Performance Measurement of Differential Step Size Standardized-Power Algorithm with Filtered-x Least Mean for Impulsive Active Noise Control System

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This study presents a comparison of several impulsive active noise control system techniques. The Filtered-x LMP algorithm (FxLMP), Sun's method, and Modified Sun's algorithm are three adaptive cost function modification techniques that are discussed in this article. In situations with peaky, sudden noise, the typical FxLMP algorithm performs poorly at noise reduction. The weight update equation of some common impulsive active noise control algorithms listed and characteristics discussed. A novel approach is suggested to get over this drawback by taking into account both variable step sizes and normalizing them using the FxLMP algorithm. To evaluate the performance and compare the efficacy of the suggested approach, a computer simulation using MATLAB is conducted. Both the main and alternative pathways are linear. In the presence of impulsive main noise, the benefits, and disadvantages of the suggested adaptive algorithm with changing parameter values are assessed.

Keywords: Active noise control, Filtered-x LMP algorithm (FxLMP), Impulsive noise, Modified normalized FxLMP algorithm, sun’s algorithm.

1. Introduction

Excessive noise can significantly reduce the lifespan of mechanical equipment in industrial settings, potentially leading to serious accidents. Passive method involves reducing noise by using sound absorbers or barriers. While this approach is effective at high frequencies, it is less effective at low frequencies[5]. In the low-frequency range, the active method has shown significant advantages and has the potential to offer benefits in terms of application cost, dimensions, and weights[8].

The Negative interference between two acoustic waves is the foundation of active noisecontrol (ANC). By creating and mixing an anti-phase cancelling noise near the site of another microphone, the original noise is effectively muted[1,19]. This idea is used by many adaptation algorithms to suppress noise, although the well-known filtered-x LMS (FxLMS) approach has less computational complexity and is simpler to apply than other straightforward techniques. For this approach, the weight update equation (1) is expressed as,

$$h(n+1) = h(n) + \mu e(n) f(n) \tag{1}$$

The reference signal vector is denoted by f(n) and has been filtered out and stands for the step size. Some traditional algorithms with second order statistics perform poor for impulsive noise, As the impulsive noise is non-gaussian its second order moment does not exist. The FxLMS method is unstable when the main signal is impulsive. Unlike other modified FxLMS algorithms, which need the precise present threshold parameters.[2,18] Mostly in adaptive filters the change in step size parameter μ causes variation in stability and convergence rate[3,17]. It also depends on shape parameter (α) of impulsive noise. If it were feasible to raise the step size when the power of the reference signal h(n) dropped and vice versa, the system's performance would be greatly enhanced. The concept of variable step size made it possible to modify the step size in response to the reference signal's strength, which also had an impact on the convergence rate [20]. On the other hand, the optimum technique for impulsive ANC is the one that reduces the least mean p-power (LMP) of the error signal, alters the reference signal, or does both. This study's technique combines the idea of modifying the error signal and reference signal with the idea of varying the step size in the LMP approach[4]. The practicality of the suggested strategy is shown by MATLAB simulations.

1.1. Impulsive Noise

Impulsive noise is wide range with low probability which occurs randomly by creating extremely brief impulses[7]. Some examples of that kind include switching noise, sound from the computer keyboard, faulty channel circumstances, dropout, surface deterioration etc. There are different typesof impulsive noise based on feature, such as Symmetric α stable Type (SαS), Transient type and sinusoids typeImpulsive noise shown in fig. 1.

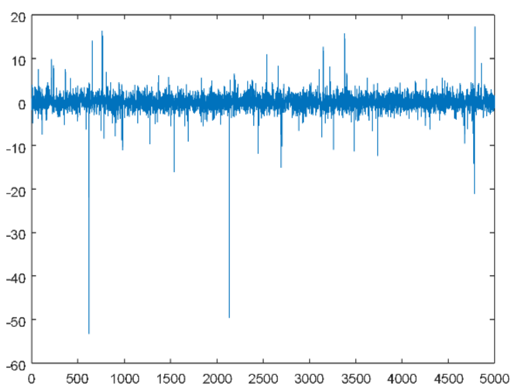

Figure 1. Impulsive noise at α=1.8

In this study only SαS type impulsive noise is included. Impulsive noise is non-gaussian. The

SαS distribution function of impulsive noise is eq. (2).

$$\phi(t) = e^{-\gamma|t|\alpha} \quad (2)$$

Here $\phi(t)$ represents characteristic function, $\gamma > 0$, called the scale parameter and α denotes the shape parameter. α is positive number and has a maximum value 2. Graphical representation of impulsive noise is shown in below figure 2.

