An Improved Feedback Filtered-X NLMS Algorithm for Noise Cancellation

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Abstract The age of unmatchable technical expertise envisages noise cancellation as an acute concern, as noise is held responsible for creating hindrances in day to day communication. To overcome the noise present in the primary signal notable traditional methods surfaced over the passage of time being listed as noise barriers, noise absorbers, silencers, etc. The advanced modern day approach suppresses noise by continuous adaptation of filter weights of an adaptive filter. The change in approach was ground breaking that accredits its success to advent of adaptive filters which employs adaptive algorithms. The various premier noise cancellation algorithms include LMS, RLS etc. Further much coveted Normalized LMS, Fractional LMS, Differential Normalized LMS, Filtered-x LMS etc. ensued out of active framework in this field. The paper looks forward to provide an improved approach for noise cancellation in noisy environment using newly developed variants of Filtered x LMS (FxLMS) algorithm, Feedback FxLMS (FB-FxLMS). An initial detailed analysis of existing FXLMS algorithm and FB-FxLMS algorithm has been carried out along with the mathematics of the new proposed algorithm. The proposed algorithm is applied to noise cancellation and the results for each individual process were produced to make a suitable comparison between the existing and proposed one.

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1 Introduction

Acoustic Noise Cancellation (ANC) is the technique which brought revolutionary changes in the field of noise cancellation. In the mediaeval era a number traditional approach were instrumented in the field of acoustic noise control which emphasised upon the application of passive methods such as enclosures, barriers and silencers to attenuate unwanted sound waves. These approaches use either the concept of impendence change or the energy loss due to sound absorbing materials. The application of these silencers were largely preferred for their ability of attenuating noise globally; however, when queried about their feasibility they were found relatively bulky, over costly and ineffective for low frequency noise. In order to overcome these primary problems, Acoustic Noise Cancellation (ANC), has received reasonable scope of research due to the fact that it employs an electro-acoustic system which is responsible to create a local silence zone to attenuate the primary noise.

In this technology dominated era an important reason for the growing acceptance of ANC is due to the fact that it is more efficient than passive devices at low frequencies and ANC also uses digital signal processing system as its principal noise canceller. This system executes various complicated mathematical operations with high accuracy and precision in real time. With the use of above system, the amplitude and phase of both the primary and the secondary waves match closely. By virtue of it, maximum noise suppression can be achieved with enormous stability, and reliability. Generally ANC is widely regarded as one of the application of Active control of sound, which can be coined by the phenomenon by virtue of which the existing original sound field (primary field), due to some original (primary) sound sources, is modified to something else (desired sound field) by the help of controlled sound sources (secondary sources). Again Acoustic Noise Cancellation (ANC) can be implemented by using three broadly options: Active Noise Absorption (ANA), Active Noise Reflection (ANR) or Active Potential Energy Minimization. The active absorption (or Active Acoustic Attenuation (AAA)) utilises the secondary sources to absorb the original sound field which are being directed towards them, while in the active noise reflection (or active sound reflection), the original sound field is reflected back towards the primary sources by secondary sources. The last part which is the Active Potential Energy Minimization, the sound pressure can be minimized at selected points. While in active absorption the secondary sources acts like passive absorbents, the same secondary sources act as noise barriers in active noise reflection.

Generally the generation of the secondary signal is controlled by a suitable adaptive algorithm which adaptively changes the weight of the filter being used.

Table 1 Comparison of existing algorithms

Name of algorithm	Strengths	Weaknesses
LMS	Low computational complexity, stable	Slow speed of convergence and less robust
NLMS	Fast speed of convergence, stable	More computational complexity than LMS and less robust than RLS
FLMS	Faster speed of convergence, more stable	More computational complexity than NLMS
RLS	Fast speed of convergence, more robust	Very high computational complexity and unstable
FxLMS	Less computational complexity, simple real time realization	Slow speed of convergence
FxRLS	Fast convergence, Low steady state residual noise	Large computational complexity
FB-FxLMS	Better convergence than FxLMS, simple real time realization	More computational complexity than FxLMS and LMS

ANC is mainly classified into two categories i.e. "feed-forward ANC" and "feedback ANC". In feed-forward ANC method a coherent reference noise input is sensed before it propagates past the secondary source while feedback ANC employs a method where the active noise controller attempts to cancel the noise without the benefit of an upstream reference input. In other words the first method uses a reference sensor for the noise cancellation while the latter one doesn't utilizes it all.

