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A Hypothetical Approach of Eliminating Active Noise from A System

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Abstract

In many application of noise cancellation, the changes in signal characteristics could be quite fast. This requires the utilization of adaptive algorithms, which converge rapidly. Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) adaptive filters have been used in a wide range of signal processing application because of its simplicity in computation and implementation. The Recursive Least Squares (RLS) algorithm has established itself as the "ultimate" adaptive filtering algorithm in the sense that it is the adaptive filter exhibiting the best convergence behaviour. Unfortunately, practical implementations of the algorithm are often associated with high computational complexity and/or poor numerical properties. Recently adaptive filtering was presented, have a nice trade off between complexity and the convergence speed.

1. Introduction

Any unwanted signal that interferes with the communication or measurement of an information carrying signal is termed as noise. Noise is present in various form or percentage in almost all environments. For example, in a digital cellular mobile telephone system, there may be several varieties of noise that could degrade the quality of communication, such as acoustic background noise, electromagnetic radio-frequency noise, co-channel radio interference, radio-channel distortion, outage and signal processing noise. Noise can cause various transmission errors and may even disrupt a communication process and hence noise processing is an important and integral part of modern signal processing systems.

2. Basic structure of active noise control systems:

Modern active sound control systems consist of a control source used to introduce a controlling signal into the acoustic system. This disturbance reduces the unwanted noise originating from the primary sources by adding to it a signal of same magnitude but opposite in phase. The control signals that drive the control actuators are generated by an electronic controller, which uses as inputs, the feedback error from the error microphone. Active noise control systems are mostly used in the low frequency range, usually below 500-600 Hz. At higher frequencies, passive control measures generally become more cost effective.

a. Two major types of active noise control system will be considered here

- *Adaptive filtering* - the coefficients are updated adaptively to reduce the error output, and
- *Waveform synthesis*- a type of feed-forward control that is suited only to periodic noise.

b. Adaptive Control

An adaptive controller is a controller that can change its nature in response to changes in the process and the disturbances occurring dynamically. An adaptive controller is a controller with adjustable parameter and a mechanism for adjusting the parameters. The adaptive control mechanism includes a digital filter with dynamically changing coefficients as per the requirement and with the changes in the environment.

c. Adaptive Filter

The term 'adaptive' signifies that that the filter weights are not fixed, rather these are adjustable according to the variation in external environment. The weights are randomly initialized and according to an adaptive algorithm the controller updates its weights so as to minimize the residual noise at the listener side. The significances of an adaptive filter can be summarized as Filter parameters such as bandwidth and resonant frequency change with time. The coefficients vary with time and are adjusted automatically by an adaptive algorithm.

d. Coefficient Adaptation

- The purpose of determining the coefficients of the filter model is to maximize the statistical correlation between the reference signal and the coefficients.
- This in turn is done by minimizing the correlation between the error signal and the filter state as is relevant to the coefficients.

- When the adaptive filter is working, the error signal decreases in magnitude, and this slows down the movement of the coefficients. The filter is observed to be converging to a solution.

3. FIR ADAPTIVE FILTER

The controller filter may take a number of forms, the most common of which is the Finite Impulse Response (FIR) filter. An FIR filter may be represented as shown in the Figure below. Here, z-1 represents a delay of one (input) sample and wi represents filter weight i. FIR filters are ideally suited to tonal noise problems, i.e. noise with harmonics, where the reference signal is a few sinusoids and where the control signal does not in any way corrupt the reference signal.

