ABSTRACT

SIMPLIFIED HYBRID ADAPTIVE FEEDBACK ALGORITHM
FOR ACTIVE NOISE CONTROL

Mustafa Oztoprak, M.s Electrical Engineering,
Electrical Engineering Department
Northern Illinois University, April 2020

The main goal of this paper is to present a simulation scheme to simulate simplified hybrid adaptive feedback algorithm along with design constraints for active noise control. It is physically improbable in practice to achieve complete noise cancellation, especially in open backed conditions. The main objective of the noise cancellation is to estimate the noise signal and to subtract it from original input signal to obtain the noise free signal. There is an alternative method called adaptive noise cancellation for estimating a speech signal corrupted by an additive noise or interference. This method uses a primary input signal that contains the speech signal and a reference input containing noise. The reference input is adaptively filtered and subtracted from the primary input signal to obtain the estimated signal. In this method the desired signal corrupted by an additive noise can be recovered by an adaptive noise canceller using LMS (least mean square) algorithm. Here, we will use the residual noise as a reference signal directly to adapt a feedback FxLMS algorithm. A fixed analog feedback controller is concatenated into the FxLMS system, whose design constraints are derived from existing feedback based active and passive control systems. The resulting simplified hybrid algorithm using analog elements and digital elements, provides adequate noise control of both broadband and narrowband ranges, remaining robustly stable in open-backed plant changes throughout. Here we estimate the adaptive filter using MATLAB environment .

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SIMPLIFIED HYBRID ADAPTIVE FEEDBACK ALGORITHM FOR ACTIVE NOISE CONTROL

BY

MUSTAFA OZTOPRAK

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CHAPTER 1

INTRODUCTION

Noise can be a negative effect on many aspects of life. Luckily, thanks to technological improvements we can deal with many different types of noises. The principle of noise control is based on destructive interference in space. This is done by introducing the anti-noise through secondary sources such as loudspeakers where superposition with primary noise takes place. These loudspeakers are part of a control system where a specific signal processing algorithm is employed to control the noise in the desired space. Active noise control systems are particularly advantageous in low frequency attenuation where passive techniques fail to do so within budget or viability. Characteristics of real noise in most environments are time varying, i.e., non-stationary therefore noise control must be adaptive to those changes for it to have maximum effectiveness.

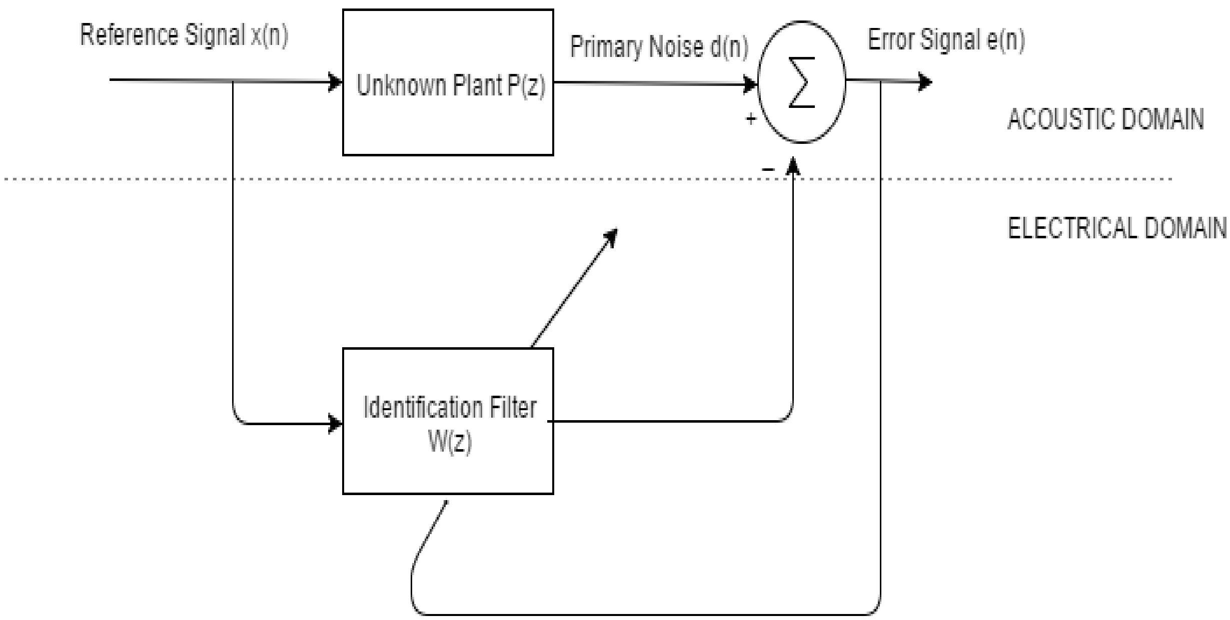

FIGURE 1. Active noise control (ANC) as a system identification scheme

The digital revolution brought in the ability to keep up with noise variations by adapting the filter's coefficients, usually through the FxLMS (Filtered Reference Least Mean Square) algorithm which will be explained in the coming sections.

When any type of active noise control is deployed in real applications, several issues need to be pointed. Kuo and Morgan [3] stated that the ANC's performance should be analyzed by using a hierarchy of techniques, starting with an ideal simplified problem and progressively adding practical constraints and other complexities.

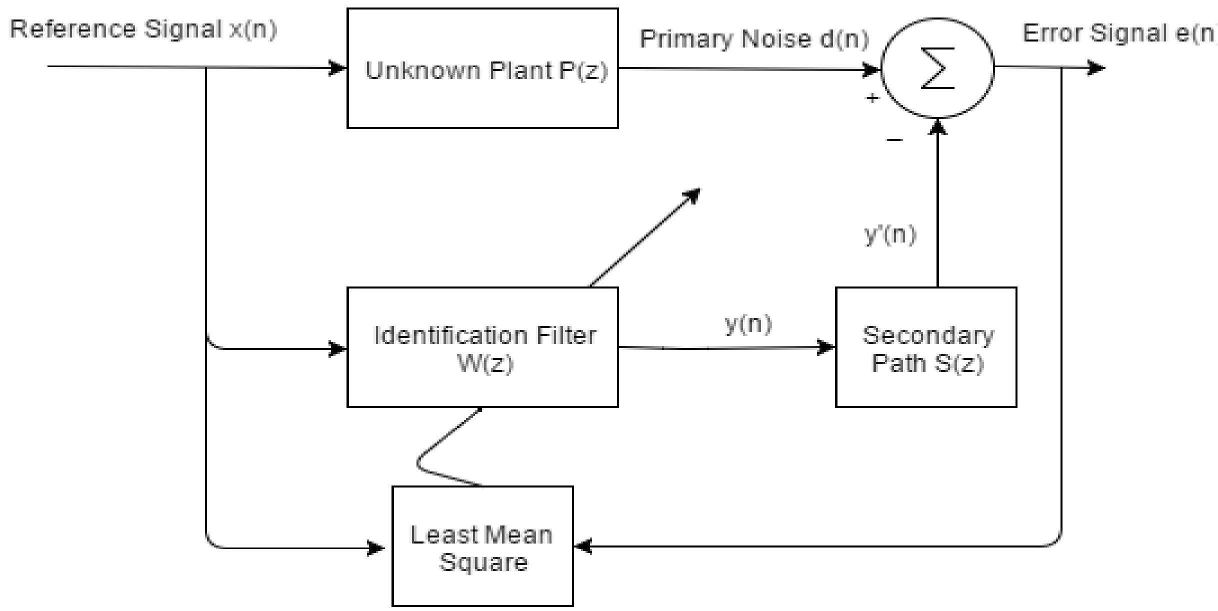

FIGURE 2. Classic ANC block diagram.