An active noise control system usually based upon four main parts. These include the plant or control path which acts as a physical system between the actuator and the sensor. The sensors generally perform the work of picking up the reference signal and the error signal respectively. The noise measured as the primary noise present in the system is cancelled out around the location of the error microphone by a process of generating and combining an anti-phase cancelling noise that is closely correlated to the spectral content of the unwanted noise. The actuators are also regarded as loudspeakers. The last part is the controller which controls the actuators using the signals picked up by the sensors. The comparative data of earlier existing algorithms are highlighted in Table 1 [1–7].

2 Proposed Algorithm and Implementation

The proposed algorithm is applied for both feed-forward as well as for feedback system. Hence we look forward to divide this section into two halves where in the first half the new proposed algorithm has been applied in feed-forward ANC and in the second half the proposed algorithm is applied for the feedback ANC. This section on a whole requires prior knowledge of both FxLMS and FB-FxLMS algorithm respectively.

2.1 Feedforward ANC

The above system primarily uses the FxLMS algorithm to cancel the noise source. The structure of the algorithm comprises of a primary plant through which noise propagates. This noise then reaches to the error sensor in the form of desired signal that is represented by $d(n)$. To cancel this approaching noise the controller generates a signal which has the same amplitude but opposite phase to the noise signal. The control signal $y(n)$ is then produced by filtering the reference signal $x(n)$ at the cancelling loudspeaker with the weight updating adaptive LMS algorithm at its disposal. The filter weight coefficients are defined by $W(n)$ with $y(n)$ being the convoluted signal between the reference signal $x(n)$ and filter coefficient. In the subsequent process $y(n)$ is filtered by the secondary path transfer function $S(n)$ that finally reaches the error sensor as output signal $y'(n)$. When this output signal is mixed with the noise signal, error signal $e(n)$ is obtained that is measured by error sensor. The residual error is obtained by acoustic combination of desired signal and control signal which is subsequently minimised by the adaptive algorithm that optimizes the filter coefficients. The wiener optimum filter for the filter to optimize is designated by W_{opt}. The weight update equation of FxLMS algorithm is given by:

$$W(n+1) = W(n) + \mu x'(n)e(n) \tag{1}$$

where the error signal is estimated by,

$$e(n) = d(n) - s(n) * \{W^T(n)x(n)\} \tag{2}$$

where

n Time index

$S(n)$ Impulse response of secondary path $S(z)$

* Linear convolution

$$W(n) = [W_0(n), W_1(n), \ldots\ldots\ldots W_{L-1}(n)]^T \text{ Filter coefficient}$$

$$x(n) = [x(n), x(n-1), \ldots\ldots\ldots x(n-L+1)]^T \text{ Signal vectors}$$

$$x'(n) = \hat{S}(n) * x(n) \text{ Filtered response}$$

In order to improve the speed of convergence along with increasing the accuracy in system identification and cancelling the noise signal the following modifications are proposed to the existing Filtered x adaptive system. Here the existing LMS adaptive algorithm which appears to be the heart of noise cancellation has been suitably replaced by a new advanced version of normalised LMS adaptive structure. The weight adaptation coefficient of the new proposed advanced algorithm improves the existing one by,

$$\mu(n) = \frac{\alpha}{\beta + R} = \frac{\alpha}{\beta + x(n) * x^T(n)} \tag{3}$$

where the value scope of $\mu(n)$ is kept between the values ranging from 0 to unity or 1. The other parameter known as β is made quite small as possible to overcome the lacuna of SSM degradation with a conditional point of $r(n)$ being very small. This assumption increases the SSM performance of advanced NLMS by fore fold when compared to traditional LMS. The above relationship uses the concept of normalised value of LMS adaptation. The proposed advanced algorithm updates the step size by,

$$W(n+1) = W(n) + \left(\frac{\alpha}{\beta + R}\right) x'(n) e(n) \tag{4}$$

The proposed algorithm operates at larger step sizes as compared to the previous stated algorithm when the case of decreasing trend of residual error. Assuming the FIR filter weight to be $W(z)$ the filter length is taken L and the output results are computed likewise.

