Proceedings of IOE Graduate Conference, 2015
pp. 186–192

Suppression of Acoustic Feedback in Hearing Aids using Dual Adaptive Filtering

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Abstract
Acoustic feedback is a major problem in most of the hearing aid users. This feedback corrupts the speech signal and causes instability. In this paper, we propose a solution for the suppression of continuous acoustic feedback in the digital hearing aids. In the proposed method, two adaptive filters work in tandem to mitigate the acoustic feedback. The error signal of the first adaptive filter is used as a desired response for the second adaptive filter and the filter weights are adapted using the proposed modified Normalized Least Mean Square (NLMS) algorithm. Due to the correlation between input and desired response, a bias is found in the adaptive filter's estimate of the feedback path. An appropriate delay is inserted at the output of the hearing aid to reduce this bias. Based on this delay based processing, a new strategy is proposed to exchange the weights between the two adaptive filters. Computer simulations are performed and the results verify the effectiveness of the proposed method.

Keywords
Acoustic Feedback – Hearing Aids – Adaptive Filters – NLMS

1. Introduction

Hearing loss is one of the most prevalent chronic health conditions, affecting large number of world's population. Because of the increased exposure to noise in daily life, this number is expected to further increase in the future. Therefore it is necessary to amplify the perceived sound signal and also reduce the background noise with respect to the desired speech signal. Hearing aid, a small amplifying device which fits on the ear, worn by a partially impaired person, is used for this purpose. As hearing aids become smaller and smaller, acoustic feedback, i.e., the acoustic coupling between the loudspeaker and the microphone of the hearing aid, poses a major problem to hearing aid users. Acoustic feedback results in severe distortion of the desired signal and howling if the hearing aid gain is increased. As a result, the maximum amplification that can be used in a commercial hearing aid is often too small to compensate for the hearing loss in a patient.[1]

A generic digital hearing aid system is shown in Fig. 1, where $G(z)$ represents the forward path of the hearing aid and comprises all signal processing for noise reduction and signal amplification, and $s(n)$ is the desired input signal to be processed by $G(z)$. Assume that the components for the adaptive feedback cancelation (AFC) (shown in a dashed box) are not present, and hence, $u(n) = x(n)$. The input signal $x(n)$ picked up by the microphone is processed by $G(z)$ and the output signal $y(n)$ is generated. The output signal $y(n)$ to the loudspeaker is not only propagated to the user ear, but is also fed back via acoustic feedback path $F(z)$ to the input microphone thus generating a corrupted input signal $u(n) = x(n) = s(n) + y_f(n)$, where $y_f(n)$ is the feedback component due to the output $y(n)$.

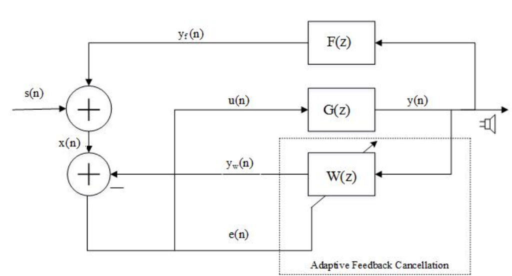

Figure 1: A simplified block diagram of hearing aid employing NLMS algorithm-based conventional adaptive filtering approach for AFC

A literature review shows that a number of approaches have been proposed to solve the problem of acoustic feedback [1, 2, 3, 4, 5, 6]. The most successful approach is based on adaptive filtering as shown in Fig. 1, where $W(z)$ is adapted (usually by the normalized least mean square (NLMS) algorithm [7]) to model $F(z)$. It is evident from Fig. 1 that the input $y(n)$ and the desired response $x(n)$ to $W(z)$, are correlated with each other. This scheme, therefore, cannnot be used for continuous AFC [8], and hence the acoustic feedback cannot be estimated accurately. A simple approach to decorrelate these two signals is to use an appropriate delay either in the cancelation path [1] or in the forward path [9], however, it degrades the speech quality.