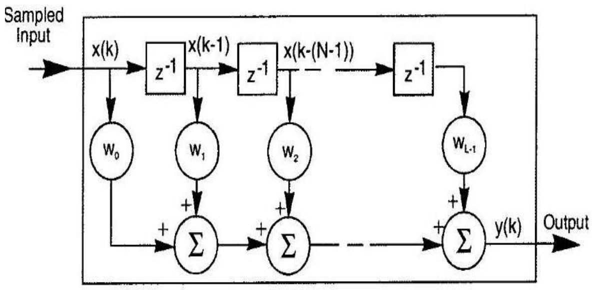


Figure 1. FIR Model

When there are resonances in the system or if there is some noise feedback from the control source to the reference sensor, resulting in the corruption of the reference signal, the FIR filter is not the best choice and then the Infinite Impulse Response (IIR) filter is often chosen for its ability to directly model the poles in the system resulting from such effects. The main advantage of the IIR filter is that it uses fewer weight coefficients than required by an FIR filter for a complex system, thus reducing computational load. But this advantage comes at the cost of instability, slower convergence and also the possibility of convergence to a local minimum in the error surface increases instead of a global minimum.

The three parameters that affect the performance of a digital filter in an active noise cancelling system are: the type of filter, the filter weight values and the number of weights. The adaptation algorithm of the controller is responsible for tuning the adaptive filter so that the resulting control signal minimises the error signal received by the controller. We shall read about various algorithms depending upon if the noise in the environment is linearly varying or non-linearly varying.

Least Mean Square Algorithm (LMS)

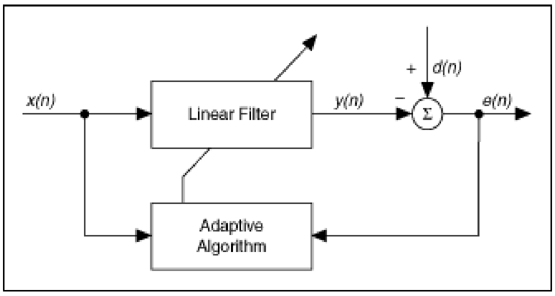


Figure 2. Architecture of a system with LMS algorithm implementation

Where, x(n) : input signal to the linear filter
y(n) : corresponding output signal
d(n) : noise entering the path
e(n) : error signal that denotes the difference between d(n) & y(n).

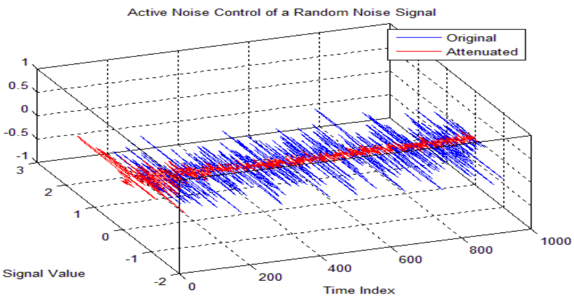
The LMS algorithm performs the underneath operations to update the coefficients of an adaptive FIR filter:
"h" calculate the output signal y(n) from the FIR filter, is filter input vector
Calculates the error signal e(n) by using :
e(n) = d(n)–y(n)……………………………………. (1)
Updates the filter coefficients by using the update equation:
w(n+1) = w(n) + μ*u(n)e*(n)……………………… (2)
where μ is the step size of the adaptive filter
w(n) : filter coefficients vector
μ(n) : filter input vector.
μ in other words is the convergence factor of the filter i.e. if μ is chosen to be very small the rate of convergence reduces. While a larger value μ will lead to faster convergence but will reduce the stability of the system around the minimum value.

The LMS algorithm is the most widely used adaptive algorithm because of its simplicity and its reasonable performance. It has a stable and robust performance in various noise environments but it may not have equally fast convergence speed compared to other complicated adaptive algorithms. There are several upgraded versions of the LMS algorithm that deal with the shortcomings of its basic form

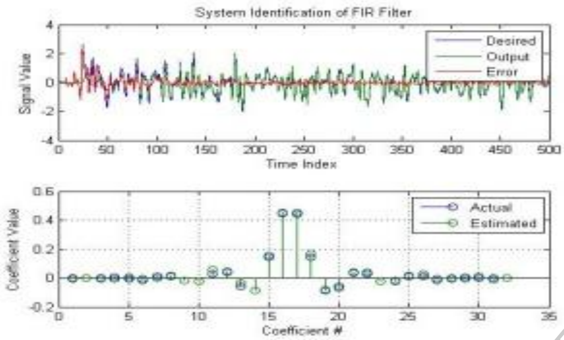
4. Types of LMS Algorithm and Result in Quick View

The different types of LMS algorithm proposed earlier by Researchers have been accumulated here. Only their graphical representations are included here to cut it short and make it brief [1-10].

