma_2 = 0.85$, $\eta = 0.9$ and $G_{min} = 6$ dB. The input signals to the hearing aid were clean speech waveforms taken from the TIMIT database.

The global masking thresholds $T(k, m)$ for different frequency bins for one signal frame from a MATLAB simulation are shown in Figure 2. The hearing aid gain was 15 dB above the critical gain for this experiment. It can be seen from Figure 2 that there were many components below the masking threshold in this simulation.

To demonstrate the improvement in the feedback cancellation with adaptive gain processing over fixed gain systems, we define signal-to-feedback-ratio (SFR) for frame k as

$$\text{SFR} = 20 \log \left(\frac{\sum_{i=(k-1)L+1}^{kL} v^2(i)}{\sum_{i=(k-1)L+1}^{kL} (e(i) - v(i))^2} \right) \quad (3)$$

In our case the clean speech is mostly contaminated by feedback, therefore, we can assume that higher values of SFR indicate more feedback cancellation. The average SFR for all frames after the adaptive filter converged was calculated for both methods at different gains. The results are tabulated in Table 3. As one would expect, the SFR values decrease for both schemes with increasing gain values. However, the adaptive gain processing system exhibited 1 – 2 dB improvements in performance over fixed gain system. This is due to intermittent gain reductions done by the adaptive gain processing algorithm at redundant components of the input signal, which in turn reduces the feedback coupling.

Table 3. Signal-to-feedback-ratio (SFR) for two methods

Gain Above the CG (dB)	Average SFR in dBs	
	Fixed Gain	Adaptive Gain
2	12.33	14.41
6	10.06	11.87
10	7.32	8.73
15	2.42	3.43

The power spectra of the output produced with the two methods are shown in Figure 3. The spectra were estimated using the Welch method by dividing data into frames of 512 samples with 256 sample overlap. There are noticeable differences between the spectra of the output of the fixed gain system and the input speech at higher frequencies. The spectrum of the output of the adaptive gain processing scheme is closer to the input signal's spectrum especially at higher frequencies where the conventional method did not perform well.

In the next experiment, both algorithms were evaluated in real-time. A prototype inside-the-ear (ITE) hearing aid that can fit into the ear piece of the Knowles Electronics Manikin for Auditory Research (KEMAR) was used in the experiment. We used a standard EXPRESSfit hearing aid programming cable to drive and access microphones and the speaker of the hearing aid. The programming cable was connected to an interface board through an 8-pin mini DIN plug that provided the required power to the programming cable and amplified the received signal. The adaptive gain processing system and the feedback cancellation algorithm were implemented using an ADSP-21161N processor. With the above setup, output of the hearing aid system was recorded with a sound card for both schemes.

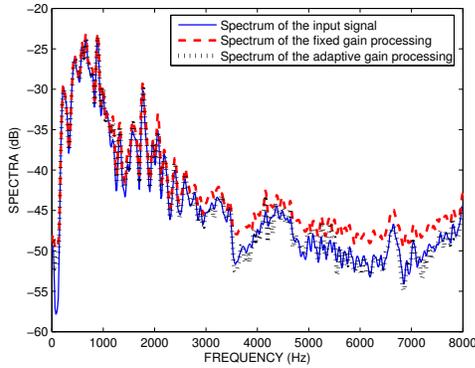


Fig. 3. Comparison of the output spectra of the two methods

The recorded outputs for both algorithms at different gains are shown in Figure 4. Figure 4a shows that the classical scheme became unstable at a gain of 10.6 dB above the critical gain. Figure 4b and 4c show that the adaptive gain processing produces stable output at gains of 10.6 dB and 12.3 dB above the critical gain.

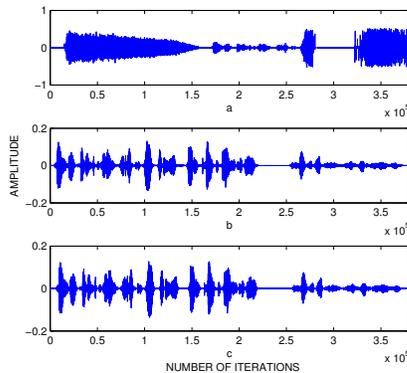


Fig. 4. Scaled output signals in the steady-state: (a) the fixed gain processing at 10.6 dB above the CG (b) the adaptive gain processing 10.6 dB above the CG (c) the adaptive gain processing at 12.3 dB above the CG

We performed an informal subjective evaluation of the recorded data with both schemes. The subjects evaluated the feedback canceled audio for the amount of residual feedback components and loudness perception. To assess the feedback components, the subjects were asked to characterize the amount of feedback components (whistling, ringing, howling) perceived in each sentence into one of the six classes enumerated in Table 4.

Loudness ratings refer to the volume of the words in each sentence. The subjects were asked to rate the loudness on a scale of 0 – 5. 0 indicates that the sentence is inaudible, a 5 means that the sentence is uncomfortably loud and a 3 is the most comfortable level of sound. Five subjects participated in this procedure and they rated each system’s output twice. During the test, recorded speech signals were played in a random order through a headphone in a quiet place.

The average subjective ratings for both the methods at different gains are summarized in Table 5. As can be seen from the table, the

Table 4. Description of ratings to the subject

Ratings	Feedback	Loudness
0	Loud howling	Inaudible
1	Loud continuous whistling	Soft
2	Soft continuous whistling	Somewhat soft
3	Soft intermittent whistling	Comfortable
4	No audible feedback, acceptable quality	Somewhat loud
5	No audible feedback, good quality	Extremely loud

ratings for the feedback and the loudness obtained from the test at a gain 12.3 dB is approximately same as those for the fixed gain at 8 dB gain. The low perceptual ratings for the fixed gain processing at 10.6 and 12.3 dB along with the acceptable performance of the adaptive gain processing indicates the viability of the hearing aid system presented in this paper.

Table 5. Average ratings for the two schemes

Gain above CG (dB)		8	10	10.6	12.3
Fixed gain processing	Feedback	4.21	4.06	0.43	0
	Loudness	3.11	2.93	4.67	5
Adaptive gain processing	Feedback	4.23	4.18	4.06	4.11
	Loudness	2.98	3.07	3.08	3.02

5. CONCLUSION

A perceptually motivated feedback cancellation for digital hearing aids scheme is presented in this paper. MATLAB simulations and real-time experiments indicate that this scheme provides an additional stable gain over traditional approaches. Psychophysical experiments suggest that this paper’s method also delivers perceptually better output sound quality. Further improvements in hearing aid performance are feasible by the incorporation of additional properties of the human auditory system.

6. REFERENCES

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