They posited that in order for an ANC system to be suitable for industrial-grade use, it had to have the following properties:

A) Maximum efficiency over largest frequency band
B) Autonomy of setting up and installation
C) Adaptability to variations in acoustic domain
D) Robustness and reliability of all elements.

We shall use this principles as a guideline to examine the problem at hand in the particular application of noise control and create effective solutions. In Chapter 2 will explain the main principles of the FxLMS adaptive algorithm along with its block diagrams and equations. Then we will explore the adaptation of FxLMS for a feedback system. Chapter 3 will examine the problem statement at hand followed by its answers in Chapter 4, where the proposed structure is derived. Chapter 5 will take you step by step through the simulation of the acoustic environment and design of the hybrid ANC System using MATLAB. Finally, Chapter 6 offers the conclusion.

CHAPTER 2
FILTERED-X LMS ADAPTIVE ALGORITHMS
Feedforward FxLMS Algorithm

Let us consider a feedforward system that has a single reference sensor, a single error sensor, and a single secondary source. The reference microphone input is processed by the ANC to generate a signal through a secondary source loudspeaker, whose objective is to control the noise while an error microphone observes the performance of the ANC system. The block diagram of a standard single channel feedforward ANC is given in Figure 1. The unknown plant P(z) is estimated by adaptive filter W(z). P(z) consists of the acoustic response from the reference microphone to the error microphone. If the acoustic response changes over time, then the ANC has to track them. It is important to mention that the summing junction is in the acoustic domain and not electrical like in most noise cancellation applications.

The objective of W(z) is to adapt and minimize the residual error e(n) just as in a regular system identification problem. If W(z) adapts to be P(z) perfectly, then z transform of the error signal E(z) = 0. This would mean that in Figure 2 adaptive filter output y(n) = primary noise d(n), implying the filter output and plant output are the same. Based on acoustic superposition, e(n) = d(n) – y(n) = 0. It is also necessary for the electrical delay from reference to loudspeaker to be shorter than the acoustic delay to maintain causality. The inherent problem of this model is that there is a change from electrical to acoustic domain where the superposition takes place whose residue is measured by a sensor and sent back to the electrical domain, i.e., from the cancelling loudspeaker to the error microphone. We must therefore account for the secondary path S(z) which is between the adaptive filter output and error input signal; this embodies the digital-analog converters, reconstruction filter, power amplifier, loudspeaker, acoustic path from loudspeaker to error microphone, preamplifier, anti-aliasing filter, and finally the analog digital converter. The system is now better characterized by Figure 2. Introducing S(z) into a standard LMS control process will lead to unstable behavior due to the fact that the error signal would arrive later at the LMS block than the reference input. The only practical way to compensate for the effects of S(z) would be to have a copy of the secondary path block S(z) at the reference input [3]. The filtering of the reference signal via a copy (or estimate) of the secondary path is the reason this algorithm is called filtered-x (reference) LMS algorithm can be seen in Figure 3.

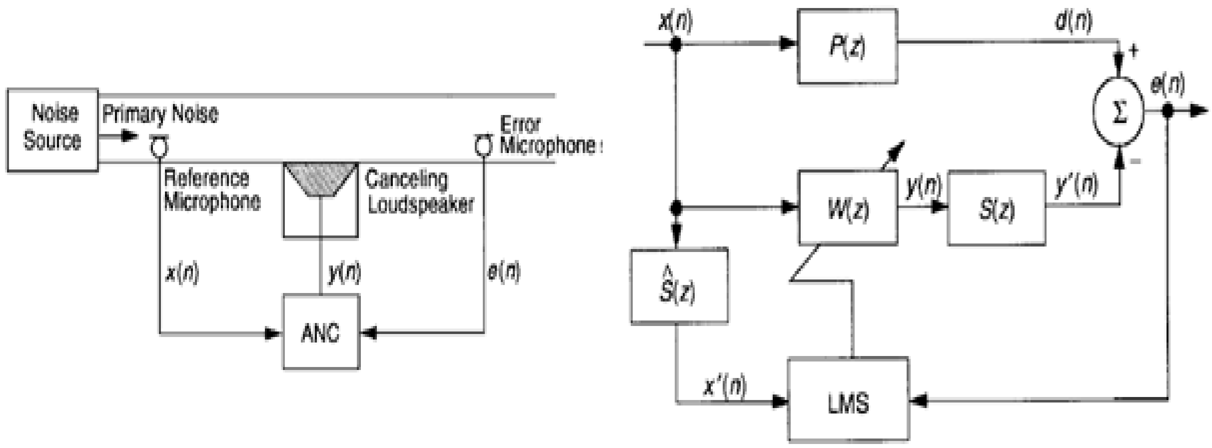

Figure 3: Block diagrams of FxLMS.

Practically, S(z) must be estimated in the first place for it to be filtered by the reference input. $\hat{S}$(z) is the additional filter that is required to do so. Figure 4 shows the offline modelling of S(z), which is sufficient as the FxLMS algorithm is quite tolerant of errors made by $\hat{S}$(z) in the estimation of S(z), it will converge for errors up to 90° in phase error between them as no correlation was found to exist between the stability and phase error in this range [2]. The training is done using bandlimited white noise as the reference within the range of operation of the acoustic device. It is possible to use simpler training reference signal to simplify the number of coefficients.

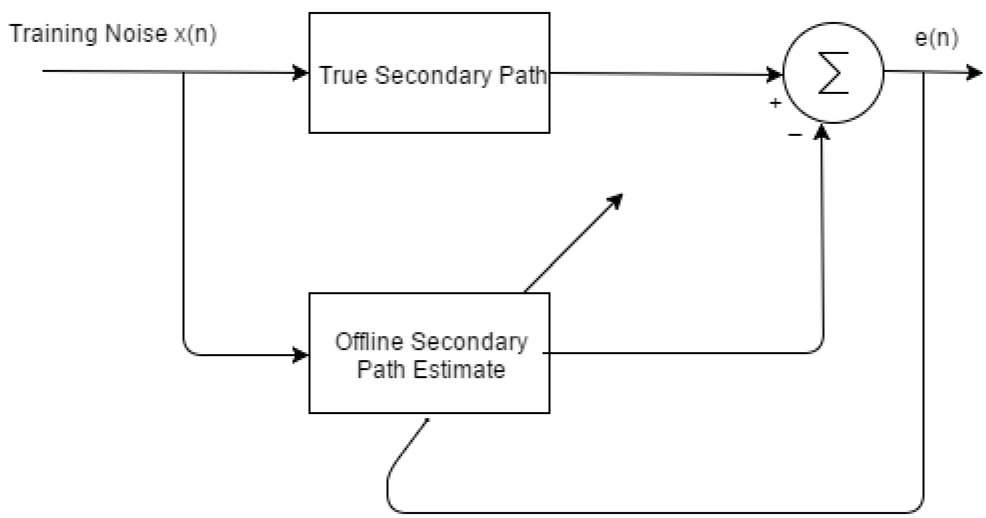

FIGURE 4. Offline secondary path estimation.