2.2 Feedback ANC

The above system primarily uses the FxLMS algorithm to cancel the noise source in the feedback path. This christens its name to FB-FxLMS. The FxLMS algorithm showed that anti-noise output to the loudspeaker not only cancels acoustic noise downstream, but unfortunately, it also radiates upstream to the input microphone, resulting in a contaminated reference input *x(n)*. This inherent problem was solved by the use of FB-FxLMS. Initially the system components are all the same parts as that same of FxLMS with slight modifications. Instead of the application of secondary sensors the linear predictor is used for generating the requisite reference signal. The linear predictor provides a robust, reliable and accurate way for estimating the parameters of secondary path.

From the diagram it can be figured out that $y(n)$ is the anti-noise signal produced by the controller $W(z)$. The output of $W(z)$ enters to the secondary path which goes on to get inverted and results in the generation of $y'(n)$. The signal is then added to the primary noise $d(n)$ and resulting into subsequent generation of error signal $e(n)$. It is also regarded as residual noise which is then fed back to the controller $W(z)$. By filtering the output of the controller and then adding it to the error signal, an estimate of the filtered primary noise $\hat{d}(n)$ is generated. This signal is then used as the reference signal $x(n)$, and is filtered through the model of the secondary path before being fed to the adaptive block. The expressions for the anti-noise $y(n)$, filtered x signal $x'(n)$, and the adaptation equation for the FB-FxLMS algorithm are the same as that for the FxLMS ANC system, except that $x(n)$ in FB-FxLMS algorithm is a feedback-free signal that can be expressed as:

$$x(n) \equiv \hat{d}(n) = e(n) + \sum_{m=0}^{M-1} \hat{s}_m y(n - m - 1) \tag{5}$$

where $S_m(n)$, m $= 0,\ 1, \ldots.., \mathrm{M} - 1$ are the coefficients of the Mth order finite impulse (FIR) filter $\hat{S}(z)$ used to estimate the secondary path $S(z)$.

The weight update equation of existing FB-FxLMS algorithm is given by,

$$W(n+1) = W(n) + \mu x'(n)e(n) \tag{6}$$

In order to improve the existing algorithm the proposed adaptation is being applied in place of existing LMS and the Feedback Filtered x structure is optimized accordingly.

$$W(n+1) = W(n) + \left(\frac{\alpha}{\beta + R}\right)x'(n)e(n) \tag{7}$$

The important thing to underline that the phase error between $S(n)$ and $\hat{S}(n)$ should be less than orthogonal shift following rise of which leads to slowing of convergence. The performance of the above listed as well as new proposed algorithms depends widely upon the nature of physical plant, secondary path impulse response, noise bandwidth and the length of the traversal filter. It is clear from the above that these algorithms malfunction for long impulse response and large noise bandwidth while larger filter length leads to compromise in convergence. In the given paper various results for both types of systems are found out using different filter lengths (Fig. 1).

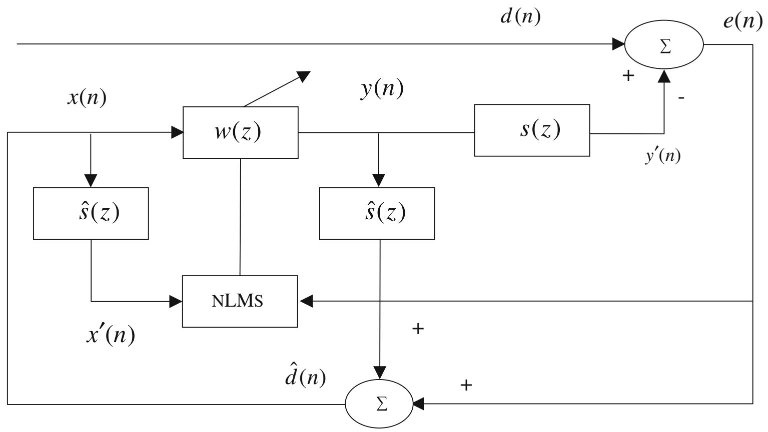

Fig. 1 Block diagram of proposed algorithm for feedback ANC

3 Simulation and Results

In the following section various results using FxLMS, FB-FxLMS and the proposed algorithm for noise cancellation are shown. For the above simulation process 100 Hz fundamental frequency is chosen along with a sampling frequency of 200 Hz. The filter length is specified to 16 along with a 1000 number of iterations being performed.