Another solution is to filter the error and/or input signal of $W(z)$, through appropriate decorrelation filters, before being used in the update equation of the NLMS algorithm [10], resulting in the so-called Filtered-x adaptive algorithm. It is not, however, easy to design an appropriate decorrelation filter [11]. Yet another solution is a non continuous adaptation or an open-loop algorithm in which the hearing aid forward path is broken and a probe noise is injected during particular intervals, for example, when howling is detected by an appropriate oscillation detector [12]. The ON/OFF switching of the probe signal produces annoying effects to the hearing aid user.

Working principle of the different AFR subsystems in the proposed hearing aid model has been dealt in [13, 14, 15]. These subsystems adapt the feedback-reduction FIR filter based on the LMS algorithm or a filtered version of this algorithm, i.e., the FXLMS. Moreover, the normalized versions of both algorithms (i.e., NLMS and NFXLMS) are also proposed to adapt.

2. Problem with the Existing System

Acoustic feedback in hearing aids occurs when the aid's receiver produces an acoustic signal that leaks back to the microphone. Feedback usually results from leakage from the ear canal via a vent or from mechanical coupling of receiver motion via the hearing aid housing. Although there are a number of signal-processing elements involved, for present purpose the essence of the problem can be pictured as in Fig. 1, where H represents the net feedback path and G represents the intended transfer function of the hearing aid. The transfer function of this system is:

$$H(z) = \frac{G(z)}{1 - G(z)F(z)}$$

which shows that due to acoustic feedback the hearing aid will be unstable if $G(z)$ is large enough so that $G(z)F(z) = 1$ at some frequency. Stated differently, when a frequency component of the feedback signal arrives at the microphone in phase with and with magnitude equal to or greater than the sound that produced it, oscillation will occur, driving the hearing aid at its maximum level and rendering it useless. The conditions for oscillation in hearing aids are common. Consider the NLMS-algorithm-based conventional method as shown in Fig. 1. The signal pricked up by the input microphone, $s(n)$, is given as:

$$x(n) = s(n) + y_f(n) \tag{1}$$

where $y_f(n) = f(n) * y(n)$ is the feedback component due to the output signal $y(n)$, * denotes linear convolution and $f(n)$ represents the impulse response of $F(z)$. The error signal for $W(z)$ is generated as:

$$e(n) = x(n) - y_w(n) = s(n) + y_f(n) - y_w(n) \tag{2}$$

which is also used as an input to the hearing aid processing unit $G(z)$, i.e., $u(n) = e(n)$. The coefficient vector for $W(z)$, $w(n) = [w_o(n), w_1(n), \ldots.., w_{L-1}(n)]]^T$, is updated using the NLMS algorithm as

$$w(n+1) = w(n) + \frac{\mu}{y^T(n)y(n) + \delta} g(n)y(n) \tag{3}$$

where μ is step-size for $W(z)$, and δ is a small positive constant to avoid division by zero. Ideally, $W(z)$ is expected to generate a replica of $y_f(n)$, so that $x(n) = e(n) \approx s(n)$. However, the input and desired-response signals of $G(z)$, $y(n)$ and $x(n)$, respectively, are correlated with each other and would result in a biased convergence, i.e., $u(n) = e(n) \rightarrow$ ZERO.

3. Theoretical Background

3.1 Adaptive Filtering

A filter is designed and used to extract or enhance the desired information contained in a signal. An adaptive filter is a filter with an associated adaptive algorithm for updating filter coefficients so that the filter can be operated in an unknown and changing environment. The adaptive algorithm determines filter characteristics by adjusting filter coefficients (or tap weights) according to the signal conditions and performance criteria (or quality assessment). A typical performance criterion is based on an error signal, which is the difference between the filter output signal and a given reference (or desired) signal.

As shown in Fig. 2, an adaptive filter is a digital filter with coefficients that are determined and updated by an adaptive algorithm. Therefore, the adaptive algorithm behaves like a human operator that has the ability to adapt in a changing environment. For example, a human operator can avoid a collision by examining the visual information (input signal) based on his/her past experience (desired or reference signal) and by using visual guidance (performance feedback signal) to direct the vehicle to a safe position (output signal).

