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# Improving performance of FxLMS algorithm for active noise control of impulsive noise

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ABSTRACT

This paper concerns active noise control (ANC) of impulsive noise modeled using non-Gaussian stable processes. The most famous filtered-x least mean square (FxLMS) algorithm for ANC systems is based on minimization of variance of error signal. For the impulse noise, the FxLMS algorithm becomes unstable, as second-order moments do not exist for non-Gaussian processes. Among the existing algorithms for ANC of impulsive noise, one is based on minimizing least mean *p*-power (LMP) of the error signal, resulting in FxLMP algorithm. The other is based on modifying, on the basis of statistical properties, the reference signal in update of FxLMS algorithm. In this paper, the proposed algorithm is an extension of the later approach. Extensive simulations are carried out, which demonstrate the effectiveness of the proposed algorithm. It achieves the best performance among the existing algorithms, and at the same computational complexity as that of FxLMS algorithm.

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## 1. Introduction

Active noise control (ANC) is based on the principle of destructive interference between acoustic waves [1]. Essentially, the primary noise is canceled around the location of the error microphone by generating and combining an antiphase canceling noise [2]. As shown in Fig. 1, a single-channel feedforward ANC system comprises one reference sensor to pick up the reference noise $x(n)$, one canceling loudspeaker to propagate the canceling signal $y(n)$ generated by an adaptive filter $W(z)$, and one error microphone to pick up the residual noise $e(n)$. The most famous adaptation algorithm for ANC systems is the filtered-x LMS (FxLMS) algorithm [3], which is a modified version of the LMS algorithm [4]. Minimizing the mean square error cost function; $J(n)=E\{e^2(n)\}\approx e^2(n)$, where $E\{\cdot\}$ is the expectation operator; the FxLMS algorithm [3] is given as

$$\boldsymbol{w}(n+1)=\boldsymbol{w}(n)+\mu e(n)[\hat{s}(n)*\boldsymbol{x}(n)], \tag{1}$$

where $\mu$ is the step size parameter, $\boldsymbol{w}(n)$ is the tap-weight vector, $\boldsymbol{x}(n)$ is the reference signal vector, and $\hat{s}(n)$ is the impulse response of the secondary path modeling filter $\hat{S}(z)$. The FxLMS algorithm is a popular ANC algorithm due to its robust performance, low computational complexity and ease of implementation [3].

Over the past few decades a great progress has been made in ANC, yet the practical applications are limited. One important challenge comes from the control of impulsive noise. In practice, the impulsive noises are often due to the occurrence of noise disturbance with low probability but large amplitude. An impulsive noise can be modeled by stable

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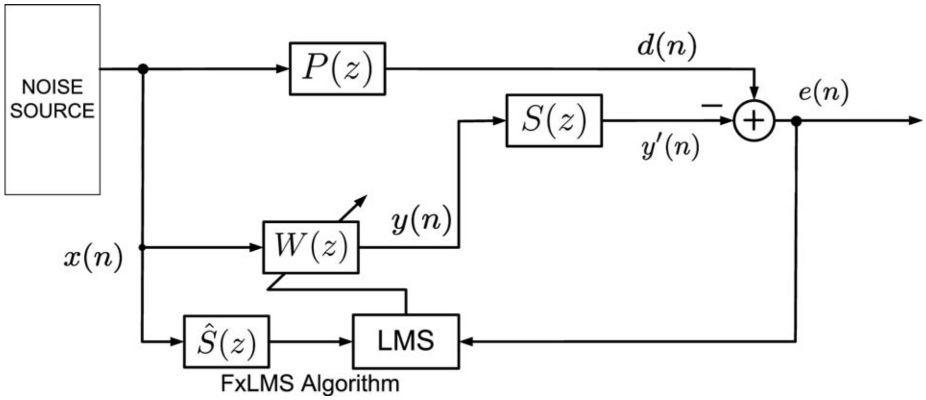


**Fig. 1.** Block diagram of FxLMS algorithm based single-channel feedforward ANC systems.

non-Gaussian distribution [5]. We consider impulse noise with symmetric $\alpha$-stable (S$\alpha$S) distribution $f(x)$ having characteristic function of the form [5]

$$\varphi(t) = e^{-\gamma|t|^{\alpha}}, \tag{2}$$

where $0<\alpha<2$ is called the characteristics exponent and it is the shape parameter, and $\gamma>0$ is the scale parameter called as dispersion. If a stable random variable has a small value for $\alpha$, then distribution has a very heavy tail, i.e., it is likely to observe values of random variable which are far from its central location. For $\alpha=2$ it is the Gaussian distribution, and for $\alpha=1$ it is the Cauchy distribution. An S$\alpha$S distribution is called standard if $\gamma=1$. In this paper, we consider ANC of impulsive noise with standard S$\alpha$S distribution, i.e., $0<\alpha<2$ and $\gamma=1$. The PDFs of standard S$\alpha$S process for various values of $\alpha$ are shown in Fig. 2. It is evident that for small value of $\alpha$ process has a peaky and heavy tailed distribution.

