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# Adaptive Active Noise Control Schemes for Headset Applications ⋆

**Veeravasantarao D** [*] **Ajay S** [**] **Premkumar P** [*] **Laxmidhar Behera** [*]

[*] *Department of Electrical Engineering, Indian Institute of Technology Kanpur, Uttar Pradesh - 208 016 India.*
[**] *Department of Electronics and communication Engineering, National Institute of Technology Karnataka, Surathkal - 575 025, India.*
*email: dvvrao@iitk.ac.in, ajays.nitk@gmail.com, premkanip@iitk.ac.in, lbehera@iitk.ac.in, l.behera@ulster.ac.uk*

**Abstract:** This paper presents the design and implementation of adaptive feedback active noise control system (ANC) for head phone applications. Active Noise Control is a technique of acoustic noise reduction using a secondary source of sound which produces "antinoise" to cancel the primary noise. In this paper, narrow band single channel feedback ANC for headsets application is focused upon. The filter weights are updated by using the feedback form of Filtered-X LMS (FXLMS) algorithm. Performances for the IIR-based filter, FIR-based filter are compared with those of the algorithm by using ADALINE. The real time implementation of the system is performed using TMS320C6713 DSP Starter Kit (DSK) and the performance is analyzed for two tone sinusoidal noise.

## 1. INTRODUCTION

An active noise control (ANC) headset is used in high noisy environment for protecting human hearing ability and to improve the communication quality. The passive methods such as earmuffs are either ineffective or tend to be very expensive and bulky at low frequencies. Thus the ANC systems which efficiently attenuate low-frequency noises, have become an effective technique for designing ANC headphones. Active noise cancellation or control [S.J. and P.A., 1993], [D.Synder, 2000] is a technique of noise cancellation by the principle of superposition. The active noise control system contains an electroacoustic device that cancels the unwanted sound by generating an anti sound (antinoise) of equal amplitude and opposite phase. ANC can be implemented by using either feedforward or feedback technique. Analog controllers [Rafaely, 2001] have been employed using feedback configuration for active noise cancellation in the headsets. Since this is a nonadaptive approach, no on-line modeling of the ear-cup environment is carried out in real time, resulting in deteriorating performance with changing environment. Current research in ANC for communication headset focuses on using adaptive feedforward technology. In practice, however, the feedforward ANC system for headset [M.Kuo and R.Morgan, 1996] have to handle causality and performance deficiencies caused by non - stationary reference inputs, measurement noise, acoustic feedback, and higher cost of using additional reference microphones. More recently, techniques have been developed to combine the analog feedback with digital feedforward technique[Rafaely, 2001] to achieve better noise canceling performance. In Feedback ANC [Kuo et al., 2005], only one microphone is employed to measure the residual noise at the noise cancellation location.

Adaptive single channel narrow band feedback active noise control for headset application is the main problem addressed in this paper. The system is designed to cancel periodic narrow band noise. Single channel implementation is assumed for simplicity. Feedback control is chosen because of its simpler practical implementation. Headset application poses a good challenge for algorithm development.

This paper focusses on adaptive FIR, IIR filter and ADALINE structures for ANC algorithms to reduce undesired noise in a time-varying environment. In practical applications, the FIR filter is popular because of its stability and linear characteristics. However, adaptive algorithms with FIR structures need a large number of weights to control lightly damped systems. In many practical ANC systems, where the reference or desired error signals are narrow band, it is inefficient to control such a system with an FIR filter because we cannot select the control frequency range where the control efforts should be concentrated on.

Fundamentally, the choice of Adaptive Linear Neuron (ADALINE) to perform the task of noise cancellation is made based on two considerations, i.e., its ability to act as an adaptive filter and the high processing speed that it can provide. ADALINE is certainly an approach worth to be explored based on the fact that it is the most widely used neural network approach in practical applications today. Its fast processing speed is attributed to its simple network architecture with minimum elements. Performance of the

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ADALINE system will be best evaluated if it can be compared to the performances of other systems.