Adaptive filtering finds practical applications in many diverse fields such as communications, radar, sonar, control, navigation, seismology, biomedical engineering and even in financial engineering. The high-order filter together with a highly correlated input signal degrades the performances of most time-domain adaptive filters. Adaptive algorithms that are effective in dealing with ill-conditioning problems are available; however, such algorithms are usually computationally demanding, thereby limiting their use in many real-world applications.

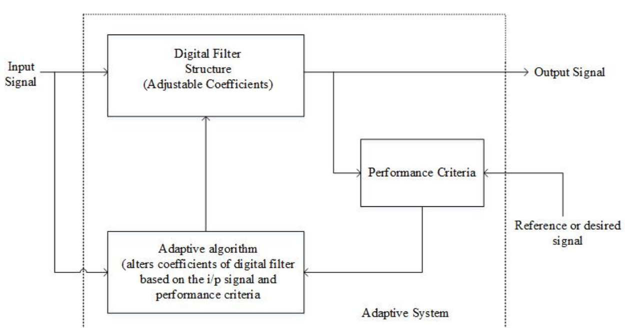

Figure 2: Basic Functional Blocks of an Adaptive Filter

3.2 Adaptive transversal filters

An adaptive filter is a self-designing and time-varying system that uses a recursive algorithm continuously to adjust its tap weights for operation in an unknown environment. Fig. 3 shows a typical structure of the adaptive filter, which consists of two basic functional blocks:

1) a digital filter to perform the desired filtering and
2) an adaptive algorithm to adjust the tap weights of the filter

The digital filter computes the output $y(n)$ in response to the input signal $u(n)$, and generates an error signal $e(n)$ by comparing $y(n)$ with the desired response $d(n)$, which is also called the reference signal, as shown in Fig. 2. The performance feedback signal $e(n)$ (also called the error signal) is used by the adaptive algorithm to adjust the tap weights of the digital filter. The digital filter shown in Fig. 3 can be realized using many different structures. The commonly used filter is a transversal or finite impulse response (FIR) filter. The adjustable tap weights, $w_m(n), m = 0, 1, \ldots, M-1$ indicated by circles with arrows through them, are the filter tap weights at time instance n and M is the filter length. These time varying tap weights form an $M \times 1$ weight vector expressed as

$$w(n) = [w_0(n), w_1(n), ..., w_{M-1}(n)]^T \tag{4}$$

where the superscript T denotes the transpose operation of the matrix. Similarly, the input signal samples, $u(n-m), m = 0, 1, ..., M-1$ form an $M \times 1$ input vector

$$u(n) = [u(n), u(n-1), ..., u(n-M+1)]^T \tag{5}$$

With these vectors, the output signal $y(n)$ of the adaptive FIR filter can be computed as the inner product of w(n) and u(n), expressed as

$$y(n) = \sum_{m=0}^{m-1} w_m(n)u(n-m) = w^T(n)u(n) \tag{6}$$

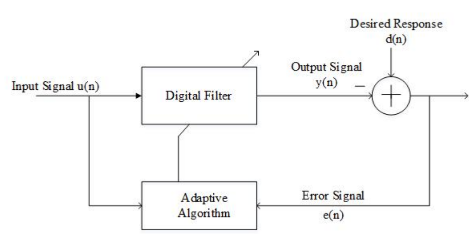

Figure 3: Typical structure of the adaptive filter using i/p and error signals to update its tap weights

4. System Model

The block diagram of the new method is shown in Fig. 4. This method employs two adaptive filters $W_1(z)$ and $W_2(z)$ working in tandem. The important difference, however, is that the delay is inserted at the output of the hearing maid. Traditionally such type of delay is used to solve the correlation problem in the AFC filter [9]. In our approach, the objective of the appended delay is twofold:
1) to provide (some) decorrelation, as well as
2) to help designing an efficient strategy for weight transfer between the two adaptive filters as explained below.