There has been a very little research on active control of impulsive noise, at least up to the best knowledge of authors. In practice the impulsive noises do exist and it is of great meaning to study its control. For stable distributions, the moments only exist for the order less than the characteristic exponent [5], and hence the mean-square-error criterion, which is bases for FxLMS algorithm, is not an adequate optimization criterion. Thus FxLMS algorithm may become unstable, when the primary noise is impulsive.

For an S$\alpha$S process with $\alpha<2$, only moments of order less than $\alpha$ are finite. Since in these cases the variance is not finite [8], the minimum mean squared error criterion is not an appropriate objective for adaptive filtering. Instead the minimum dispersion serves as a measure of optimality is stable signal processing. The dispersion is a parameter of S$\alpha$S process which plays a similar role to the variance in the Gaussian process. It is shown in [5] that minimizing dispersion is equivalent to minimizing a fractional lower order moment of the residual error, $E\{|e(n)|^p\}$, for $p<\alpha$. In [6], the filtered-x least mean $p$-power algorithm (FxLMP) has been proposed, which is based on minimizing a fractional lower order moment ($p$-power of error) that does exist for stable distributions. It has been shown that FxLMP algorithm with $p<\alpha$ shows better robustness to ANC of impulsive noise. However, due to the calculation of fractional power at each iteration, the computational complexity of FxLMP algorithm may be formidable. In this paper, therefore, we restrict ourselves to adaptive algorithm based on modifying the signals used in adaptation.

In [7] a simplified variant of FxLMS algorithm has been proposed for ANC of impulsive noise. The basic idea is here to ignore the samples of the reference signal $x(n)$ if its amplitude is above a certain value set by its statistics. As compared with the FxLMS algorithm, this algorithm gives stable and robust performance. However, its performance degrades heavily for small values of $\alpha$. In this paper, we modify this algorithm to get improved performance for ANC of impulse noise. We see that for almost same computational load, a better robustness and stability is achieved. Extensive simulations are carried out which demonstrate the effectiveness of the proposed method.

The rest of the paper is organized as follows. Section 2 describes the existing algorithms for ANC of impulse noise. Section 3 describes the proposed algorithm in comparison with that in [7]. Simulation results are discussed in Section 4, and concluding remarks are given in Section 5.

## 2. Existing algorithms

In order to improve the robustness of adaptive algorithms for processes having PDFs with heavy tails (i.e. signals with outliers), one of the following solution may be adopted:

(i) A robust optimization criterion may be used to derive the adaptive algorithm.
(ii) The large amplitude samples may be ignored.
(iii) The large amplitude samples may be replaced by an appropriate threshold value.

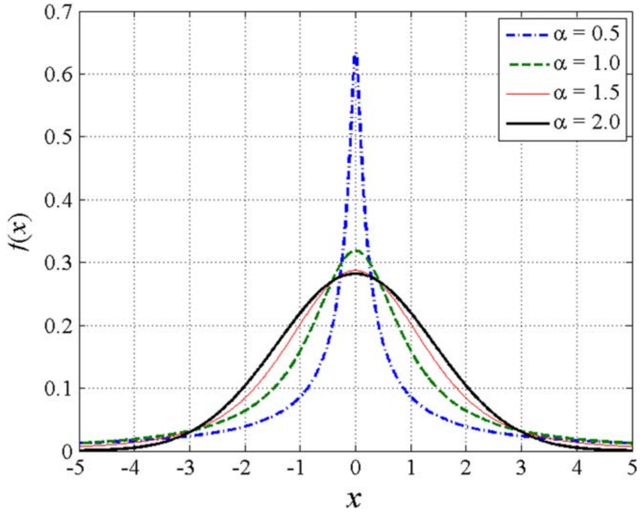


**Fig. 2.** The PDFs of standard symmetric α-stable (SαS) process for various values of α.

The existing algorithms for ANC of impulsive noise are based on first two approaches (as explained in this section) and we consider third approach in the proposed algorithm (as explained in the next section).