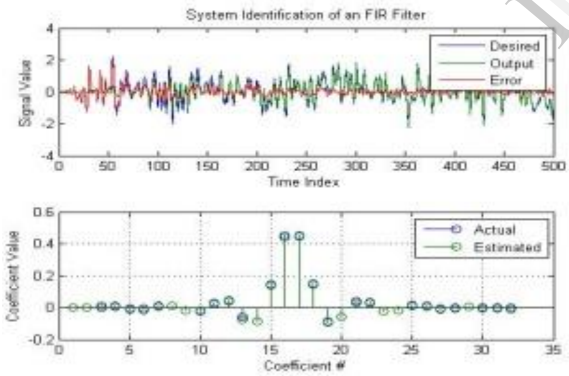
a. *Adjoint Type LMS Algorithm*



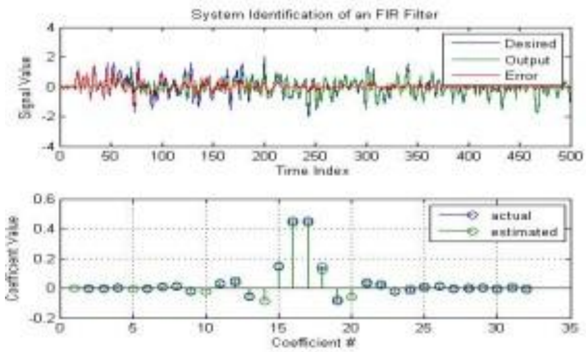
b. *FIR Adaptive Filter that uses NLMS*



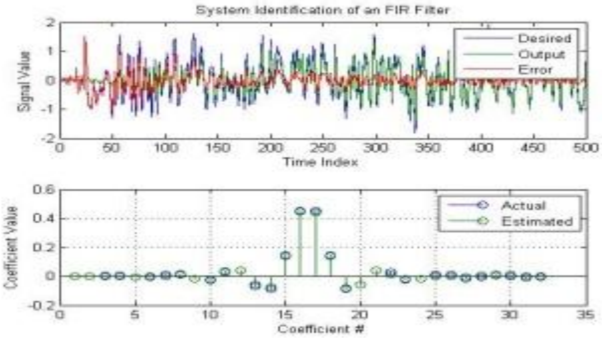
c. *FIR Filter that uses BLMS*



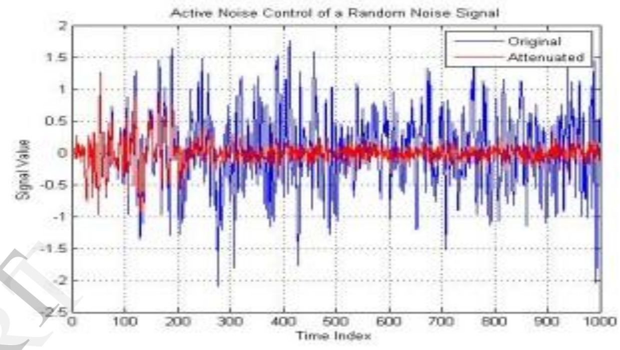
d. FIR Filter that uses FFT based BLMS



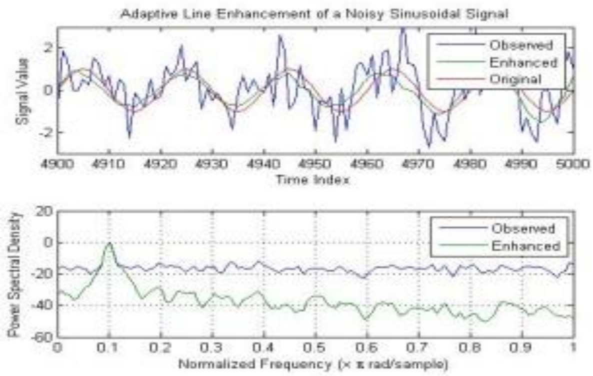
e. *FIR Filter that uses a delayed LMS*



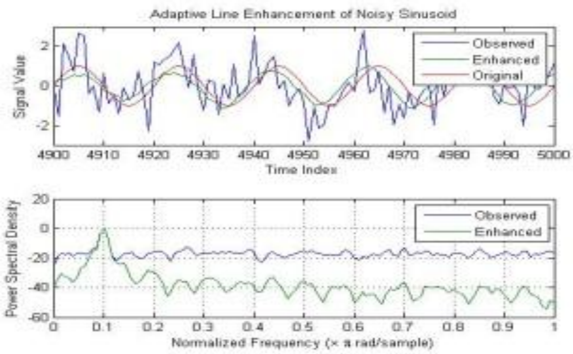
f. *FIR Adaptive Filter that uses a X-LMS Algorithm*



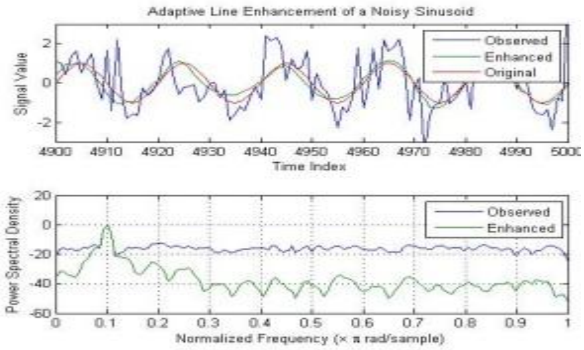
g. *FIR Filter that uses a Signed Data Algorithm*



h. *FIR Adaptive Filter that uses a Signed Error Algorithm*



i. FIR Filter that uses a Sign-Sign Algorithm



Based on simple LMS algorithm a simple block diagram of Automatic Noise Control (ANC) system is depicted in the Figure below.

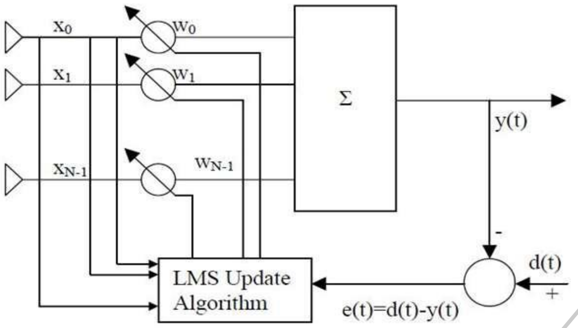


Figure 3. Block Diagram of ANC system using LMS Algorithm

5. Filtered X-LMS Algorithm

The filtered–X LMS algorithm is one of the most popular adaptive control algorithm used in active noise control systems. There are several reasons for this algorithm's popularity. It is well-suited to both broadband and narrowband control tasks, with a structure that can be adjusted according to the problem at hand. Most importantly it behaves robustly when there are physical modelling errors and numerical effects caused by finite-precision calculations. This algorithm is relatively simple to set up and tune in a real-world environment.

It is called the "filtered-x" algorithm because it requires a filtered version of the reference signal as input, with the filter having the same impulse response as the cancellation path i.e. it include the effects of the acoustic cancellation path. During implementation of LMS algorithm in the ANC system the secondary path (from the loudspeaker to the error microphone) needs to be identified so that during updating weights the reference signal must be filtered through the secondary path in order to nullify the effect. The complexity of the system increases as it needs to identify the secondary path.