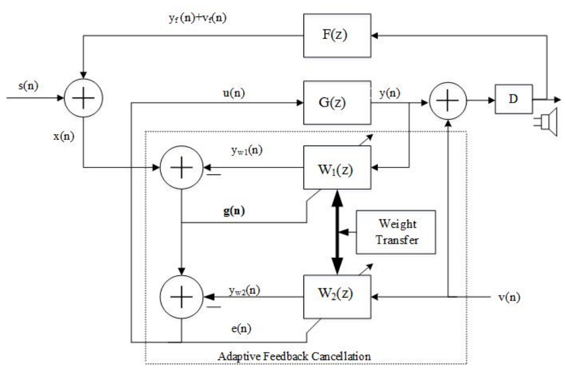

Figure 4: Block diagram of the proposed method for continuous AFC in hearing aids

The adaptive filter $W_1(z)$ is excited by y(n) and is expected to provide a neutralization signal for the feedback component $y_f(n)$. The second adaptive filter $W_2(z)$ is excited by the feedback component $v_f(n)$ due to the added probe signal $v(n)$. It is assumed that $v(n)$ is a low level white signal and is uncorrelated with the input signal $s(n)$ and hence with the output signal $y(n)$. The signal picked up by the input microphone, $x(n)$ is now given as

$$x(n) = s(n) + y_f(n) + v_f(n) \tag{7}$$

where $v_f(n) = f(n) * v(n-D)$ is the acoustic feedback component due to probe signal $v(n-D)$ where D is an appropriately selected delay. The error signal for $W_1(z)$, $g(n)$, is computed as

$$g(n) = x(n) - y_{w_1}(n) = s(n) + [y_f n - y_{w_1}(n)] + v_f(n) \tag{8}$$

which is also used as the desired response for $W_2(z)$, and hence the error signal for $W_2(z)$, $e(n) = g(n) - y_w 2(n)$, is given as

$$e(n) = s(n) + [y_f(n) - y_{w_1}(n)] + [v_f(n) - y_{w_2}(n)] \tag{9}$$

A delay based technique has been employed which has been largely applied in the field of acoustic echo cancelation [14] A measure of the filter convergence is the deviation or the system mismatch. The normalized squared deviation (NSD) of the adaptive filter $W_1(z)$ and $W_2(z)$ can be respectively estimated as:

$$\Delta\tilde{W}_1(n) = 10\log\{\frac{\|\tilde{f}(n) - w_{1F}(n)\|^2}{\|\tilde{f}(n)\|^2}\} \tag{10}$$

$$\Delta\tilde{W}_2(n) = 10\log\{\frac{\|\tilde{f}(n) - w_{2F}(n)\|^2}{\|\tilde{f}(n)\|^2}\} \tag{11}$$

It is worth mentioning that both adaptive filters are continuously adapted and hence, $W_1(z)$ would tend to a biased solution and $W_2(z)$ would slowly fine tune to a better estimate Now the following weight transfer strategy has been employed such that both filters give good estimate of $F(z)$.

4.1 Weight-Transfer Strategy

Since the delay is inserted at the output of the hearing aid; this increases the effective path to be identified by the AFC filters $W_1(z)$ and $W_2(z)$. Thus both the adaptive filters $W_1(z)$ and $W_2(z)$ are considered with extended-length coefficient vectors as being given as:

$$w_1(n) = \begin{bmatrix} w_{1z}(n) \\ w_{1f}(n) \end{bmatrix} \quad \text{and} \quad w_2(n) = \begin{bmatrix} w_{2z}(n) \\ w_{2f}(n) \end{bmatrix}$$

where; $w_{1z}(n) = [w_{1z,0}(n), w_{1z,1}(n), ..., w_{1z,D-1}(n)]^T$ and $w_{2z}(n)$ represent the part used to model the delay (and would eventually converge to zeros), and both $w_{1f}(n)$ and $w_{2f}(n)$ model $F(z)$. Now convergence of the two adaptive adaptive filters $W_1(z)$ and $W_2(z)$ can be monitored on the basis of norm of extension coefficients modeling the appended delay as