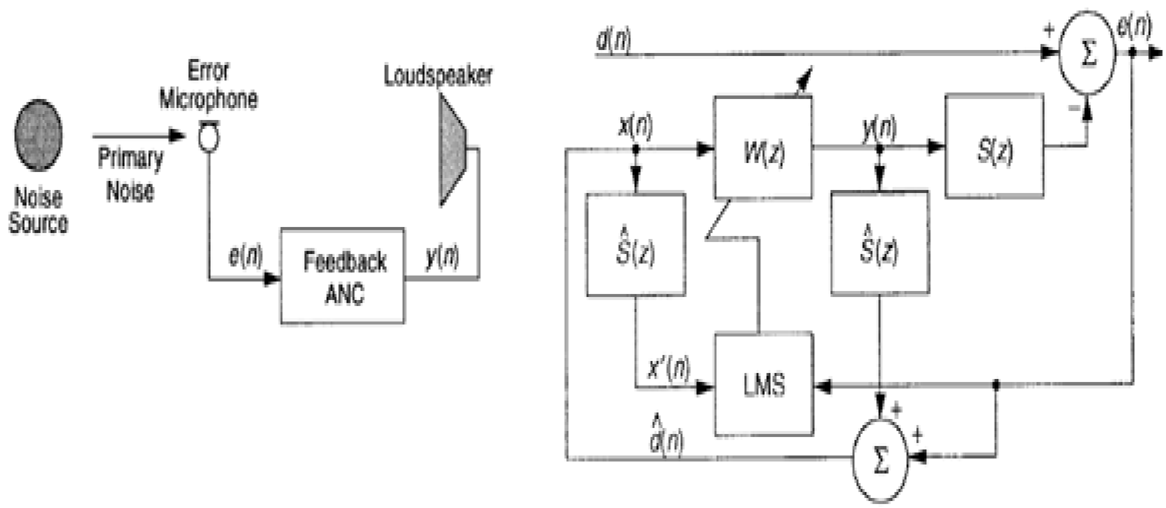

Figure 5: Block diagrams of Feedback ANC

Feedback FxLMS Algorithm

Given Figure 5 is a fixed single-channel feedback noise control system with d(n) as the primary noise which is a resultant of some exogenous noise passed through an acoustic plant; e(n) is the residual error picked up by the microphone. There is no reference sensor. The sensitivity function of the fixed feedback system is given by:

$$S_F(z) = \frac{E(z)}{D(z)} = \frac{1}{1 - W_F(z)S(z)} \tag{1}$$

The choice of W_F(z) will determine the limits of noise control both in terms of magnitude as well as bandwidth if it were not for S(z) which in practical conditions is not ideally flat real life conditions, the phase of the secondary path will shift due to acoustic delay, delay in electronics, or any non-minimum phase characteristics of elements involved, causing phase shifts of the cancelling noise from 180° and beyond. This results in destabilizing positive feedback. A choice between good attenuation and robust stability with dynamic S(z) must be made.

In terms of stability, the feedback equivalent of the FxLMS' 90° condition is that the optimum filter weights depend on the spectral features of the primary noise d(n), and the transfer function of secondary path S(z). [2] This characteristic would cause the system to become unstable when d(n) or S(z) change. To overcome with these changes, an adaptive version of this feedback system can be developed. This model is known as the internal model control based FxLMS algorithm [4][1], where the reference signal is a continuous estimate of the exogenous noise perceived by the sensor. $\hat{d}(n)$ is assumed to be the input to the system as the reference signal and y(n) drives the plant. The feedback controller has the transfer function of

$$H(z) = \frac{Y(z)}{\hat{D}(z)} = \frac{-W_a(z)}{1+\hat{S}(z)W_a(z)} \tag{2}$$

This results in the sensitivity function for the complete feedback control system as:

$$S_a(z) = \frac{E(z)}{D(z)} = \frac{1+\hat{S}(z)W(z)}{1-[S(z)-\hat{S}(z)]W_F(z)} \tag{3}$$

In the event that S(z) is perfectly estimated, there still exists a propagation time delay from secondary source to error sensor resulting in the synthesized reference signal to be a version of the primary noise delayed by the length of $\hat{S}(z)$. Even though W(z) depends on frequency response of the noise and the secondary path, the 90° condition is still considered a close enough sufficient condition for stability of the feedback system.[2] The feedback FxLMS algorithm, in its most fundamental form, is an adaptive predictor trying to estimate d(n).

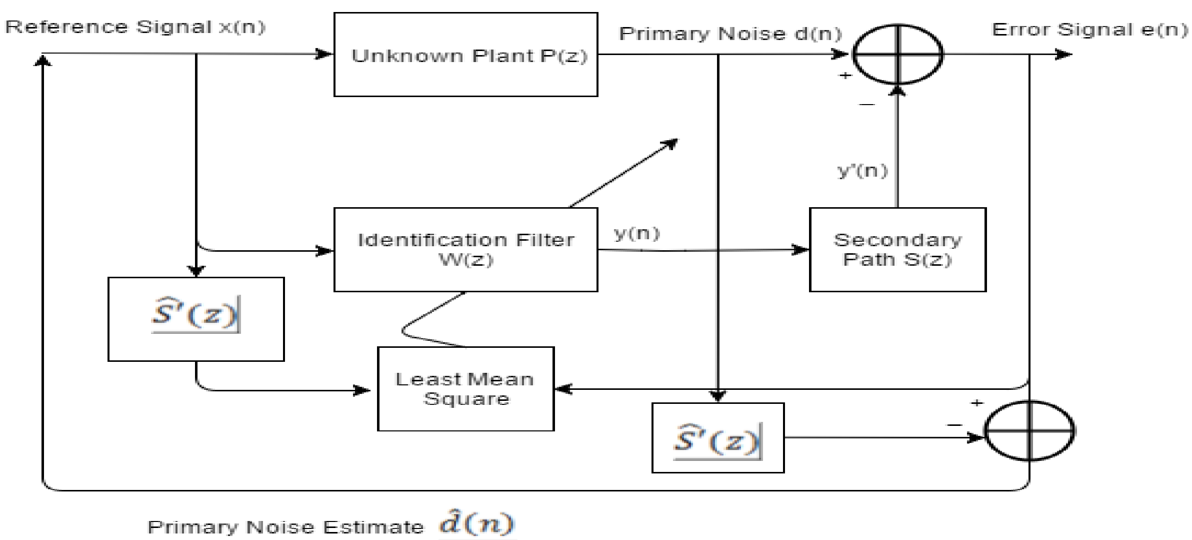

FIGURE 6. Internal model control based feedback FxLMS.

CHAPTER 3
PROBLEM STATEMENT

In a practical environment. The user will experience a combination of deterministic noise such as fans, motors, compressors, as well as non-stationary noises such as crowd noise, traffic etc. These may be a combination of narrowband and broadband noises. Analog feedback systems can be used to attenuate broadband noises and digital feedback systems can be used to treat the remaining non-stationary narrowband components. This results in the best overall performance active noise control. The analog feedback system to be used has to fulfil certain criteria by itself, most of which are age-old and well researched [5][6][7], such as: controller stability with sufficient margin, noise attenuation over prescribed frequency range, waterbed effect, and robust to plant changes.