The block diagram of an ANC system using the F-XLMS algorithm is illustrated in the Figure-4, where P(z) is the transfer function of the primary path from the noise source to the error microphones, S(z) is the transfer function of secondary path and is its estimate. The adaptive filter W(z) generates the anti-noise, y(n) which cancels the primary noised(n) present in the primary path. The secondary loudspeakers generate the anti-noise and e(n) is the residual noise picked up by the error microphone.

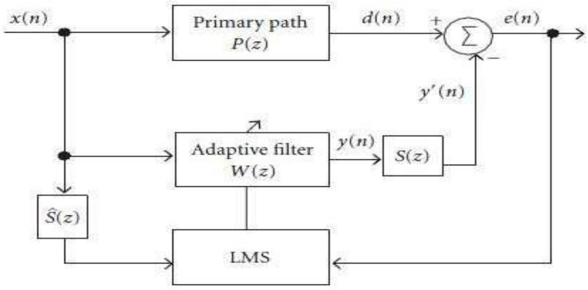


Figure 4. Block Diagram of ANC system with the FXLMS algorithm

In the figure, S(z) which is the secondary path between e(n) and y(n), includes the secondary loudspeakers, error microphones, and acoustic path between the loudspeakers and the error microphones. The estimate compensates for the secondary-path effects. The output of the adaptive filter can be represented as

$y(n) = (n)x(n)$………………………………………..(3)

where $w(n) = [w0(n)\ w1(n) \bullet\bullet\bullet\ wL-1(n)]T$ is the coefficient vector of the adaptive filter W(z) and

$x(n) = [x(n)\ x(n-1) \bullet\bullet\bullet\ x(n-L+1)]T$……………(4)

is the L×1 reference signal vector.

The signal y(n) is filtered through the secondary path S(z) and is subtracted from the primary noise d(n) to generate the residual error e(n). The equations for simulation are given by

$d(n) = p(n)*x(n)$……………………………………..(5)

$y'(n) = s(n)*y(n)$……………………………………(6)

$e(n) = d(n) - y'(n) = d(n) - s(n)*[\ (n)x(n)]$…………(7)

where * represents the convolution operator,

p(n) is the primary path response

s(n) is the secondary path response

All operations are carried out by the system internally and the signals picked up in real-time ANC are the reference signal x(n) and the residual error e(n).

The weight update equation for the adaptive filter is

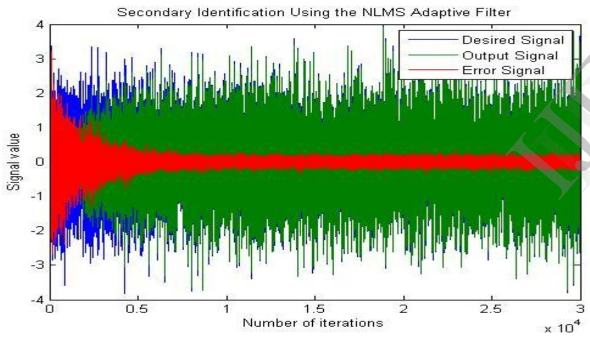
$w(n+1) = w(n) + ìe(n)x'(n)$………………………...(8)

ì: step size

This is the standard FXLMS algorithm, used with an adaptive FIR filter. The algorithm effectively calculates the "slope" of the error surface and hence calculates weights that will cause the error to move down the slope to a smaller value. When the slope is reduced to zero, the algorithm will stop converging.