### *2.1. Filtered-x least mean p-power (FxLMP) algorithm [6]*

For some $0<p<\alpha$, minimizing the $p$th moment $E\{|e(n)|^p\} \approx |e(n)|^p$, the stochastic gradient method to update $W(z)$ is given as [6]

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu p|e(n)|^{p-1}\,\mathrm{sgn}(e(n))[\hat{s}(n) * \mathbf{x}(n)], \tag{3}$$

where

$$\mathrm{sgn}(e(n)) = \begin{cases} 1, & e(n)>0, \\ 0, & e(n)=0, \\ -1, & e(n)<0. \end{cases} \tag{4}$$

This is FxLMP algorithm, which is LMP generalization of the FxLMS algorithm and for $p=2$, it reduces to FxLMS algorithm. It has been concluded in [6] that $p$ as close as possible to $\alpha$ gives the fastest convergence, with a natural upper bound being $p<\alpha$, since the moment does not exist for the larger values.

### *2.2. Sun's (modified-reference FxLMS) algorithm [7]*

Sun's algorithm is a slightly modified version of the FxLMS algorithm given in (1). In order to improve the stability of the FxLMS algorithm for ANC of impulsive noise, here the samples of the reference signal $x(n)$ are ignored, if their magnitude is above a certain threshold set by statistics of the signal. Thus the reference signal is modified as

$$x'(n) = \begin{cases} x(n), & \text{if } x(n) \in [c_1, c_2], \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

and using this modified reference signal Sun's algorithm is given as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)[\hat{s}(n) * \mathbf{x}'(n)]. \tag{6}$$

Here, the thresholding parameters $c_1$ and $c_2$ can be obtained offline for ANC systems. A few comments on choosing these parameters are given later. The transformation between $x(n)$ and $x'(n)$ is shown in Fig. 3(a). In our experience, this algorithm becomes unstable for $\alpha<1.5$, when the PDF is peaky and reference noise is highly impulsive. The main advantage is that the computational complexity of this algorithm is same as that of the FxLMS algorithm.

## 3. Proposed algorithm

The proposed algorithm is a modified and extended version of Sun's algorithm [7]. Consider the block diagram of FxLMS algorithm based single-channel feedforward ANC is shown in Fig. 1. Assuming that $W(z)$ is an FIR filter of tap-weight

