A Review of Active Noise Control System using LMS and FxLMS Algorithms

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ABSTRACT
Active noise control system is based on the principle of destructive interference. An anti noise signal is generated with the help of adaptive filter and is superimposed on the noise signal and this result the unwanted noise reduction. We use the adaptive filter for anti noise control in digital domain. However there is some time delay between the original noise signal and an anti-noise signal. That is why a secondary path is taken into consideration. The secondary path of ANC is assessed by offline or online. In offline secondary path we consider that there is no reference noise exist, but reference noise exist in practical application and the secondary path changes with respect to the time. This lead to the instability of ANC system and adaptive filter do not converge. In such cases for proper functioning of ANC system time varying secondary path should be modelled online. Online secondary modelling evolved from simple Eriksson methods to cross updated online modelling. Noise can be controlled in online secondary path modelling with the help of FxLMS Algorithm.

Keywords: active noise control, online secondary path model, active noise attenuation, LMS, FxLMS

1. INTRODUCTION
1.1. Overview
Active noise attenuation is a type of technique in which we uses an offending signal and digital signal processing to synthesize a new signal that containing a destructive interference in order to cancel the unwanted noise. The idea of attenuating noise actively appeared first in 1936 in which a system utilizing a microphone and an electronically driven loudspeaker. ANC includes various advantage over passive noise control systems of acoustic noise including lighter weight, smaller size, and ability to target only a particular frequencies.

![Figure- 1. Simple feedforward ANC system](image-url)
Figure 1 shows the basic dimensional structural of an ANC system. ANC system consists of a reference microphone at the noise source and it also consists of a cancelling loudspeaker and an error microphone at the receiver side where attenuation of noise source is required.

The primary microphone and reference micro-phone are used to update the coefficient of filter in the the ANC algorithm and then out-puts an updated cancellation noise signal.

As we know that the characteristics of the unwanted noise signal will be time-varying in frequency, phase and amplitude, so our ANC system adapt to this changing signal in order to do work efficiently. The Least-Mean-Squares (LMS) algorithm is an efficient and very useful solution to the problem of updating the coefficient of anti-noise signal. LMS for ANC remains one of the most popular and useful algorithms for ANC today because it is simple and robust. LMS algorithm uses the gradient vector of the active filter weights to converge on the optimal Wiener solution [2], thus minimizing the mean error signal. In LMS Algorithm in every iteration weight of adaptive filter are updated as using formula 1. In this formula, w(n) represents the weights of the adaptive filter, µ represents the learning rate or step size of the LMS algorithm, x(n) represents the reference microphone input, and e(n) represents the instantaneous error.

\[ w(n + 1) = w(n) - \mu x(n)e(n) \] (1)

In practical noise control applications, the so-called secondary path signal - the path from the canceling speaker to the error microphone - introduces considerable phase and frequency distortion which can cause LMS not to successfully converge. Thus a modified LMS algorithm, filtered extended LMS or FxLMS[1], is introduced to cope with the secondary path signal problems. A second issue which can arise in practical applications is output from the cancellation speaker bleeding into the reference sensor, which can cause feedback loops. A second modified LMS algorithm, filtered-u LMS or FuLMS[7], is introduced to counteract issues caused by the feedback.

1.2. Learning Rate

The learning rate of the LMS algorithm plays a very important role to determining the conversion rate of adaptive filter and by measuring the learning rate we can determine the overall performance of ANC system. however mostly LMS algorithm uses a constant learning rate and than a no. of algorithm has been developed in order to speed convergence with variable step size learning rate and that algorithm is known as normalized LMS. NLMS is a variant of LMS that updates the step size in proportion to the inverse of the total expected energy of the input buffer. This can also be expressed as the inverse of the dot product, or L2 norm of the input vector with itself.

2. METHODS

Adaptive filters adjust their coefficients to minimize an error signal and can be realized as (transversal) finite impulse response (FIR), (recursive) infinite impulse response (IR), lattice, and transform-domain filters.

Manily LMS, FxLMS, and FuLMS are three type of ANC algorithms are used in Matlab for both constant and variable step sizes. This include six overall: LMS, NLMS, FxLMS, FxNLMS, FuLMS and FuNLMS. The algorithms were tested against linear transfer functions and feedback. For comparison of convergence rate, all algorithm are tested at the same step size. More sophisticated algorithm show faster convergence and greater noise attenuation and are more robust to interference. The development of improved DSP hardware allows these more sophisticated algorithms to be implemented in real time to improve system performance. This method has been applied to many industrial applications such as air conditioning systems, industrial motors, exhaust fan, aircrafts. ANC system is designed using adaptive filters which are based on Least Mean Square (LMS) algorithm. Secondary path model is used in design of ANC system, as it takes into account the time delay caused by electronic components used in ANC system. The realization of LMS algorithm with secondary path transfer function is called Filtered-x Least Mean Square algorithm (FxLMS).
3. ALGORITHMS

3.1. LMS

LMS is the basis of most active noise control systems today. The block diagram of the LMS algorithm in an ANC application is shown in Figure 2. The signal is picked up at a reference microphone $x(n)$ and sent through an adaptive filter $W(z)$ which is constantly being updated by LMS. $W(z)$ adaptive filter is used to estimate an unknown plant $P(z)$. The primary path $P(z)$ consists of the acoustic response from the reference sensor to the error sensor where the noise attenuation is to be realized. If the plant is dynamic, the adaptive algorithm then has the task of continuously tracking time variations of the plant dynamics.