The stability of the digital feedback ANC system, as explained above, is dependent on the criteria that the S(z) and $\hat{S}$(z) have a maximum phase shift of 90°. The effect of the plant changes can be made minimal by adding one more constraint to the concatenated analog feedback controller [2]. Optimization of the algorithm has to be performed by analyzing the practicality. Its autonomous adoptability to commercially available FxLMS controllers would be considered desirable.

CHAPTER 4

DESIGN

HYBRID ANC STRUCTURE

The block diagram of the hybrid ANC system using the FxLMS algorithm is shown in Fig 8. The transfer function of the equivalent secondary path which includes the analog feedback system is given as:

$$S'(s) = \frac{S(s)}{1+S(s)H(s)} \quad (4)$$

H(s) and S(s) are the transfer functions of the analog controller and secondary path in continuous time domain. The FxLMS algorithm for weight update is given as:

$$w(n+1) = w(n) - \mu e(n)\hat{r}(n) \quad (5)$$

$$x(n) = \hat{d}(n) \quad (6)$$

Where μ is the step size, w(n) is the weight at time n. $\hat{d}(n)$ is the approximation of the primary noise. The error is given as:

$$e(n) = d(n) + w^T(n)r(n) \quad (7)$$

$$r(n) = s'(n) * x(n) \quad (8)$$

$$\hat{r}(n) = \hat{s}'(n) * x(n) \quad (9)$$

$s'(n)$ and $\hat{s}'(n)$ are the impulse responses of $S'(z)$ and $S'(z)$ respectively.

SIMPLIFIED HYBRID ANC STRUCTURE

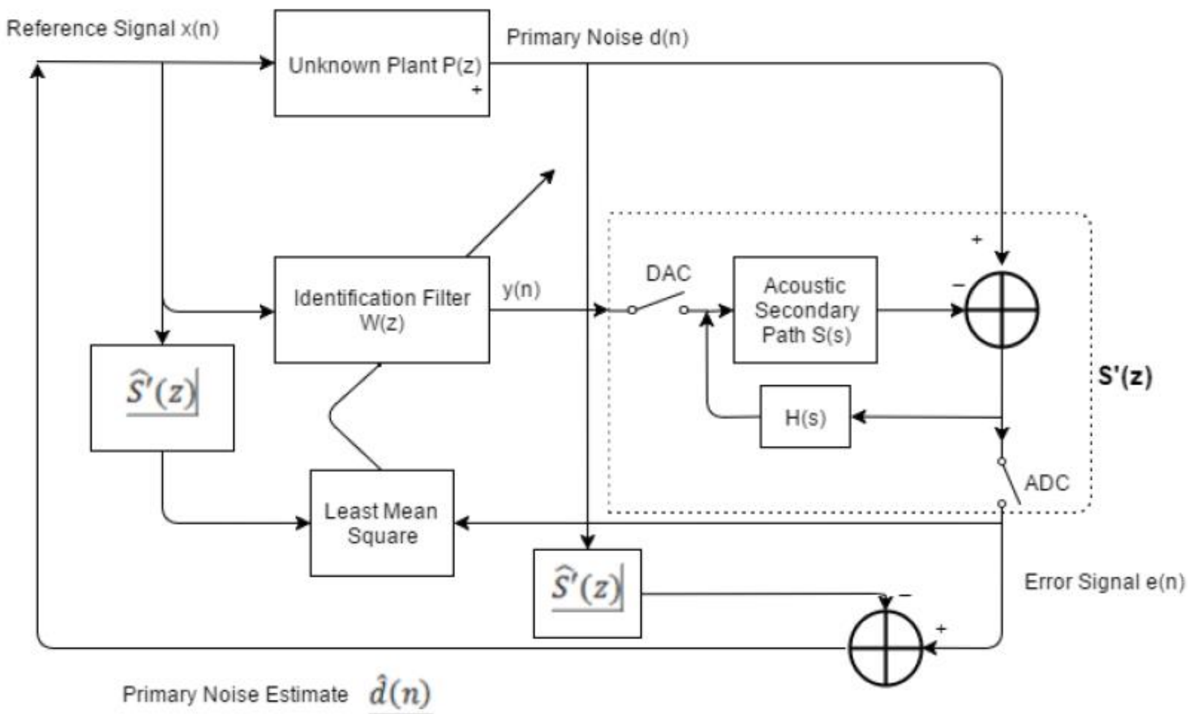

FIGURE 7. Block diagram of hybrid FxLMS algorithm

In Chapter 2, the internal model control based feedback FxLMS algorithm, from what was said, it is known that d(n) may not be completely predictable in real noise conditions and consequently the perfect cancellation of primary noise is usually unpractical and the error signal often contains a residue of the primary noise. The ideal weight of the algorithm is W(z) =1/S(z) for perfect noise control which is impossible for non-minimum phase systems.. Owing to the fact that some difference always exists between the secondary path and its estimate, we can say that complete noise control can never take place.