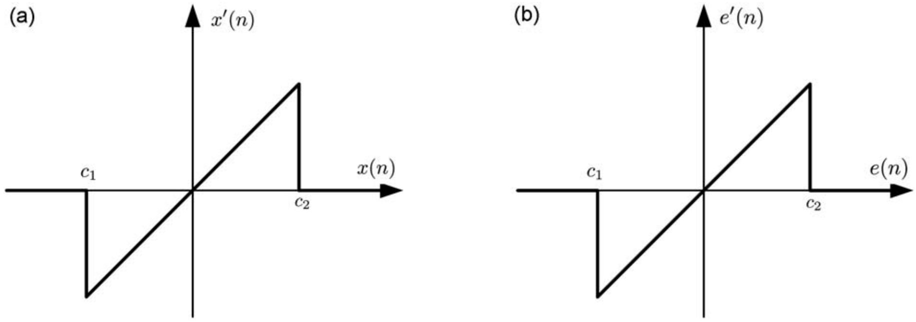


**Fig. 3.** Transformation for (a) reference signal in Sun's algorithm and (b) error signal in modified-Sun's algorithm.

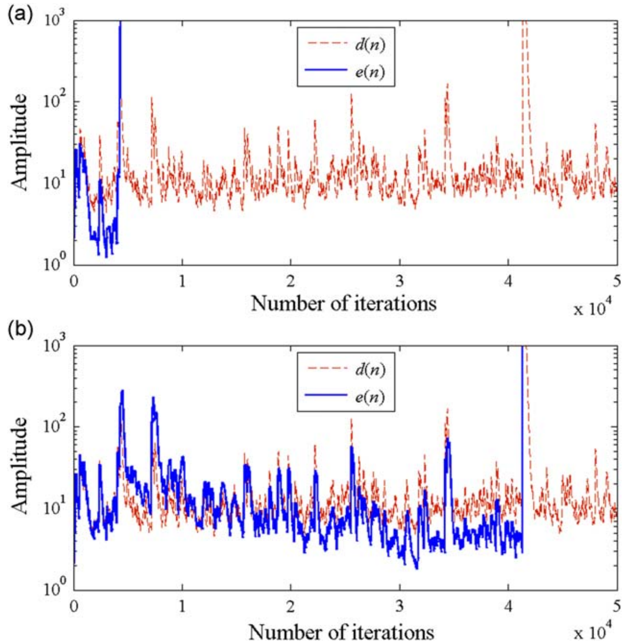


**Fig. 4.** Trend of residual error signal $e(n)$ for one realization of S$\alpha$S process with $\alpha = 1.3$. (a) FxLMS algorithm and (b) Sun's algorithm.

length $L$, the secondary signal $y(n)$ is expressed as

$$y(n) = \boldsymbol{w}^{\mathrm{T}}(n)\boldsymbol{x}(n), \tag{7}$$

where $\boldsymbol{w}(n)$ is the tap-weight vector given as

$$\boldsymbol{w}(n) = [w_0(n), w_1(n), \ldots, w_{L-1}(n)]^{\mathrm{T}}, \tag{8}$$

and using the recent $L$ samples, the reference signal vector $\boldsymbol{x}(n)$ is constructed as

$$\boldsymbol{x}(n) = [x(n), x(n-1), \ldots, x(n-L+1)]^{\mathrm{T}}. \tag{9}$$

The residual error signal $e(n)$ is given as

$$e(n) = d(n) - y'(n), \tag{10}$$

where $d(n) = p(n) * x(n)$ is the primary disturbance signal, $y'(n) = s(n) * y(n)$ is the secondary canceling signal, $*$ denotes linear convolution and $p(n)$ and $s(n)$ are impulse responses of the primary path $P(z)$ and secondary path $S(z)$, respectively. The primary disturbance $d(n)$, being correlated with the reference signal $x(n)$, is impulsive in nature and hence, the residual error signal $e(n)$ is also impulsive in nature. For example, the curves of absolute value of residual error signal $e(n)$ in a typical simulation for ANC of S$\alpha$S process are shown in Fig. 4. It is clear that error signal is impulsive in nature, and it may perturb the adaptation of the adaptive algorithm. In the worst case the ANC system may become unstable, even if (robust criterion-based) FxLMP algorithm or (modified reference signal-based) Sun's algorithm is employed.

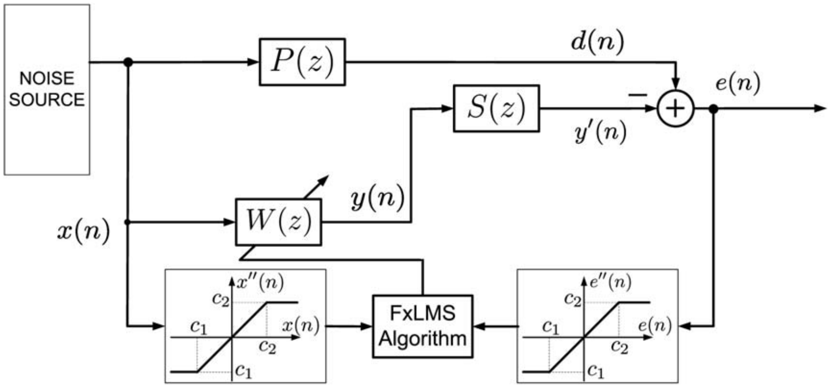


**Fig. 5.** Block diagram of proposed algorithm for single-channel feedforward ANC systems.

In order to improve the robustness of Sun's algorithm, we extend the idea of (5) to the error signal as well and compute a new error signal as

$$e'(n) = \begin{cases} e(n), & \text{if } x(n) \in [c_1, c_2], \\ 0, & \text{otherwise}. \end{cases} \tag{11}$$

Now the update equation for FxLMS algorithm is modified as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e'(n)[\hat{s}(n) * \mathbf{x}'(n)]. \tag{12}$$

Effectively, the idea is to freeze the adaptation of $W(z)$ when a large amplitude is detected in the error signal $e(n)$, and hereafter this is called modified-Sun's algorithm [9].