FxLMS and normalized FxLMS algorithms([Kuo et al., 2005]) are used for paraemter estimation of filters. The algorithms are implemented on Spectrum Digital Inc. DSP Starter Kit with Texas Instruments® TMS320C6713 floating point DSP (TMS320C6713 DSK) using Code Composer Studio v3.1.

## 2. ADAPTIVE ANC MODEL

The characteristics of the acoustic noise source and the environment are time varying. The frequency content, amplitude, phase, and sound velocity of the undesired noise are non-stationary. An ANC system must therefore be adaptive in order to cope with these variations. The controller should be an adaptive filter which identifies the noise and produces the antinoise in proper phase to destructively interfere the noise and cancels it. Single Channel Narrow band Feedback ANC system has a sensor to sense the residual noise and a secondary source to produce the antinoise. The entire Feedback ANC system is shown in fig. 2 ([Kuo et al., 2005], [Kuo et al., 2006]).

The antinoise produced by the controller travels through the acoustic environment. This acoustic environment alters the signal characteristics of the antinoise. Moreover, the speaker sensitivity and impedance, microphone sensitivity and impedance, A/D and D/A converters, microphone and speaker pre-amplifiers, temperature and other physical conditions affect the antinoise produced. The entire path shown in Fig 1 containing the D/A converter through A/D converter is called the secondary path.The effects of this secondary path are to be considered for better cancellation [Kuo et al., 1996]. The effect of the secondary path on filter design is discussed in [Morgan, 1980]. It is similar to stating that the antinoise $y(n)$ is input to the secondary path transfer function $S(z)$. The output from the system $S(z)$ is the actual antinoise $\hat{y}(n)$which cancels the noise. The secondary path from the controller $W(z)$ to the acoustic space is shown as $S(z)$. To account for the secondary path effects, an estimate of secondary path $S(z)$ is included as $\hat{S}(z)$ in the update algorithm.

In our implementation [Kuo and S.Gan, 2002], the secondary path is modeled using an FIR adaptive filter $\hat{S}(z)$, of order M.

$$\hat{y}(n) = \sum_{i=0}^{M} \hat{s}_i y(n-i) \tag{1}$$

The secondary path can be identified using Least Mean Square algorithm effectively. The update law is given by,

$$\hat{s}_i(n+1) = \hat{s}_i(n) + \mu e(n) y(n-i) \tag{2}$$

### *2.1 FIR Based FxLMS Algorithm*

The Active Noise Filter model generating antinoise is taken as an FIR filter of order N.

$$y(n) = \sum_{i=0}^{N} w_i \hat{x}(n-i) \tag{3}$$

where $\hat{x}(n)$ is the estimate of noise signal which has to be cancelled and $w_i$ are the parameters of FIR filter. In

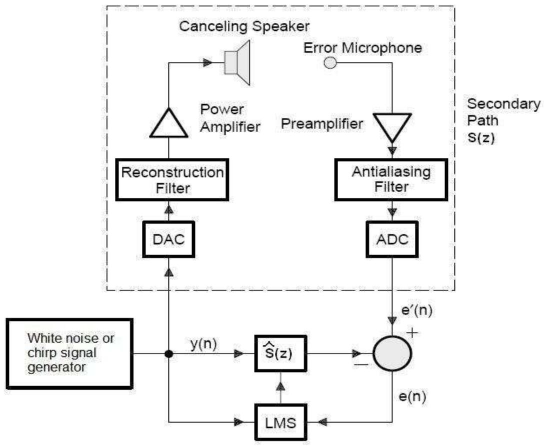



Fig. 1. Secondary Path and its modeling

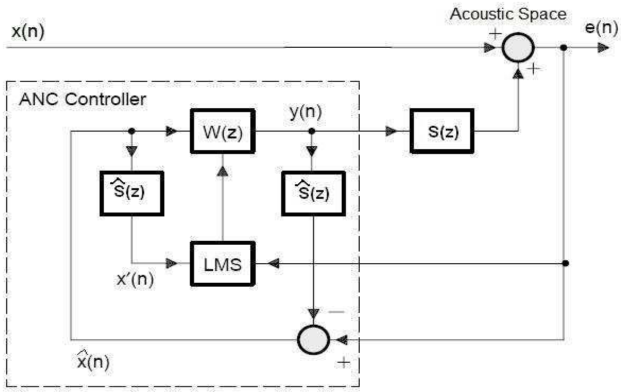



Fig. 2. FXLMS Algorithm for feedback ANC in Headsets

feedback ANC, we measure only the residual noise and hence the noise signal is not available. The estimate of the noise signal can be obtained from the residual noise since we know that the residual noise is the superposition of noise and antinoise at the sensor location.