$$\rho_1(n) = \|w_{1z}(n)\|^2 \tag{12}$$

$$\rho_2(n) = \|w_{2z}(n)\|^2 \tag{13}$$

The power estimates for the error signals in (8) and (9) can be respectively expressed as;

$$P_g(n) = P_{\{s+(y_f-y_{w1})\}}(n) + P_{vf}(n) \tag{14}$$

$$P_e(n) = P_{\{s+(y_f-y_{w1})\}}(n) + P_{(vf-y_{w2})}(n) \tag{15}$$

These power estimates can be recursively computed using lowpass estimator of type

$$P_q(n) = \lambda P_q(n-1) + (1-\lambda)q^2(n) \tag{16}$$

where λ is the forgetting factor ($0.9 < \lambda < 1$) and $q(n)$ is the signal of interest. At the start up ($n = 0$), $P_g(n) \approx P_e(n)$. However, $W_1(z)$ converges faster as compared with $W_2(z)$ ($W_2(z)$ being excited by a low level probe noise $v(n)$), and hence $P_g(n) < P_e(n)$ for $n > 0$. Finally as $n \to \infty$, $W_2(z)$ converges too and hence $P_e(n) \approx P_g(n)$.

Both $w_{1z}(n)$ and $w_{2z}(n)$ are initialized with all 1's and $w_{1f}(n)$ and $w_{2f}(n)$ may be initialized by null vectors of appropriate orders. The convergence of $W_1(z)$ is faster than $W_2(z)$ and initially $\rho_1(n) < \rho_2(n)$, and hence weights from $W_1(z)$ are copied to $W_2(z)$ as $w_{1f}(n) \to w_{2f}(n)$.

4.2 The Adaptation Algorithm

The output of the adaptive filter $W_1(z)$ is given as

$$y_{w1}(n) = w_1^T(n)y(n) \tag{17}$$

where $w_1(n) = [w_{1,0}(n), w_{1,1}(n), ..., w_{1,L-1}(n)]^T$ is the tapweight vector for $W_1(z)$, $L_1 = D+L$ is the tap-weight length of $W_1(z)$, and $y(n) = [y(n-1), y(n-2), ..., y(n-L_1)]^T$ is the signal vector comprising L_1 recent samples of $y(n)$. It is worth mentioning that there is inherent one-sample delay which is not shown in figures just for the sake of simplicity. The coefficient vector for $W_1(z)$, $w_1(n)$, is updated using the NLMS algorithm as;

$$w_1(n+1) = w_1(n) + \frac{\mu_1(n)}{y^T(n)y(n)+\delta_1} g(n)y(n) \tag{18}$$

where δ_1 is another positive constant to avoid division by zero, and $\mu_1(n)$ is a time varying step-size parameters being computed as;

$$\mu_1(n) = \begin{cases} \frac{\hat{N}_{D_1}(n)}{P_g(n)} & \text{if } \frac{\hat{N}_{D_1}(n)}{P_g(n)} > \mu_1(n); \\ \mu_{1_{min}} & \text{if } otherwise; \end{cases} \tag{19}$$

where $\mu_{1_{min}}$ is the minimum value of the step-size parameter $\mu_1(n)$, and $\hat{N}_{D_1}(n)$ is being computed as

$$\hat{N}_{D_1}(n) = \lambda \hat{N}_{D_1}(n-1) + (1-\lambda)\frac{w_{1z}^T(n)w_{1z}(n)y^T(n)y(n)}{D} \tag{20}$$

The output of the extended-length adaptive filter $W_2(z)$, $y_{w_2}(n)$ is given as;

$$y_{w_2}(n) = w_2^T(n)v(n) \tag{21}$$

where $w_2(n) = [w_{2,0}(n), w_{2,1}(n), ..., w_{2,L_2-1}(n)]^T$ is the tap-weight vector for $W_2(z)$, $L_2 = D+L$ is the tap-weight length of $W_2(z)$, and $v(n) = [v(n), v(n-1), ..., v(n-L_2+1]^T$ is a signal vector for the probe signal $v(n)$. The coefficient vector for $W_2(z)$, $w_2(n)$, is updated using the NLMS algorithm as