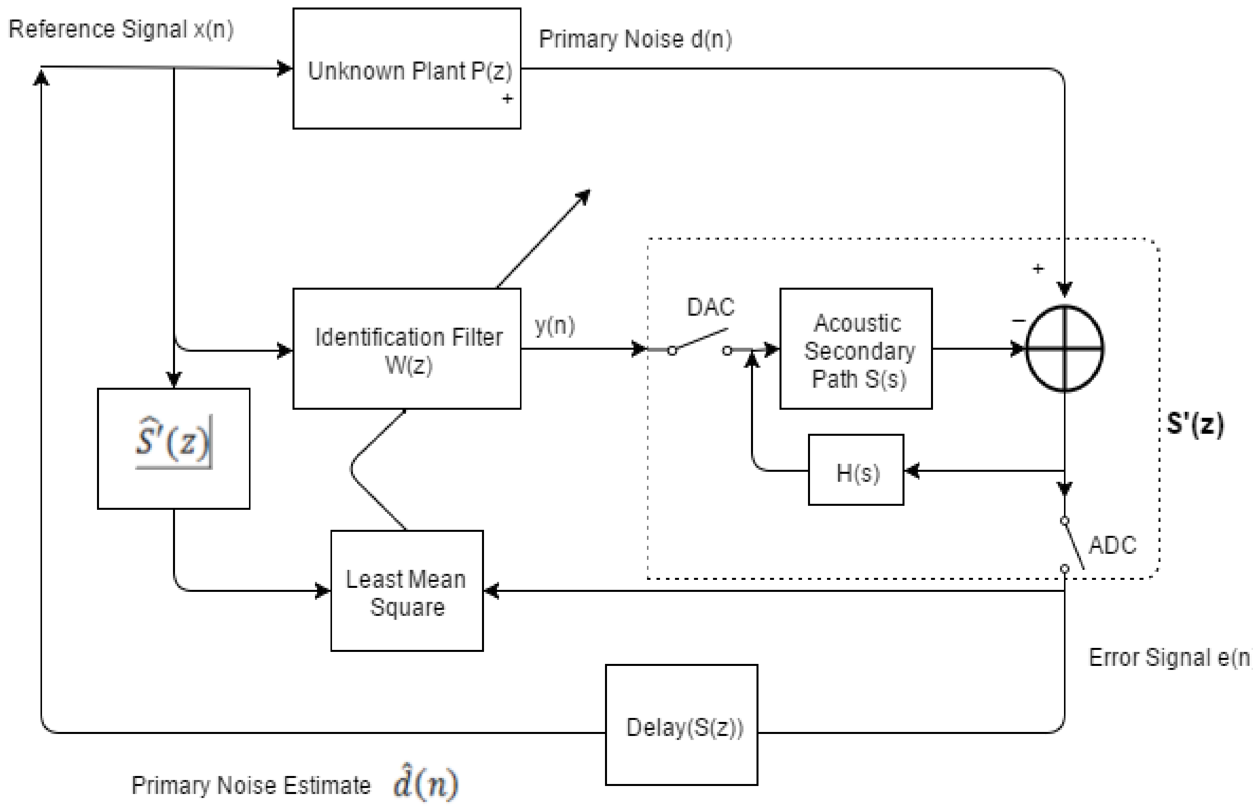

FIGURE 8. Simplified hybrid FxLMS algorithm.

The practical repercussions of this situation actually make way for an opportunity to simplify the ANC system given in Fig 8. to a new simplified hybrid ANC FxLMS system as given in Fig 9.

$$x_{simp}(n) = e(n - \Delta) \qquad (10)$$

$$X_{simp}(z) = D(z) + S'(z)Y(z) \qquad (12)$$

The sensitivity function of this simplified hybrid ANC is comparable to that of a fixed filter feedback system, which is apparent from Figure 8.by cancelation $\hat{S}$ (z Whether we refer to the fixed feedback system or the Internal model control variant, error signal is always going to carry some primary noise spoils [1][4][8]. This results in a sensitivity function given by

$$Simplified\ Sensitivity = \frac{E(z)}{D(z)} = \frac{1}{1 - S(z)W(z)}$$

Preliminary values of filter coefficients, e(n) and d(n) are comparable and hence can be used as the reference input. A feedforward FxLMS model where the reference consists of primary noise and measurement noise components, is seen . whose SNR is given by

$$SNR = \frac{Signal\ Power\ Spectral\ Density}{Noise\ Power\ Spectral\ Density} = \frac{P_{dx}}{P_{nx}}$$

Where P_{nx} is given as $E\ [(y'(n) - \hat{s}'(n) * y(n))\ ]$for the regular hybrid version and $E\ [(y'(n))]$ for the simplified version, implying if the secondary path estimate isn't accurate, which is mostly the case, the quality of the reference signals should be comparable.

CHAPTER 5

SIMULATION AND RESULTS

The entire acoustic environment of the Hybrid ANC is emulated in MATLAB step by step.

The magnitude response of the true secondary path S'(z) (Fig.9) is then modeled after which random noise is passed through it.

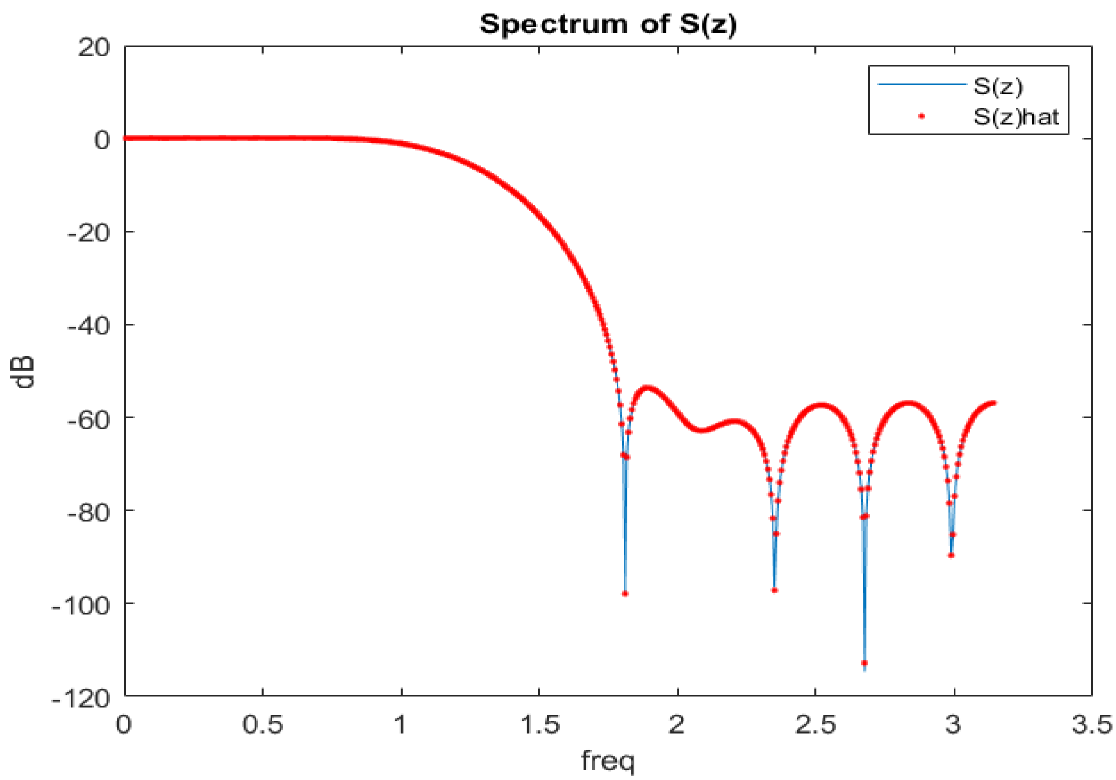

FIGURE 9. Spectrum of Secodary path.

The secondary propagation path estimate is then found through offline estimation using a LMS filter (Fig 10. And Fig. 11), The acoustic environment is now initiated and ready for adaptation using the simplified hybrid ANC algorithm. For offline part the error residue converge really fast and show good results.