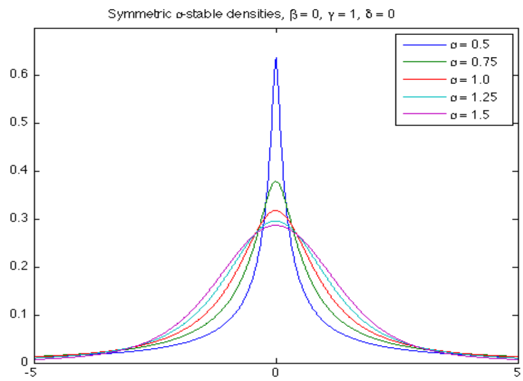

Figure 2. PDF of Impulsive noise for different values of α=1.8

1.2. Filtered x Least Mean P-power (FxLMP) Algorithm

This is a cost function modification algorithm using LMP generalization [6] suitable in impulsive noise environment. The equation for FxLMP is, Eq. (3-4).

$$h(n+1) = h(n) + \mu p|e(n)|^{p-1}(e(n))[\hat{s}(n) * x(n)] \quad (3)$$

$$h(n+1) = h(n) + \mu p|e(n)|^{p-1}(e(n))[\hat{s}(n) * x(n)]$$

Where

$$(e(n)) = \{1, e(n) > 00, e(n) = 0 - 1, e(n) < 0(4)$$

Where e(n) represents the residual error signal for the reference signal h(n). It has been concluded by author in FxLMP algorithm is that fast convergence is possible if p is closer to α with upper bound being p<α.

1.3. Sun's Algorithm (Modified FxLMS)

Sun's approach is based on the FxLMS algorithm's modified cost function. To increase the stability of the FxLMS method for ANC of impulsive noise, samples that fall outside of the threshold range are removed. Either the error signal alone or both the error signal and reference signal are changed for increased algorithmic robustness.[7] Weight update equation when the reference signal is altered eq. (5,6).

$$x'(n) = \{x(n), if x(n) \in [c1, c2]0, Otherwise \quad (5)$$

$$h(n+1) = h(n) + \mu e(n)[\hat{s}(n) * x'(n)] \quad (6)$$

Weight update equation (with reference signal and error signal both modified) eq. (7).

$$h(n+1) = h(n) + \mu e'(n)[\hat{s}(n) * x'(n)] \qquad (7)$$

Where ŝ(n) is the secondary path model's impulse response. The changed reference signal is x'(n). For ANC systems, the thresholding parameters c1 and c2 may be obtained offline. This method becomes unstable for a factor of 1.5 when the reference noise is very impulsive and the PDF of impulsive noise is peaky. The main benefit is that the computational complexity of this method is equal to that of the FxLMS algorithm.[15] The author additionally made edits to the sample to improve Sun's technique's resilience without sacrificing the massive amplitude sample.[9]

Weight update equation (8-9) is,

$$h(n+1) = h(n) + \mu e''(n)[\hat{s}(n) * x''(n)] \qquad (8)$$

$$x''(n) = \{C1, if x(n) \leq C1 C2, if x(n) \geq C2 x(n), Otherwise \qquad (9)$$

Where $x''(n)$ and $e''(n)$ is secondary modification of reference signal and error signal respectively. As previously noted, simply clipping peaky samples in the FxLMS algorithm update does not rule out the possibility of peaky samples appearing in the e(n) residual error. In the worst instance, the residual error can still be too great, making ANC unreliable[16].

1.4. Variable Step Size Modified Normalized FXLMP(VSSMNFXLMP) (Proposed Method)

This algorithm is modified version of FxLMP method. Here to achieve efficiency two concepts are combined, such as variable step size and normalized cost function.[21] The weight update equation is (10, 11, 12).

$$h(n+1) = h(n) + \mu(n) p |e(n)|^{p-1} (e(n)) [\hat{s}(n) * x(n)] \qquad (10)$$

$$(e(n)) = \{1, e(n) > 0 0, e(n) = 0 -1, e(n) < 0 \qquad (11)$$

$$\mu(n) = \frac{\mu_{th}}{\|x(n)\|_2} \qquad (12)$$

Where $\mu(n)$ is variable step size, μ_{th} represents threshold value of step size.

Table 1. Comparison of different Algorithms for Impulsive Noise

Name of the Method	**Stability factor**	**Convergence rate (speed)**	**Robustness achieved**
FxLMS	Unstable	poor convergence for α>2	less
Sun’s approach	Stability is poor for α>1	superior to FxLMS	improved robustness
FxLMP	Stable	Reliable superior to the Sun's Algorithm	superior than Sun's strategy
Modified FxLMS	Consistent performance	quicker convergence	improved robustness

Comparison of basic cost function modification algorithms in impulsive environment is represented in Table 1 shown above. FxLMS which is unstable for Impulsive noise whereas Modified FxLMS, Suns Algorithm and FxLMP achieves stability in impulsive noise, but FxLMP has better speed ofconvergence and modified FxLMS has better robustness.[10] Then further FxLMP is modified to improve stability and convergence and VSSMNFxLMP is proposed.