$$w_2(n+1) = w_2(n) + \frac{\mu_2(n)}{v^T(n)v(n)+\delta_2} e(n)v(n) \tag{22}$$

where δ_2 is another positive constant to avoid division by zero, and $\mu_2(n)$ is a time varying step-size parameters being computed as

$$\mu_2(n) = \begin{cases} \frac{\hat{N}_{D_2}(n)}{P_e(n)} & \text{if } \frac{\hat{N}_{D_2}(n)}{P_e(n)} > \mu_2(n); \\ \mu_{2_{min}} & \text{if } otherwise; \end{cases} \tag{23}$$

where $\mu_{2_{min}}$ is the minimum value of the step-size parameter $\mu_2(n)$, and $\hat{N}_{D_2}(n)$ is being computed as

$$\hat{N}_{D_2}(n) = \lambda \hat{N}_{D_2}(n-1) + (1-\lambda)\frac{w_{2z}^T(n)w_{2z}(n)v^T(n)v(n)}{D} \tag{24}$$

5. Results and Discussion

Simulations were conducted in MATLAB with the feedback path obtained from an in-the-ear hearing aid. The impulse response of the feedback path was modeled using a FIR filter with 32 coefficients. The sampling frequency considered is $F_s = 8000Hz$. All adaptive filters are assumed to be FIR filters of tap-weight length 32. The forward path representing the hearing aid processing unit, is assumed to be given as $G(z) = Kz^{-\Delta}$ where K and Δ respectively represent the gain and delay of the system. In the result presented below $\Delta = 10$ and the gain is chosen as $k = 3$. The signal to noise ratio

(SNR) of probe signal is chosen as $-15dB$. The forgetting factor λ is chosen as 0.97. The Normalized Squared Deviation (NSD) of filter $W_1(z)$, $W_2(z)$ and the average NSD are employed as the performance measures.

Following considerations are made while performing the simulation study (the corresponding simulation parameters are determined experimentally and adjusted for fast and stable convergence):

- NLMS-algorithm based conventional adaptive filter method as shown in Fig. 1. ($\mu = 1 \times 10^{-9}$, $\delta = 1 \times 10^{-6}$)
- Two adaptive filter based proposed method. ($D = 4$, $\mu_{1_{min}} = \mu_{2_{min}} = 1 \times 10^{-9}$, $\delta_1 = 1 \times 10^{-8}$,$\delta_2 = 2.5 \times 10^{-3}$)

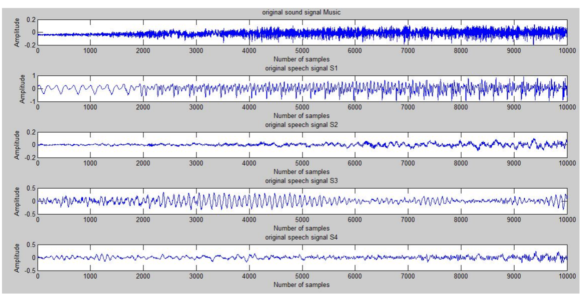

Figure 5: Plots for various signals used in computer simulations

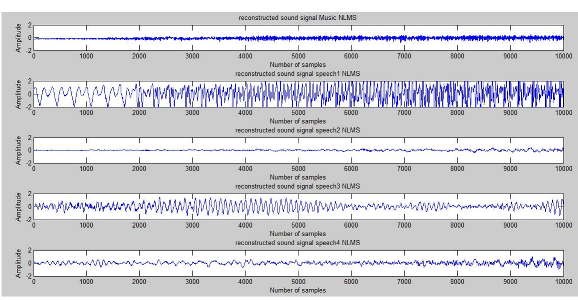

Figure 6: Plots for the output signals with conventional NLMS algorithm

The NSD curves in Fig. 9 shows the characteristics of estimated feedback path in comparison with F(z). We observe that the proposed method outperforms the conventional method in both the convergence speed and the steady state mismatch.