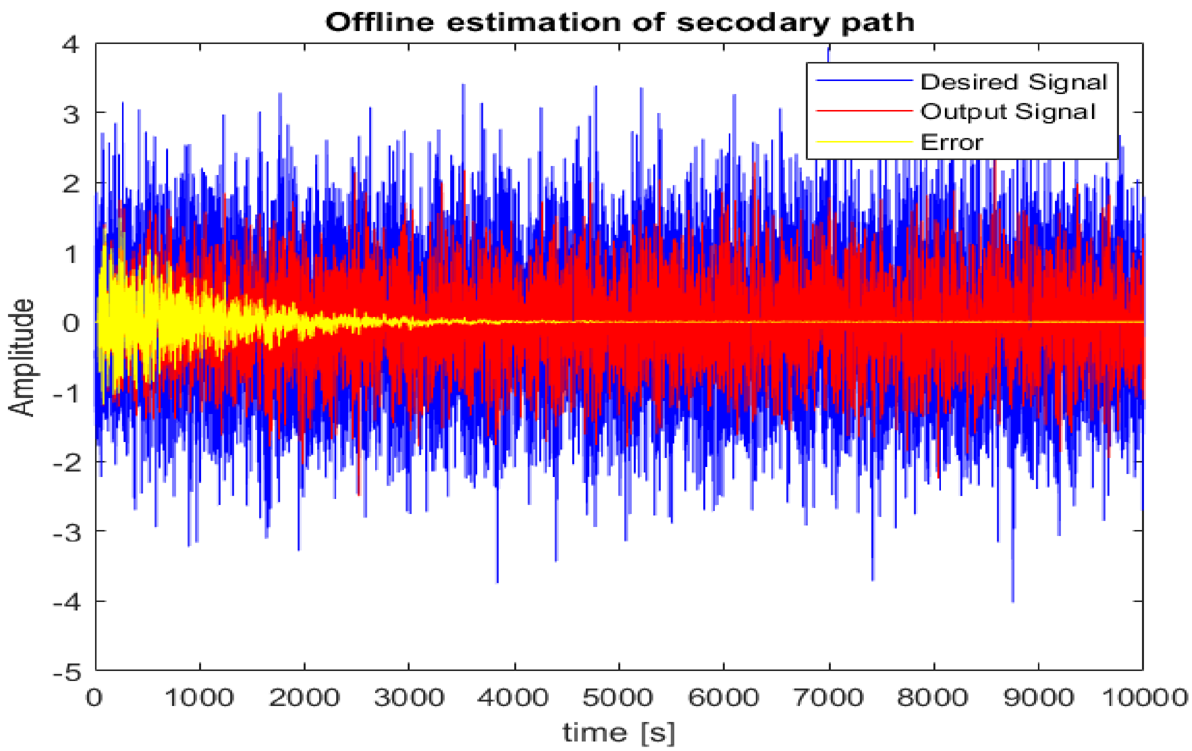

FIGURE 10. Offline estimation of secondary path.

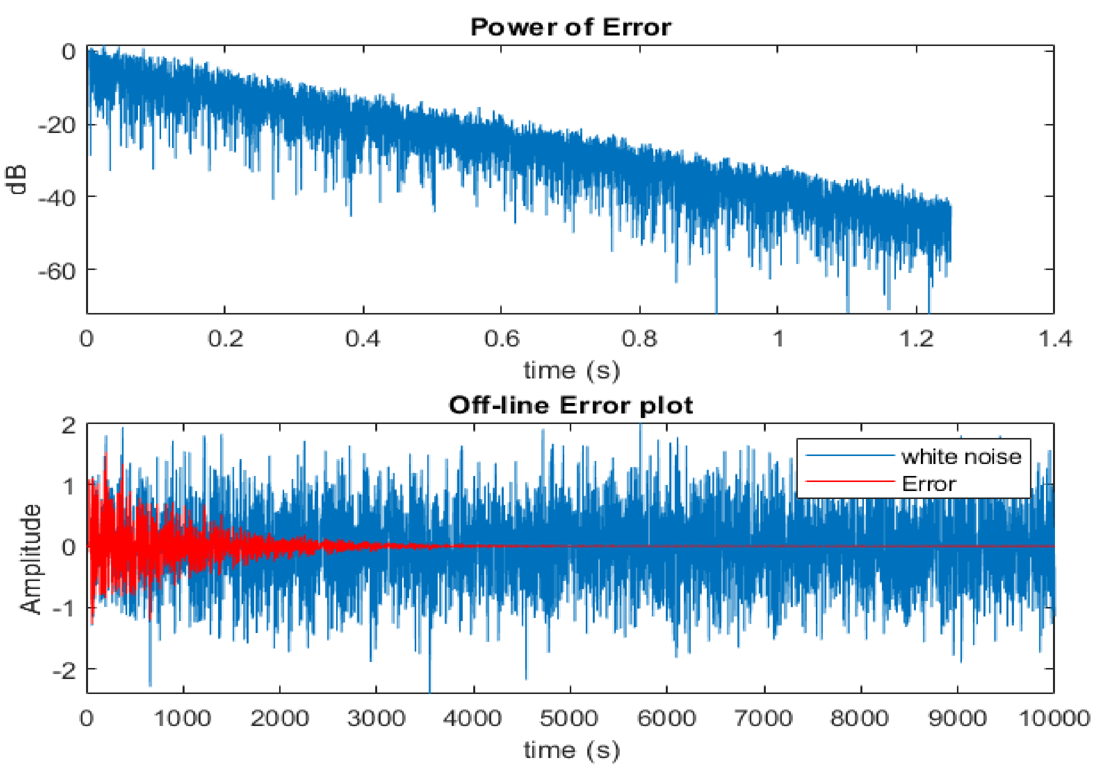

FIGURE 11. Error residue of the Off-line Part

Audio objects are initialized in MATLAB for stream processing and the acoustic environment is then tested with a sine wave generator consisting of both narrow and broadband elements. Real-time adaptation is allowed to take place showing the power spectrum of the attenuated noise along with the original

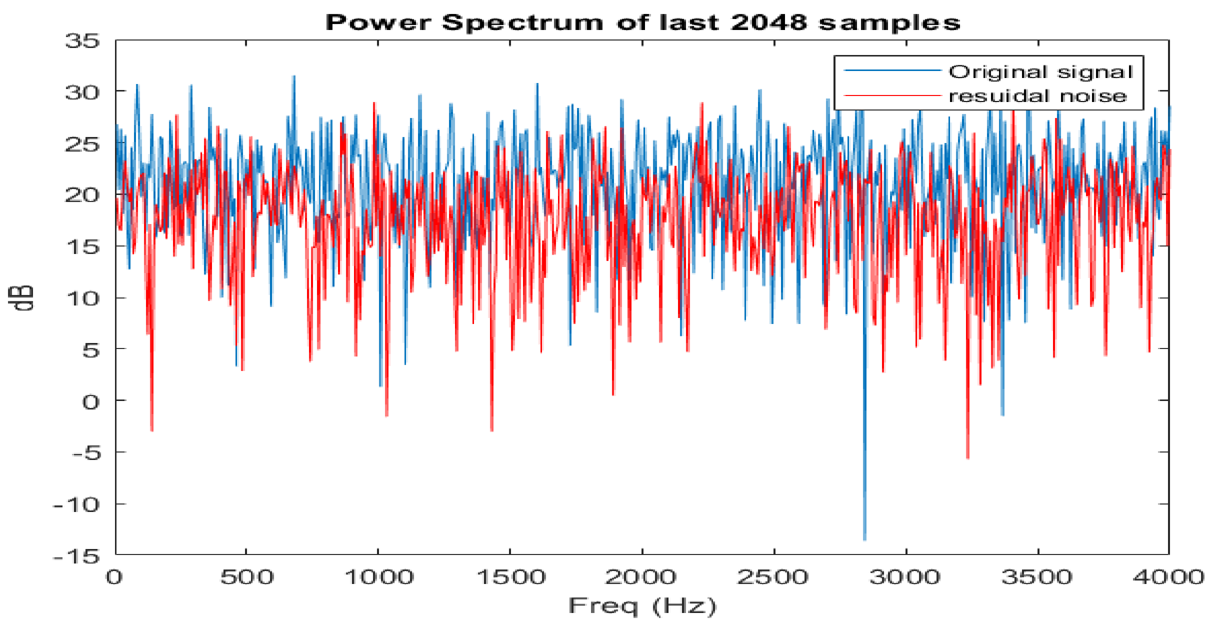

FIGURE 12. Power spectrum of hybrid feedback FxLMS(Narrowband).