2. Results and Discussion

In this simulation work the reference signal is impulsive noise with α=1.68 and γ=1 and δ=0. The primary path considered as $P(z)= 0.01+ 0.25z^{-1}+ 0.5z^{-2}+z^{-3} + 0.5z^{-4}+ 0.25z^{-5}+ 0.01z^{-6}+ 0.1z^{-7}$ and secondary path $S(z)= 0.0025+ 0.062z^{-1}+ 0.12z^{-2}+0.25z^{-3} + 0.12z^{-4}+ 0.062z^{-5}+ 0.0025z^{-6}+ 0.025z^{-7}$. Both primary and secondary paths are linear.[11] Here the simulation is conducted using FxLMP, sun's algorithm, modified sun's algorithm and mean noise ratio (MNR) obtained is displayed in figure 3. The step size μ is $5x10^{-5}$ and threshold parameters c1=0.1 and c2=99.9 were taken for all the algorithms in Figure.3. From this it can be observed that all the algorithms are stable, the VSSMNFxLMP algorithm (Proposed method) displays the lowest MNR when compared to the other three simulated approaches.[12] The suggested technique makes use of the ideas of variable step size and normalization. In this case step size varies according to change in reference signal with $\mu_{th}=\boldsymbol{\mu_{th}}$ $=5x10^{-4}$. Here for both the LMP based algorithm p=2.18 is considered for simulation. MNR is defined as

$$MNR(n) = E\left\{\frac{A_e(n)}{A_d(n)}\right\} \tag{13}$$

$$A_e(n) = \lambda A_e(n-1) + (1-\lambda)|e(n)| \tag{14}$$

$$A_d(n) = \lambda A_d(n-1) + (1-\lambda)|d(n)| \tag{15}$$

The symbol E represents the ensemble averaging of the quantity within. and $\boldsymbol{A_e(n)}$and $\boldsymbol{A_d(n)}$, are estimates of the absolute value of the error signal e(n) and the disturbance signal d(n), respectively. The forgetting factor, denoted as κ, is a numerical number that ranges from 0.9 to 1.

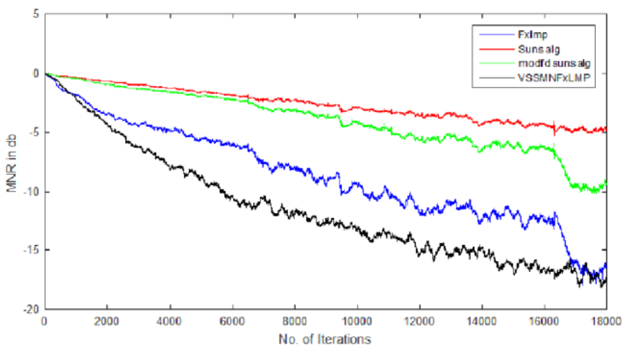

Figure 3. Performance evaluation of the Sun algorithm, the Sun algorithm as modified, the FxLMP method, and the VSSMNFxLMP algorithm

In Figure 4, again the simulation of all above discussed methods represented and step size μ is $5x10^{-5}$, threshold parameters c1=0.1 and c2=99.9 were taken. Here simulation of VSSMNFxLMP is done with lesser power value increasing value of reference step size i.e. $\mu_{th}=\boldsymbol{\mu_{th}}$ $=1x10^{-3}$ and p=1.78 is considered. It is observed that with increase in μ the MNR minimized.

From the simulation it is observed that with reducing p value MNR becomes less. A standard p value 1<p<3 is considered to attain stability of proposed algorithm. Considering p≥3 algorithm losses stability.

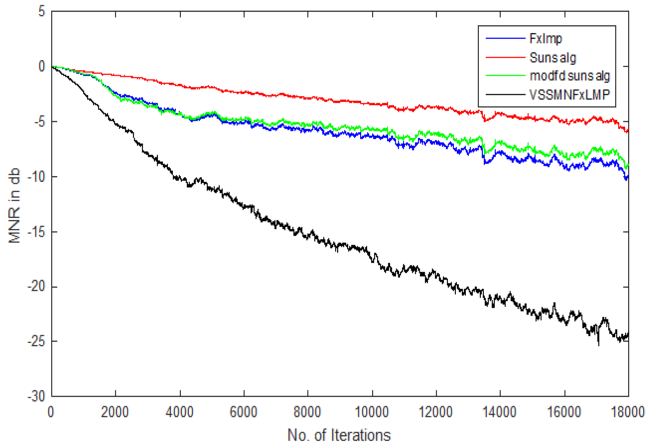

Figure 4. Performance evaluation of the Sun algorithm, the Sun algorithm as modified, the FxLMP method, and the VSSMNFxLMP algorithm

3. Conclusion

In this study, the VSSMNFxLMP algorithm—which can perform better and provide low MNR values—is proposed for environments with peaky impulsive noise. This algorithm is developed by using variable step size concept with combining effect of normalized concept in FxLMP algorithm. The effectiveness and performance measurement of proposed algorithm is compared with Standard FxLMP, sun's algorithm and its modified version.[13] Despite the fact that it requires a somewhat larger computing burden, the performance advantage may disregard this drawback. [14] The findings of the simulation demonstrate that in comparison to the other simulated algorithms, the approach that was recommended has a lower MNR, better stability, and a quicker rate of convergence.

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