The primary noise $\hat{x}(n)$ is estimated from the residual noise using,

$$\hat{x}(n) = e(n) - \sum_{i=0}^{M} \hat{s}_i y(n-i) \tag{4}$$

The FxLMS update rule for antinoise filter, minimizing the instantaneous squared error is,

$$w_i(n+1) = w_i(n) - \mu e(n) x'(n-i), i = 0, 1, \ldots, N \tag{5}$$

where $x'(n)$ is given by,

$$x'(n) = \sum_{i=0}^{M} \hat{s}_i \hat{x}(n-i) \tag{6}$$

In FxLMS the learning rate $\mu$ is fixed. The larger variation of noise may lead to algorithm instability. To make the learning robust to noise variation, the normalized FxLMS uses adaptive learning rate which is inversely proportional to the power of noise. The normalized FxLMS algorithm is given by,

$$w_i(n+1) = w_i(n) - \frac{\mu}{\hat{P}_{x(n)} + c} e(n)x'(n-i), i = 0, 1, \ldots, N \tag{7}$$

where $\hat{P}_{x(n)}$ is power estimate of noise given by,

$$\hat{P}_{x(n)} = (1-\alpha)\hat{P}_{x(n)} + \alpha x^2(n) \tag{8}$$

### *2.2 IIR based Filter Design*

In FIR structure, a sufficiently large number of filter weights are necessary to maintain desired control performance especially for a lightly damped system. The necessary computational power can be reduced using an IIR structure with a smaller number of weights; however this may cause instability and non-linearity problems in the adaptive update process of filter weights.The basic IIR filter structure is

$$y(n) = b_0x(n) + b_1x(n-1) + b_2x(n-2) + \ldots\ldots.. + b_Px(n-P) \\ - a_1y(n-1) - a_2y(n-2) - \ldots\ldots.. - a_Qy(n-Q) \tag{9}$$

P is the feedforward filter order,Q is the feedback filter order, $b_i$ are the feedforward filter coefficients, $a_i$ are the feedback filter coefficients The output can be written as

$$y(n) = X_n^T W_n \tag{10}$$

$$where, X_n = [x(n) \;\; x(n-1) \;\; \ldots \;\; x(n-P) \\ y(n-1) \; y(n-2) \;\; \ldots \;\; y(n-Q)]^T. \tag{11}$$

$W(n) = [b_0 \; b_1 \;\; \ldots \;\; b_P \;\; -a_1 \;\; -a_2 \;\; \ldots \;\; -a_Q]^T$. The update law for weights is same as in case of FIR filter shown in equation (7).

### *2.3 ANC Filter Design by using ADALINE*

Adaline is a single layer neural network with multiple nodes where each node accepts multiple inputs and generates one output.Based on the learning principal of the ADALINE, weight and bias of the network are adapted by using the Least Mean Squares (LMS) or Widrow-Hoff rule [Widrow and Lehr, 1990]. The architecture of the network is relatively simple compared to the larger networks such as the famous back-propagation network. It only consists of a single neuron with a single connecting weight and bias. Fig 3 shows a "sigmoid ADALINE" elements which incorporates a sigmoidal nonlinearity. The input - output relationship of the sigmoid can be denoted by $y_n = sgm(s_n)$.A typical sigmoid function is the hyperbolic tangent:

$$y_n = tanh(s_n) = \frac{1 - e^{-2s_n}}{1 + e^{-2s_n}}. \tag{12}$$

The linear output is $s_n$.

$$s_n = X_n^T W_n \tag{13}$$

where X is input vector and W is weight vector, N is the number of nodes in .