3.1 Feedforward ANC

Figure 2 visualises the application of FxLMS in identifying error while Fig. 3 shows the application of proposed FxNLMS for noise cancellation in feed-forward scenario. From the given set of figures we can see that when traditional algorithm is applied the convergence starts after 250 number of iterations while the value is close to 100 for the new proposed algorithm. Hence the proposed algorithm converges faster than FxLMS algorithm though it involves more computational complexity. The signal power distribution for the proposed system is also provided in Fig. 4.

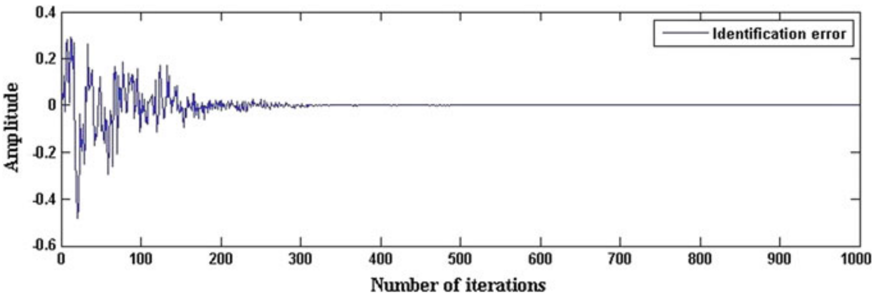

Fig. 2 Convergence of FxLMS

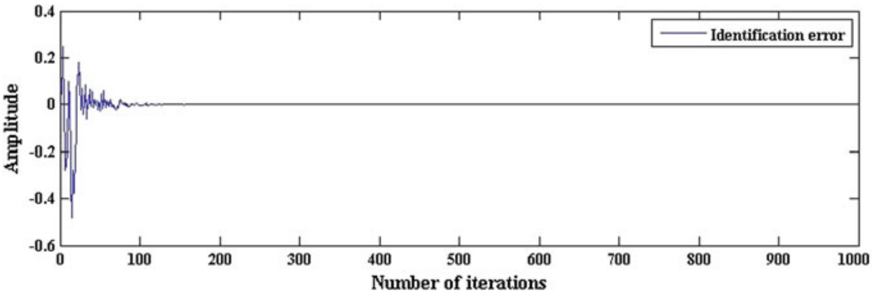

Fig. 3 Convergence of FxNLMS

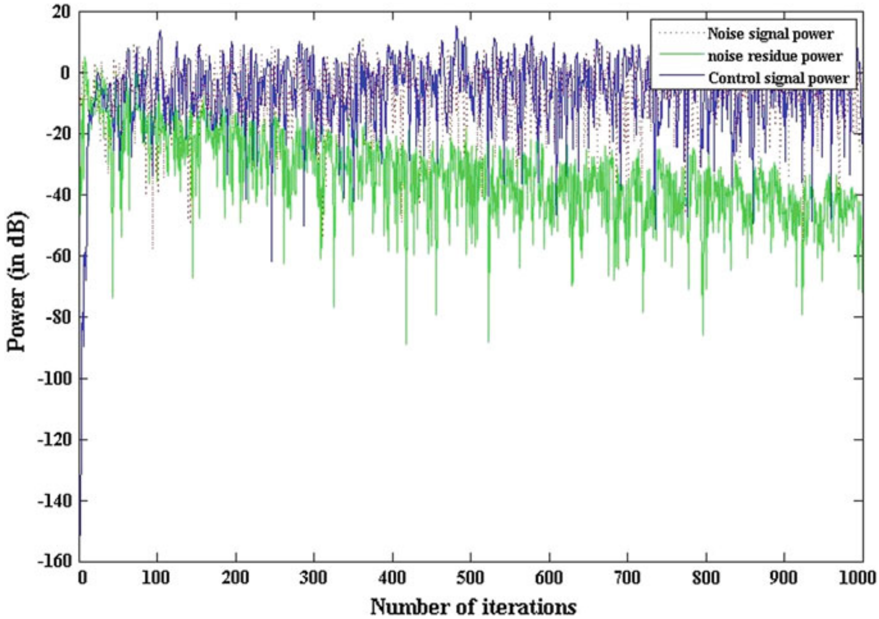

Fig. 4 Signal power distribution of FxNLMS

3.2 Feedback ANC

Figure 5 visualises the application of FB-FxLMS in identifying error while Fig. 6 shows the application of proposed FB-FxNLMS for noise cancellation in feedback scenario. From the given set of figures we can see that when traditional algorithm is applied the convergence starts after 150 number of iterations while the value is approaching to 100 for the new proposed algorithm. Hence the proposed algorithm