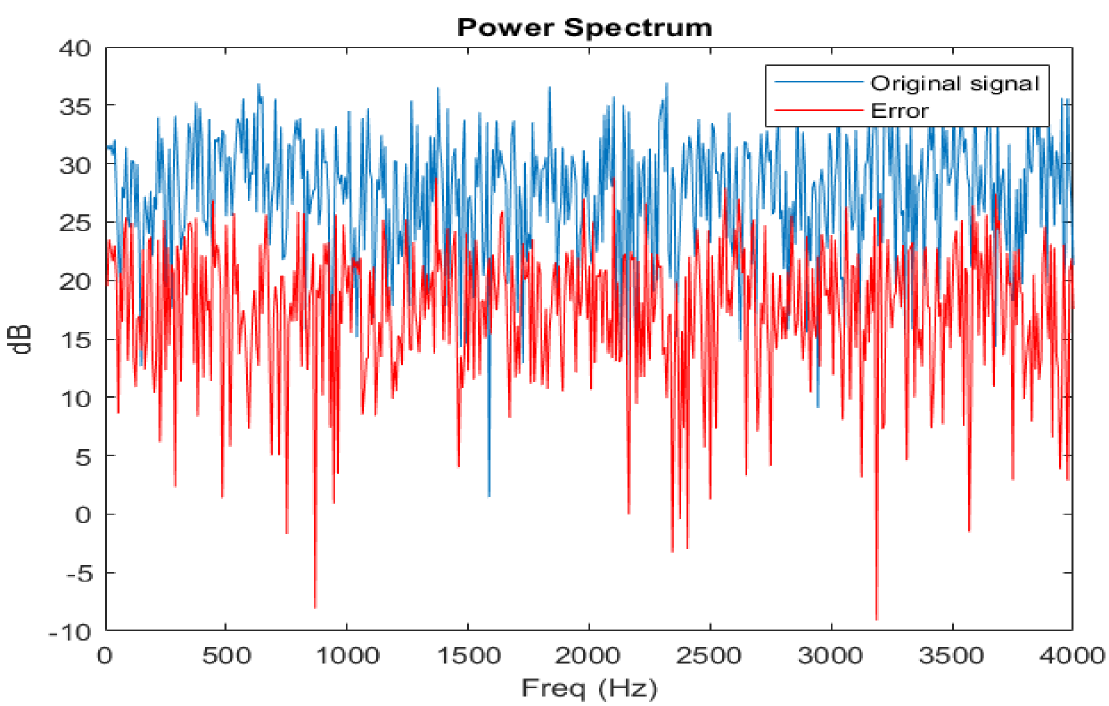

FIGURE 13. Power spectrum of hybrid feedback FxLMS(Narrowband+Broadband).

In Fig.13 and Fig. 14 the feedback FxLMS(Hybrid ANC) did not the show good result in terms of broadband performance ,we get better result with broadband+narrowband noise , due to characteristic of the algorithm.

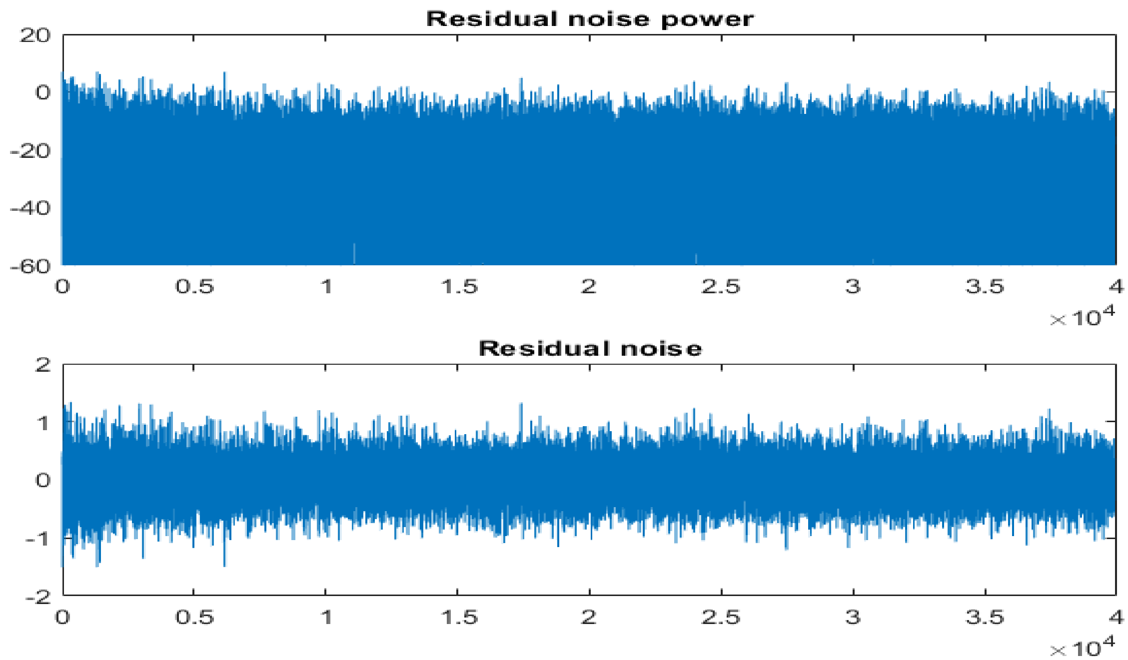

FIGURE 14. Error residue of the ANC system

RESULTS:

The final power spectrums after convergence (Fig 12 and Fig. 13) and error residue over time (Fig. 14) show similar results from the simulation of the hybrid feedback FxLMS algorithms. The digital feedback FxLMS did the poorest in terms of broadband performance, state attenuation as well as convergence speed, as is characteristic of the algorithm. The hybrid variants performed the best in terms of achieving minimum convergence at the fastest rate while covering the largest frequency band. The simplified hybrid feedback FxLMS converged to a better point than the digital variant as well as offered both broadband and narrowband attenuation, but did not perform as well as the more complex hybrid algorithm.

Absolute values of stead state error, convergence rate and power spectral density are not taken into consideration as the motivation behind the simulations were to validate the relative performance of the simplified hybrid feedback FxLMS algorithm with that of the regular hybrid variant, which has more computational load as well as lesser adoptability to commercial FxLMS systems.

CHAPTER 6

CONCLUSION

A simplified hybrid feedback FxLMS algorithm for commercial open-back headsets was proposed along with its design constraints. They were chosen in order to completely satisfy all of the four properties for an active noise control system to be considered industry-grade as specified by Kuo & Morgan [3] ; A) The maximum efficiency over largest frequency band is satisfied by making the system both broadband as well as narrowband; B) The autonomy of setting up and installation which is satisfied as simplified hybrid structure has the same form as that of a traditional and popular feedforward FxLMS structure and thus can be easily adoptable in commercial chipsets; C) The adaptability to variations in acoustic domain is satisfied by considering constraint (C5) in the design of the analog controller, the open back headsets can be more robust to plant changes in the acoustic domain; D) The robustness and reliability of all elements is ensured by utilizing constraints (C1) through (C4) in the design of the analog filter, treating it as a lone fixed filter optimizing using frequency dependent data of the headset. Simulations of an acoustic environment running variations of the feedback FxLMS algorithm show that although the simplified hybrid structure doesn't converge faster or into a steady state better than a regular hybrid variant, the trade-off for lower computational load and better adoptability is found to be justified.