$$X_n = [x(n) \;\; x(n-1) \;\; \ldots \; x(n+N-1)]^T. \tag{14}$$

$$W_n = [w_1 \;\; w_2 \;\; w_3 \ldots \; w_N]^T. \tag{15}$$

We shall adapt this ADALINE with the objective of minimizing the mean square of the sigmoid error $e_n$,defined as

$$e_n = d_n - y_n = d_n - sgm(s_n). \tag{16}$$

Here $d_n$ is the desired output. The update law for minimizing the mean square error is .

$$W_{n+1} = W_n + 2\mu e_n(1 - y_n^2)X_n'. \tag{17}$$

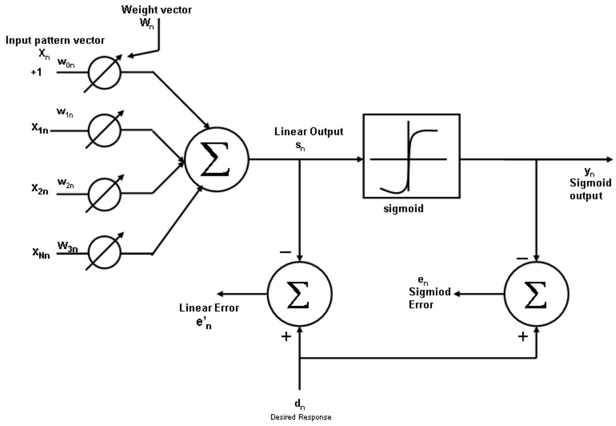



Fig. 3. ADALINE with sigmoidal nonlinearity.


Fig. 4. Basic system configuration

The filtered X vector is given by

$$X_n' = [x'(n) \;\; x'(n-1) \;\; \ldots \;\; x'(n-M)]^T. \tag{18}$$

where $x_n' = \hat{S} * X_n$. Here $\hat{S}$ is secondary path filter with order M.

$$\hat{S_n} = [s_1 \;\; s_2 \;\; s_3 \;\; \ldots \;\; s_M]. \tag{19}$$

## 3. SYSTEM CONFIGURATION

The ANC system Fig. 4 consists of a headset, mounted with a microphone. The headphone acts as a secondary source to generate the anti noise and the microphone senses the residual noise. The entire system is interfaced with Texas TMS320C6713 DSK which runs an adaptive filter algorithm to produce the antinoise. The noise is simulated by playing it through computer multimedia speakers. The sampling rate is chosen as 8kHz in order to be compatible with voice applications. The maximum output power rating of the headphone used for this purpose decides the power level of antinoise and hence the maximum sound level of the noise which can be canceled at the microphone. The microphone should be sensitive over the entire frequency spectrum which ranges from 0 to 4kHz in our case. In our experimental setup SONY MDR-XD100 HiFi stereo headphone has been used. The microphone has to be very sensitive with a good frequency response over the frequency range of interest with an *omnidirectional* spatial

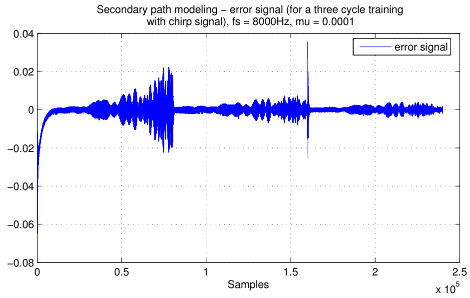



Fig. 5. Secondary Path Modeling Error

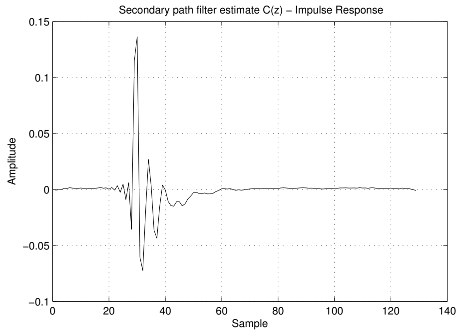



Fig. 6. Secondary Path Model $\hat{S}(z)$ - Impulse response

response. Moreover, the microphone should be small and inconspicuous so that it can be positioned inside the ear cup of the headphone. In the current setup, Ahuja CTP-10DX Tie Clip microphone is used for sensing the noise.