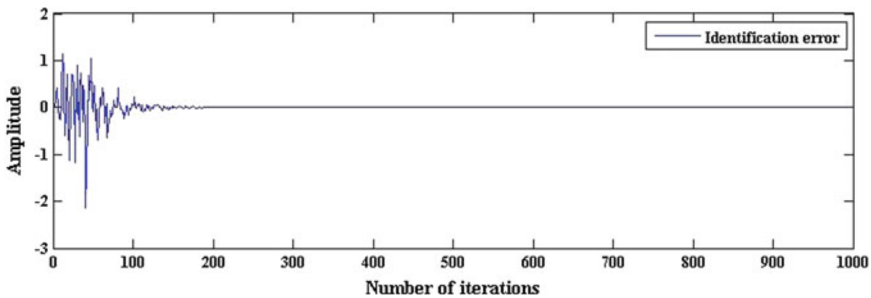

Fig. 5 Convergence of FB-FxLMS

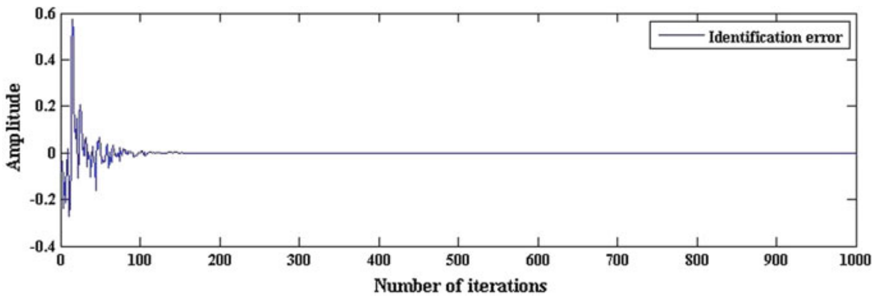

Fig. 6 Convergence of FB-FXNLMS

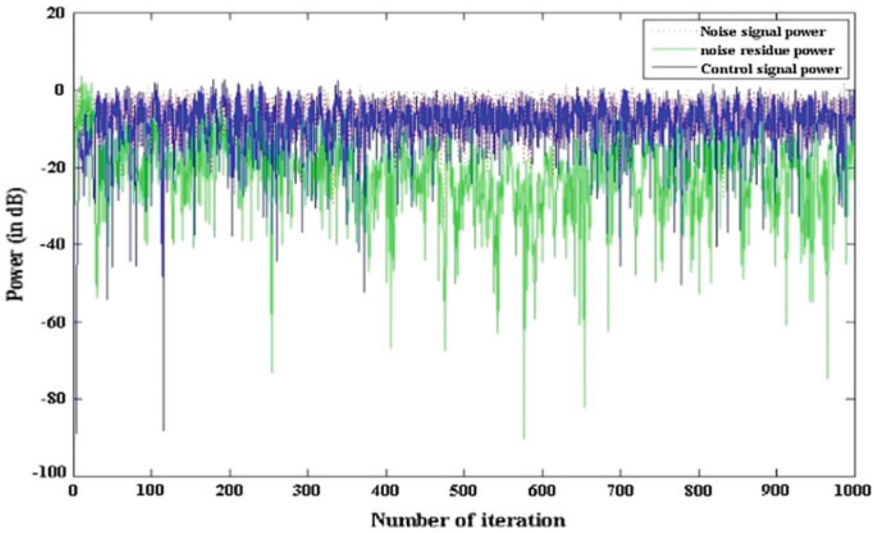

Fig. 7 Signal power distribution of FB-FxNLMS

converges faster than FB-FxLMS algorithm though it involves more computational complexity. The signal power distribution for the proposed system is also provided in Fig. 7.

4 Conclusion

In this paper the proposed algorithms were compared with the existing sets of algorithms like FxLMS and FB-FxLMS in their respective ANC systems. It is concluded from the above simulations that the results are much more acceptable for proposed algorithms as far as convergence is concerned. The proposed set of algorithms converged at about 100 iterations for feed-forward ANC and is approaching towards 100 for feedback ANC respectively. Again the feed-forward ANC involved in the attenuation of random noise at its disposal while the feedback ANC was restricted to narrowband noise respectively. This can be further improved by making requisite standard modifications to the system for wideband noise attenuation. Hence a scope for even better and accurate algorithm than the proposed one can be expected in future.

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