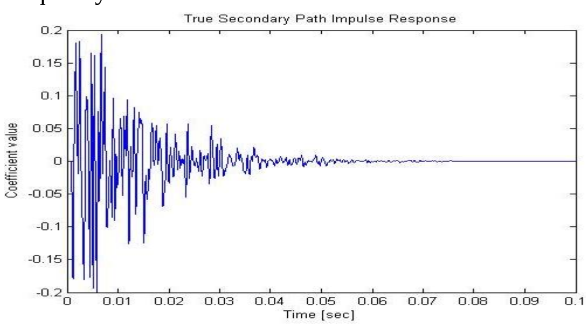
a. Active Noise Control Using a Filtered X-LMS Algorithm

One attempts to reduce the volume of an unwanted noise propagating through the air using an electro-acoustic system using measurement sensors such as microphones and output actuators such as loudspeakers. The noise signal usually comes from some device, such as a rotating machine, so that it is possible to measure the noise near its source. The goal of the active noise control system is to produce an "anti-noise" that attenuates the unwanted noise in a desired quiet region using an adaptive filter. This problem differs from traditional adaptive noise cancellation in that: - The desired response signal cannot be directly measured; only the attenuated signal is available. –The active noise control system must take into account the secondary loudspeaker-to-microphone error path in its adaptation.



b. The Secondary Propagation Path

The secondary propagation path is the path the anti-noise takes from the output loudspeaker to the error microphone within the quiet zone. The following commands generate a loudspeaker-to-error microphone impulse response that is band limited to the range 160 - 2000 hz and with a filter length of 0.1 seconds. For this active noise control task, we shall use a sampling frequency of 8000 hz.

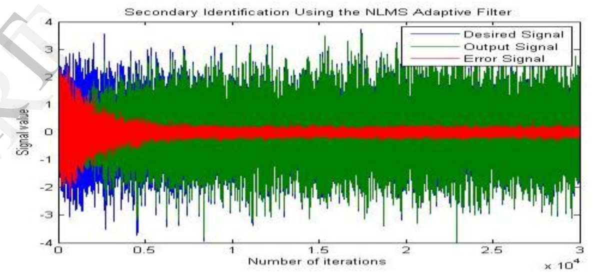


c. Estimating the Secondary Propagation Path

The first task in active noise control is to estimate the impulse response of the secondary propagation path. This step is usually performed prior to noise control using a synthetic random signal played through the output loudspeaker while the unwanted noise is not present. The following commands generate 3.75 seconds of this random noise as well as the measured signal at the error microphone.

d. Designing the Secondary Propagation Path Estimate

Typically, the length of the secondary path filter estimate is not as long as the actual secondary path and need not be for adequate control in most cases. We shall use a secondary path filter length of 250 taps, corresponding to an impulse response length of 31 msec. While any adaptive FIR filtering algorithm could be used for this purpose, the normalized LMS algorithm is often used due to its simplicity and robustness. Plots of the output and error signals show that the algorithm converges after about 10000 iterations.

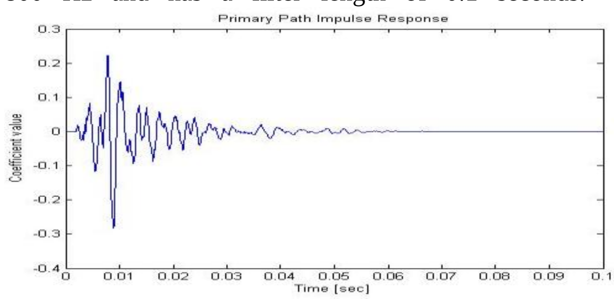


e. Accuracy of the Secondary Path Estimate

How accurate is the secondary path impulse response estimate? This plot shows the coefficients of both the true and estimated path. Only the tail of the true impulse response is not estimated accurately. This residual error does not significantly harm the performance of the active noise control system during its operation in the chosen task.