## 4. REAL TIME EXPERIMENTATION

The real time experiment is done with simulated noise from multimedia speakers. FIR filter architecture is chosen for both secondary path model and Antinoise Filter, since we are more interested in the phase characteristics of the system. The secondary path modeling is first done and the $\hat{S}(z)$ (order M) is stored. The input signal $x(n)$ rich in frequency content has to be chosen for secondary path estimation and then it is presented as the output $y(n)$ to drive the canceling loudspeaker. This internally generated signal is also used as the reference input for the adaptive filter $\hat{S}(z)$ and the LMS update adaption (2). This is called off-line modeling. Since the acoustic environment keeps changing, this training is to be done every time. Once this modeling is done, the coefficients are stored and used in noise cancellation mode.

The external narrow band noise is recorded and played back on computer multimedia speakers. In our experiments the primary noise signal used is a two tone sinusoid of low frequency 156 Hz and 352 Hz.The ANC program is run on the DSP and tested in real time conditions in the presence of noise. The testing period is chosen suitably long to observe convergence. The test is then performed with antinoise switched off and error from the microphone (in the absence of ANC) is also stored. This gives the estimate of primary noise. The results and observations in secondary path modeling and Active Filter design are discussed further.

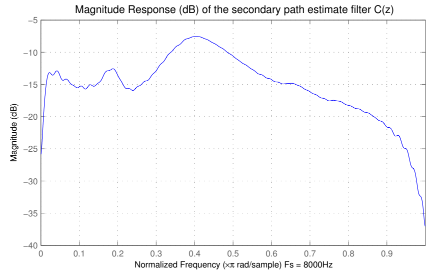



Fig. 7. Secondary Path Model $\hat{S}(z)$ - Frequency response

### *4.1 Secondary Path Identification*

Accurate modeling of secondary path is necessary for proper implementation of ANC algorithm. In our experiment, FIR filter model is used for modeling the secondary path. The secondary path comprises of DAC, headphone dynamics, the acoustic column between headphone and microphone, microphone dynamics, ADC. The experimental setup for secondary path modeling is shown in Fig 1. The secondary path is modeled by sending a known noise signal through headphone and receiving it through the error microphone. To identify the model over the entire frequency range a chirp signal ranging from 100 to 4kHz of 10 sec length is being used. The entire secondary path learning is termed as an off-line process as the training is done in the absence of noise. The FIR model is learned using gradient descent method with a learning rate $\mu =$ 0.0001 in 30 second. It can be observed that the better approximation capability of the path is achieved with FIR of order 128. The approximate error of Secondary path model, during learning process is shown in Fig 5. It can be noted that the error gradually approaches to zero.The estimated filter coefficients of the secondary-path filter, $S(z)$, is presented in Fig 6 for better understanding of the secondary path. The transportation delay from headphone to microphone is captured in FIR model. The frequency response of the secondary path in the range of 0-4kHz is shown in Fig 7, with gain falling off rapidly as we approach high frequency, thus acting as a low pass filter. A peak is observed at about 1.5kHz, which corresponds to the frequency of maximum sensitivity of the microphone.

### *4.2 Active Noise Filter Modeling*

The active noise filter is tested for two tone sinusoid noise of frequency 156 Hz and 352Hz. The noise is generated using the expression $sin(2*\pi*156*t)+0.5*sin(2*\pi*352*t)$. The noise is simulated by playing back the noise through multimedia headphone. The testing is done for 5 second with a learning rate $\mu = 0.5$ in case of FIR filter design with order 60, $\mu = 0.05$ in case of IIR filter design with order 18, $\mu = 0.4$ in case of ADALINE based filter with order 32. Fig 8 shows the experimental results for three adaptive filters. Fig 8(a) is the primary noise of two tone sinusoidal noise having three major harmonics at frequencies 78Hz, 176Hz, 333Hz. Fig 8 compares the noise cancellation performance of the ANC with three filters FIR, IIR and ADALINE method by showing their output signals (after ANC) of the error microphones over 5s. It can be observed that the noise suppression is much better in case of FIR filter and ADALINE compared that of IIR filter is shown in Fig 8.