APPENDIX

MATLAB CODE: SIMPLIFIED HYBRID FxLMS

```
%%
%Hybrid Active Noise Control
close all, clear all, clc

simulation = input('Input 0 for broadband noise only, 1 for
broadband and narrowband noise: ');
play = 0; % play error signal after noise cancellation
verbose_identification = 0; % show residual error and S_hat(z)
estimation accuracy

%% Parameters
N = 100000; % number of iterations
M_p = 41; % P(z) order
M = 21; % S(z) order
M_hat = 31; % S_hat(z) order
L = 51; % H(z) order (adaptive control filter)
frequencies = [0.03*pi; 0.06*pi; 0.09*pi]; % sinusoidal noise
component
a_r = [2.0; 1.0; 0.5]; % DFCs
b_r = [-1.0; -0.5; 0.1]; % DFCs
sigma_p = 0.1; % variance of uncorrelated noise affecting e(n)
sigma_w = 1.0; % variance of reference broadband noise component
mu_h = 0.0007; % stepsize of FxLMS
% fast convergence and low-order adaptive filter
% L = 21; mu_h = 0.0018; %(0.1/L = 0.048)
%  noise when broadband only
% mu_h = 0.01999;
%  noise when mixed
%mu_h = 0.0027;


%% Filters
P = [fir1(M_p-1, 0.4)]'; % primary path P(z)
S = [fir1(M-1, 0.4)]'; % secondary path S(z)
S_hat = zeros(M_hat,1); % secondary path estimation S^(z)
h = zeros(L,1); % adaptive control filter H(z)


%% Signals
p_0 = zeros(N,1); % primary noise
e_0 = zeros(N,1);
e_0_prime = zeros(N,1);
```

```
e = zeros(N,1);
y = zeros(N,1);
x_r_hat = zeros(N,1);
v_p = randn(N,1)*sqrt(sigma_p); % uncorrelated noise acting on
the error microphone

% compute reference noise x_r(n)
x_r = randn(N,1)*sqrt(sigma_w); % broadband component
if simulation == 1
    q = length(frequencies); % number of frequencies
    time = 1:N;
    for ii = 1:q
        x_a_i = [cos(frequencies(ii)*time)]';
        x_b_i = [sin(frequencies(ii)*time)]';
        x_r = x_r + a_r(ii)*x_a_i + b_r(ii)*x_b_i;
    end
    x_r = x_r/std(x_r);
    % normalise so that the signal power in both simulation is 1
    % bandpower(x_r) == 1 in both cases
    % sqrt(var(x)?y(n)^2/var(y)), which simplifies to
std(x)/std(y)
end

%% Identification of S_hat(z)
mu_s = 0.001;
omega = 1; % variance of excitation signal
N_s = 10000;
x_s = randn(N_s,1)*omega; % input noise for identification
d_s = zeros(N_s,1);
y_s = zeros(N_s,1);
e_s = zeros(N_s,1);

for n = M_hat+1:N_s
    % compute d_s(n)
    X_s = x_s(n:-1:n-M+1);
    d_s(n) = S'*X_s;
    % compute y_s(n)
    X_s = x_s(n:-1:n-M_hat+1);
    y_s(n) = S_hat'*X_s;
    % compute e(n) and update weights
    e_s(n) = d_s(n) - y_s(n);
    S_hat = S_hat + mu_s*e_s(n)*X_s;
end

Fs=8000;

figure
```

```
subplot(211);
plot(1/Fs:1/Fs:length(e_s)/Fs,10*log10(e_s));
xlabel('time (s)');
ylabel('dB');
title('Power of Error');

subplot(212);
plot(d_s);
hold on;
plot(e_s,'r');
title('Off-line Error plot');
xlabel('time (s)');
ylabel('Amplitude');
legend('white noise','Error');

[Hs ws]=freqz(S,1);
[Hes wes]=freqz(S_hat,1);
figure
plot(pi/512:pi/512:pi,20*log10(abs(Hs)));
hold on
plot(pi/512:pi/512:pi,20*log10(abs(Hes)),'r.');
xlabel('freq');
ylabel('dB');
title('Spectrum of S(z)');
legend('S(z)','S(z)hat')
 figure
 plot(x_s);
 hold on
plot(d_s)
hold on
plot(e_s)
lines =findall(gcf,'type','line');
set(lines(1),'color','yellow');
  set(lines(2),'color','red');
  set(lines(3),'color','blue');
  title('Offline estimation of secodary path');
xlabel('time [s]');
ylabel('Amplitude');
legend('Desired Signal','Output Signal','Error')
%% Algorithm (conventional broadband ANC)
first_sample = max([M_p, M, L, M_hat]);
for n = first_sample:N
    % compute primary noise p_0(n)
    X_r = x_r(n:-1:n-M_p+1);
    p_0(n) = P'*X_r;

    % compute y(n)
```

```
    X_r = x_r(n:-1:n-L+1);
    y(n) = h'*X_r;

    e_0(n) = p_0(n) - y(n);

    % compute e_0_prime(n)
    E_0 = e_0(n:-1:n-M+1);
    e_0_prime(n) = S'*E_0;

    e(n) = e_0_prime(n) + v_p(n); % add (uncorrelated)
measurement noise

    % compute reference signal
    X_r = x_r(n:-1:n-M_hat+1);
    x_r_hat(n) = S_hat'*X_r;

    % update filter
    X_r_hat = x_r_hat(n:-1:n-L+1);
    h = h + mu_h*e(n)*X_r_hat;

    if e(n) > 5 % diverging
       disp(['out at ', num2str(n)]), return
    end
end

figure

plot(1/Fs:1/Fs:N/Fs,10*log10(e))
title('Learning curve of e(n)');
xlabel('time (s)');
ylabel('dB');



%{d
figure
res_pow = e(first_sample:end).^2;
res_pow(res_pow < sigma_p/100) = sigma_p/100;
subplot(211), plot(20*log10(res_pow))
xlabel('time'), ylabel('dB'), title('Residual noise power')
subplot(212), plot(e(first_sample:end))
xlabel('time'), ylabel('linear'), title('Residual noise')
%}

 figure
 Spec_e2=fft(e(end-4096:end),1024);
Spec_d2=fft(x_r(end-4096:end),1024);
```

```
 Fs=8000;
plot(Fs/1024:Fs/1024:length(Spec_d2)/2*Fs/1024,20*log10(abs(Spec
_d2(1:512))));
hold on
plot(Fs/1024:Fs/1024:length(Spec_e2)/2*Fs/1024,20*log10(abs(Spec
_e2(1:512))),'r');
title('Power Spectrum ')
xlabel('Freq (Hz)');
ylabel('dB');
legend('Original signal','Error');

figure
[~,F,T,P] = spectrogram(e);
imagesc(T,F,10*log(abs(P))), colorbar
```

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