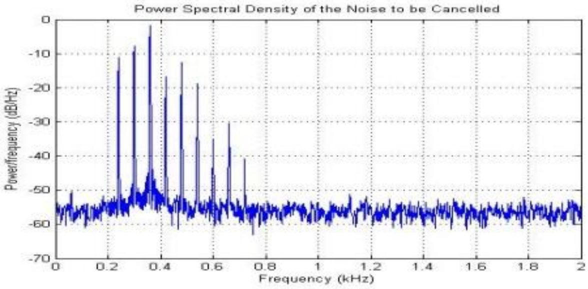
f. The Primary Propagation Path

The propagation path of the noise to be cancelled can also be characterized by a linear filter. The following commands generate an input-to-error microphone impulse response that is band limited to the range 200 - 800 Hz and has a filter length of 0.1 seconds.



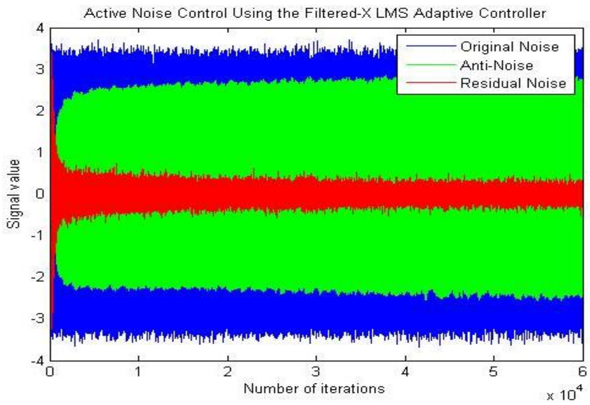
g. The Noise to be cancelled

Typical active noise control applications involve the sounds of rotating machinery due to their annoying characteristics. Here, we have synthetically generated 7.5 seconds of a noise that might come from a typical electric motor. Listening to its sound at the error microphone before cancellation, it has the characteristic industrial "whine" of such motors. The spectrum of the sound is also plotted.



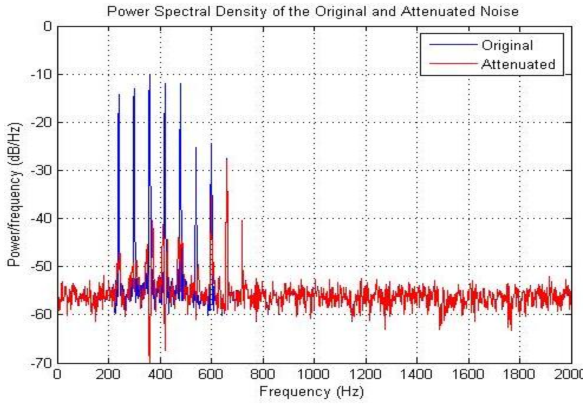
h. Active Noise Control using the filtered-X LMS Algorithm

The most popular adaptive algorithm for active noise control is the filtered-X LMS algorithm. This algorithm uses the secondary path estimate to calculate an output signal whose contribution at the error sensor destructively interferes with the undesired noise. The reference signal is a noisy version of the undesired sound measured near its source. We shall use a controller filter length of about 44 msec and a step size of 0.0001 for these signal statistics. The resulting algorithm converges after about 5 seconds of adaptation. Listening to the error signal, the annoying "whine" is reduced considerably.



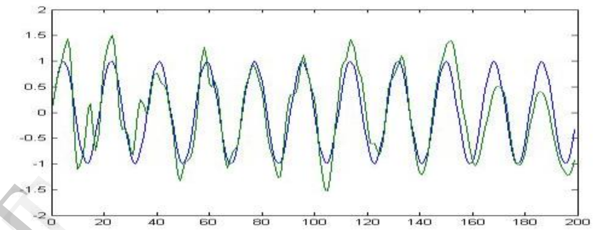
i. Residual Error Signal Spectrum

Comparing the spectrum of the residual error signal with that of the original noise signal, we see that most of the periodic components have been attenuated considerably. The steady-state cancellation performance may not be uniform across all frequencies, however. Such is often the case for real-world systems applied to active noise control tasks.