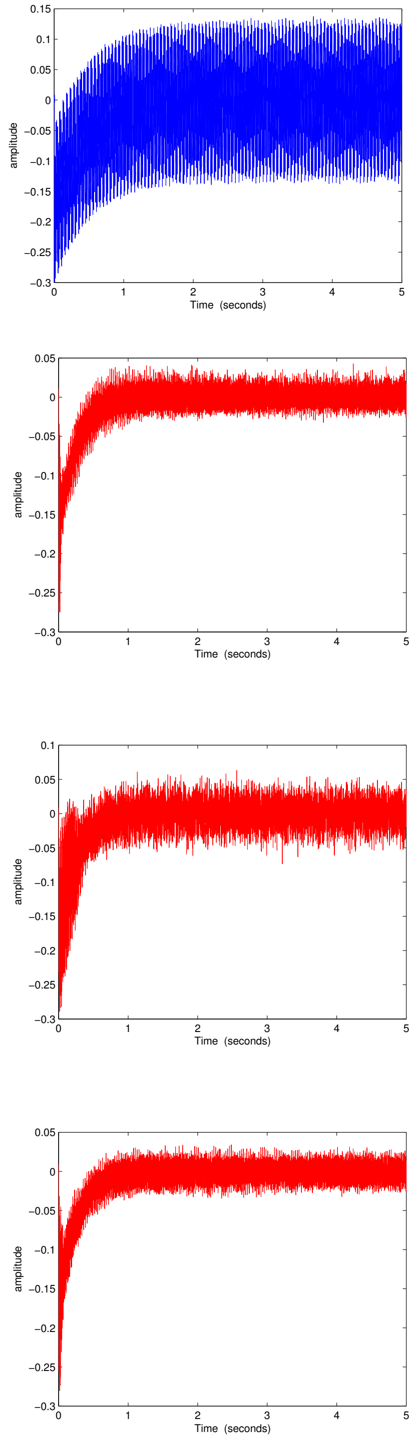
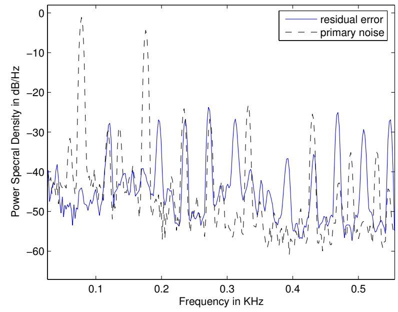
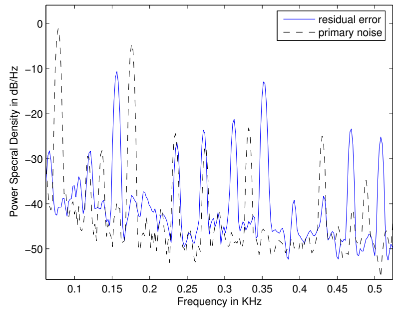



Fig. 8. Time Responses of error signal without and with ANC a) without ANC, b) with ANC using FIR filter, c) with ANC using IIR filter d) with ANC using ADALINE.

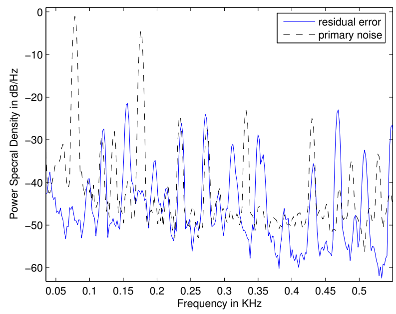
There are three dominant narrow band noise components at frequencies 78Hz, 176Hz and 333Hz is shown in Fig 9. The average noise cancellation levels at the frequency of 78Hz, 176Hz and 333Hz are 38.41dB, 32.66dB and 30.66dB respectively in case of ADALINE, FIR and IIR filter design. Among these filters high noise reduction is obtained