Fig. 8 shows the typical result for the error in reconstruction of the desired signal at the input of the hearing aid being computed as

$$\Delta S(n) = |s(n) - u(n)| \tag{25}$$

It is obvious that for a perfect reconstruction of the desired input at the hearing aid, we must have $\Delta S(n) \to 0$. From Fig. 9 we see that the proposed method gives a fast convergence speed in reproducing the desired signal at the input of the hearing aid processing unit. The original signals used in computer simulation are shown in Fig. 5.

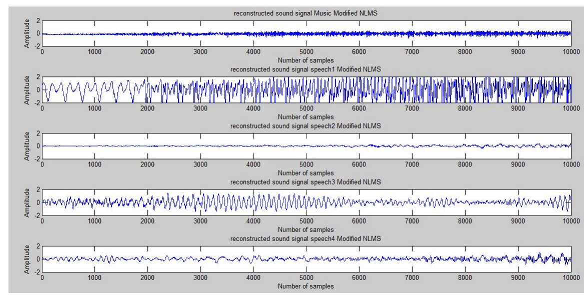

Figure 7: Plots for the output signals with modified proposed NLMS algorithm

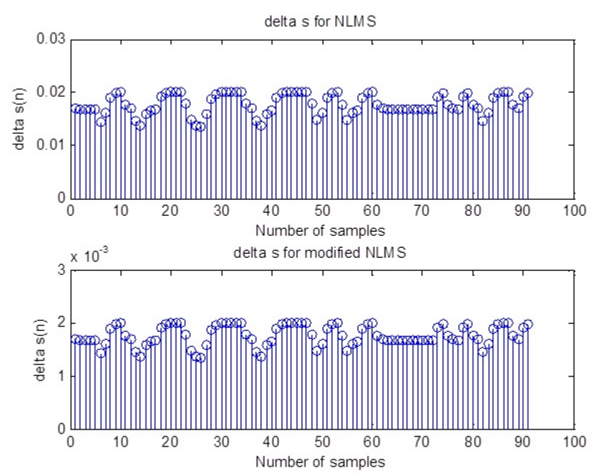

Figure 8: Error plots in reconstruction of the desired signal $\Delta S(n)$

The amplified output signals of hearing aid in comparison with the input signal is shown in Fig. 6 and Fig. 7 where amplification can be noted from the amplitude levels shown on y-axis. It is difficult to see any difference between the amplitude signals of two methods, however, a close observation reveals that the proposed method is better able to replicate the input signal. In fact we hear some 'musical' noise in the case of conventional method, whereas the proposed method produces no such noise. It is worth mentioning that the added probe signal is so low that it does not affect the hearing experience.

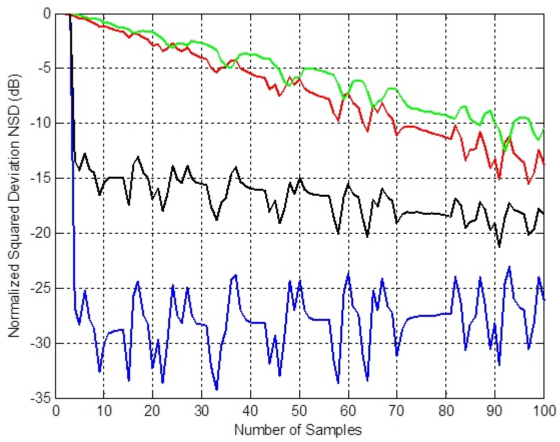

Figure 9: Normalized Squared deviation for various cases

6. Conclusion

A novel feedback suppression scheme based on modified NLMS algorithm is presented in this paper. We have presented preliminary results for a continuous AFC in the digital hearing aids. By employing the dual adaptive filters and delay at the output of the hearing aid, we were able to obtain the unbiased estimate of the feedback path. Simulation results based on real speech signals showed improved convergence rates and stable solutions. The results obtained are quite promising, however, a detailed investigation is required for the added stable gain (ASG), maximum stable gain (MSG) and comparison with other methods. MSG is defined as the maximum gain without instability assuming a flat response of the hearing-aid process. ASG is defined as the additional gain that is possible by using the feedback canceller. These are the tasks of future work.

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