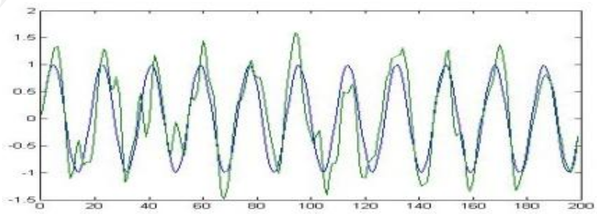


6. Comparison among other LMS Algorithm

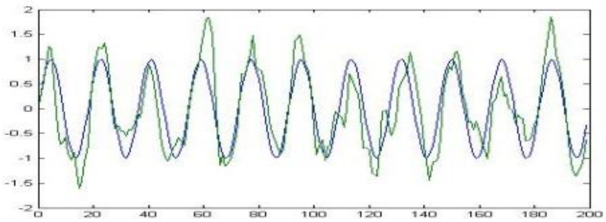
a. *Noise Cancellation using adjoin type LMS Algorithm.*



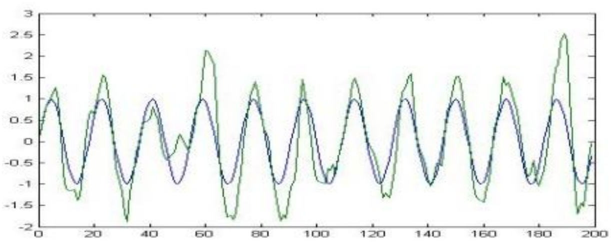
b. *Noise Cancellation using FIR Adaptive Filter that uses NLMS*



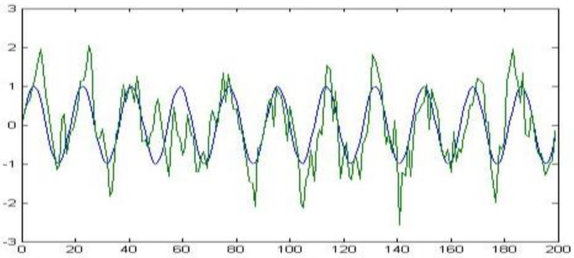
c. *Noise cancellation using FIR adaptive filter that uses LMS*



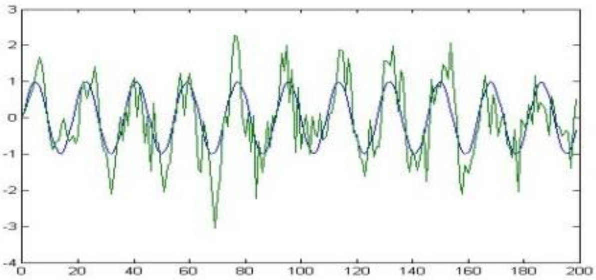
d. *Noise cancellation using FIR adaptive filter that uses SIGN Data Algorithm*



e. *Noise cancellation using FIR adaptive filter that uses SIGN ERROR Algorithm*



f. *Noise cancellation using FIR adaptive filter that uses SIGN-SIGN LMS algorithm*



7. Conclusions

This paper has described an application in which the use of an LMS and NLMS adaptive filter is particularly appropriate. The main goal of this paper is to investigate the application of an algorithm based on adaptive filtering in noise cancellation problem. The LMS algorithm has been shown to produce good results in a noise cancellation problem. Moreover the performances variants of different types of LMS Algorithm have been discussed here.

8. Future Works

The application can be extended for the noise reduction in the speech for the hearing aids in the noisy environment like crowd noise, car noise, cockpit noise, aircraft noise etc. With modified LMS algorithm convergence speech can be increased as per the real time requirement fast algorithm can be developed. Moreover, if we apply any optimization algorithm (like PSO) has been applied we can develop optimized filter design. Another scope of this work is to develop the SNR performance analysis for different variants of LMS Algorithm

9. Acknowledgements

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10. References

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