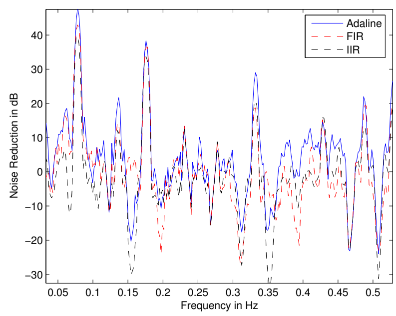

(a) Power Spectrum with FIR filter




(b) Power Spectrum with IIR filter




(c) Power Spectrum with ADALINE method




(d) Reduction in noise

Fig. 9. Power Spectrum before and with ANC; without ANC

in case of ADALINE based filter. The performances using an FIR filter with order 60 and an IIR-based filter with order 18 are similar in the selected frequency ranges. But the computational complexity of the proposed algorithm using IIR filter is one-third of that of the algorithm using the FIR filter. From Fig 9(d) it can be observed that the noise reduction in both cases, FIR and IIR, are same but in case of IIR filter two extra harmonics are introduced at the frequencies 150Hz and 350Hz.These harmonics did not appear in case of FIR filter design and incase of ADALINE, they are of lower amplitude. At frequencies 200Hz and 400Hz, FIR filter introduced harmonics, but they did not appear in case of ADALINE and IIR filters. Although the computational complexity is reduced in case of IIR , harmonics are introduced. If we increase the number of IIR filter bases, a larger amount of reduction can be achieved because the controlled frequency region is extended. But because the necessary computational complexity increases as well, the number of IIR bases should be properly chosen. Better choice of IIR filter base can effectively enhance the performance, convergence speed and calculation efficiency. The noise reduction is high with less power computation is occurred in case of ADALINE based filter. In Table 1, the noise reduction levels are compared at various frequencies with various filters. The training error of ANC in real time is shown is Fig 8. It is observed that the error reduces initially and then settles at some lower value. The complete noise cancellation is not observed in practice. This may be due to the limitation of order of active noise filter. As discussed earlier, it is also observed that in real time the inaccuracies in secondary path model also affects the result. This is attributed to the complex nature of the acoustic environment which is difficult to model accurately. The single channel assumption in feedback ANC is actually an approximation even in the small enclosed space of a headset. The interference pattern and the sound fields produced due to the primary noise and the secondary source need complex acoustic analysis. The performance also depends upon the headphone output power and the sensitivity of headphone and error microphone. Since FIR filter architecture is used for $W(z)$ and $\hat{S}(z)$, it implies that longer filter lengths are required in order to model any system accurately. Hence a better performance may be obtained by using a higher order for the model. In practice, increasing the order of filter would demand higher computation requirement.

Table 1. Comparison of noise reduction levels in ADALINE, FIR, IIR filters

| Filter Type | Order of filter | Noise reduction in dB | | | Avg. noise reduction |
|---|---|---|---|---|---|
| | | 78 Hz | 176 Hz | 333 Hz | (dB) |
| ADALINE | 32 | 47.96 | 38.3 | 28.99 | 38.41 |
| FIR | 60 | 42.92 | 36.49 | 18.57 | 32.66 |
| IIR | 18 | 39.73 | 32.93 | 19.33 | 30.66 |

## 5. CONCLUSION

The undesired noise is reduced for a lightly damped system with a smaller number of filter weights and less computational power (IIR filter) than those of the FIR filter. The proposed adaptive filter has an IIR structure but does not have instability and non-linearity problems commonly associated with the conventional IIR filter structure. It is possible to control only the desired frequency range by choosing proper IIR-based filters. We can obtain the good noise reduction with a lesser order filter in case of ADALINE method. A DSP based platform is developed for Active Noise Cancellation in headphone applications.The real time implementation of Active Noise Control is performed using Texas Instruments TMS320C6713 DSK. The real time experimentation shows a noise reduction of 38 dB in case of ADALINE. The secondary path is modeled using chirp signal. It may be modeled by a proper music signal rich in frequency content. The order of the FIR filter which performs better for the entire noise spectrum has to be investigated. The algorithm with faster convergence has to be tested as the three implemented algorithms suffer slower convergence. ANC has also been implemented using Kalman filter approaches but it does not meet the real time requirements due to very high computational complexity.

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