Where,

$x(n)$ = output electrical signal of reference sensor, that is noise we want to reduce. This is also known as reference signal.

$y(n)$ = output of adaptive filter which act as active noise controller, which is used to generate anti-noise signal through loud speaker.

$e(n)$ = error signal which is difference between noise signal and anti-noise at error sensor.

![Figure-2 Block diagram of an ANC system using the LMS algorithm.](image)

$P(z)$ = Primary path transfer function followed by noise.

$p(n)$ = coefficient of $P(z)$ filter.

$W(z)$ = Transfer function of adaptive filter controller, whose coefficients are varied according to error signal $e(n)$.

$w(n)$ = coefficient of $W(z)$ filter.

$d(n)$ = desired signal near error microphone

The output $d(n)$ of $P(z)$ is given by

$$d(n) = p(n) \times x(n)$$

Output of adaptive filter controller is given by

$$y(n) = w(n) \times x(n)$$

3.2. FxLMS

The use of the LMS algorithm in practical ANC applications is complicated by the fact that the anti noise created by the algorithm must travel from the cancellation speaker to the error microphone and thus transition from the digital domain to the analog domain and back again. This introduces frequency and phase distortions
into the signal which are known cumulatively as the secondary path $S(z)$. The secondary path includes any signal components between the output of the adaptive filter and the input of the error signal to the LMS algorithm which includes the D/A converter, reconstruction filter, amplifier, loudspeaker, acoustic path from loudspeaker to error microphone, pre-amplifier, anti-aliasing filter, and A/D converter [5].

A block diagram of the FxLMS algorithm is shown in Figure 3. To counteract distortion introduced by $S(z)$, an inverse filter $S^\dagger(z)$ is placed between the reference microphone and the LMS algorithm. This allows for the algorithm to converge. In order to obtain the impulse response of $S(z)$, the system must be tested offline before ANC is implemented. Although there are many ways to determine $S(z)$, an easy way is to simply use the LMS algorithm with white noise as an input to the system. The inverse impulse response is obtained by bringing the impulse response of $S(z)$ into the frequency domain, taking its inverse and then bringing it back into the time domain. The convergence times are much better for FxLMS with the variable step size algorithm. Also, as with LMS, the normalized variant is more tolerant to different convergence rate estimates. The results also show that the FxLMS algorithm converges to an absolute minimum at a slower rate than the LMS algorithm.

3.3. FuLMS

The FuLMS algorithm addresses another practical problem in real world implementation of ANC; the issue of feedback to the reference microphone from the cancellation speaker. The FuLMS algorithm adds an adaptive recursive IIR filter $B(z)$ to the signal chain, whose function is to minimize error based on a one sample delayed version of $y(n)$ as shown in Figure 4.
The FuLMS algorithm does come with some drawbacks, most notably that it has never been mathematically proven to guarantee convergence. This stems from the fact that the error function may converge to local minima due to the non-quadratic nature of IIR filters [5]. Additionally, IIR filters are not unconditionally stable, which may affect the overall system as well. However, a variant of the FuLMS algorithm known as SHARF [7] has been shown to be exceptionally stable. In this version, a low-pass filter is used to smooth the error signal fed to the LMS algorithm updating \( B(z) \).

The convergence trends between constant and variable step sizes are different for FuLMS than the other algorithms tested in that the variable step size version converges more slowly than the constant step size variant. This may be due to the fact that there are two adaptive filters in FuLMS which are both sharing the same updated value. Perhaps the initial should be chosen independently for the IIR filter. Convergence may also vary with the amount of feedback added to the reference microphone.

4. CONCLUSION

Our testing showed that all six algorithms tested will converge in the digital domain. We showed that the simple LMS algorithm will converge quickest of all three tested, with the FxLMS algorithm being the second fastest and the FuLMS algorithm the slowest. We also showed that in most cases NLMS variable step size algorithms show greater likelihood of convergence and higher stability than corresponding constant step size LMS algorithms. However, this does not hold true for the FuLMS algorithm which exhibits faster convergence with constant learning rates.

First, we would like to do our experiments in the acoustic domain. We plan to accomplished this by implementing an ANC system on a PC using a Matlab’s new audio streaming toolkit. We would also like to examining new and updated ANC algorithms as better more robust result, such as algorithms that do online secondary path source modeling as shown by Eriksson [3] or use that use faster methods of gradient descent as shown by Fernandez [4].

5. REFERENCES

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