In order to further improve the robustness of Sun's algorithm; instead of ignoring the large amplitude sample; we clip the sample by a threshold value. This increases the robustness of the algorithm as will be demonstrated by the simulation results. Thus the reference signal is modified as

$$x''(n) = \begin{cases} c_1, & x(n) \leqslant c_1, \\ c_2, & x(n) \geqslant c_2, \\ x(n), & \text{otherwise}. \end{cases} \tag{13}$$

As stated earlier, ignoring (or clipping) the peaky samples in the update of FxLMS algorithm does not mean that peaky samples will not appear in the residual error $e(n)$. The residual error may still be so peaky, that in the worst case might cause ANC to become unstable. We extend the idea of (13) to the error signal $e(n)$ as well, and a new error signal is obtained as

$$e''(n) = \begin{cases} c_1, & e(n) \leqslant c_1, \\ c_2, & e(n) \geqslant c_2, \\ e(n), & \text{otherwise} \end{cases} \tag{14}$$

and proposed modified FxLMS algorithm for ANC of impulse noise is as given below

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e''(n)[\hat{s}(n) * \mathbf{x}''(n)]. \tag{15}$$

The block diagram of the proposed algorithm is shown in Fig. 5. It is worth mentioning that, due to fractional power computation, the computational complexity of FxLMP algorithm might be high for practical ANC system. The proposed method has almost the same computational complexity as that of the FxLMS algorithm.

### *3.1. Comments on selection of thresholding parameters $c_1$ and $c_2$*

As stated earlier, the basic idea of Sun's algorithm is to ignore the samples of the reference signal $x(n)$ beyond certain threshold $[c_1, c_2]$ set by the statistics of the signal [7]. Here the probability of the sample less than $c_1$ or larger than $c_2$ are assumed to be 0, which is consistent with the fact that the tail of PDF for practical noise always tends to 0 when the noise value is approaching $\pm\infty$. Effectively, Sun's method assumes the same PDF for $x'(n)$ (see Eq. (5)) with in $[c_1, c_2]$ as that of $x(n)$, and neglects the tail beyond $[c_1, c_2]$. The stability of Sun's algorithms depends heavily on appropriate choice of $[c_1, c_2]$.

As shown in Fig. 5, the proposed method adds a saturation nonlinearity in the reference and error signal paths. Here, instead of ignoring, the peaky samples are replaced by the thresholding values $c_1$ and $c_2$. Thus, the performance of the proposed method also depends on the parameters $c_1$ and $c_2$. The optimal value (as well as whole interval of the stability range) of $c_1$ and $c_2$ may be different for Sun's and the proposed algorithms due to their different strategies to deal with peaky samples. The offline measurements are integral part of the practical ANC systems, and hence $c_1$ and $c_2$ can be estimated by offline-obtained statistics of the reference noise.

## 4. Computer simulations

This section provides the simulation results to verify the effectiveness of the proposed algorithm in comparison with the FxLMP algorithm and Sun's algorithm. The acoustic paths are modeled using data provided in the disk attached with [3]. Using these data $P(z)$ and $S(z)$ are modeled as FIR filter of length 256 and 128, respectively. The frequency response of the acoustic paths is shown in Fig. 6. It is assumed that the secondary path modeling filter $\hat{S}(z)$ is exactly identified as $S(z)$. The ANC filter $W(z)$ is selected as an FIR filter of tap-weight length 192. The reference noise signal $x(n)$ is modeled by standard S$\alpha$S process with the following values for the characteristics exponent $\alpha$:

- Case 1, $\alpha = 1.3$,
- Case 2, $\alpha = 1.5$, and
- Case 3, $\alpha = 1.7$.

Here Case 1 corresponds to the situation when the noise is highly impulsive, and Case 3 to the situation, when the noise is close to Gaussian with impulses occurring at rare occasions. Since second-order moment does not exist for the S$\alpha$S process, the mean square error has no significance, and hence we use noise reduction (NR) as performance measure, being defined as

$$\mathrm{NR}(n) = \frac{A_e(n)}{A_d(n)}, \tag{16}$$

where $A_e(n)$ and $A_d(n)$ are estimates of absolute values of residual error signal $e(n)$ and disturbance signal $d(n)$ at the location of error microphone. These estimates are obtained using lowpass estimators as below

$$A_e(n) = \lambda A_e(n-1) + (1-\lambda)|e(n)|, \tag{17}$$

$$A_d(n) = \lambda A_d(n-1) + (1-\lambda)|d(n)|, \tag{18}$$

where $|\cdot|$ is the absolute value of quantity, and $\lambda$ is the forgetting factor $(0.9<\lambda<1)$. In simulations, we have used $\lambda = 0.99$.

The simulation parameters for various algorithms are experimentally selected for fast and stable convergence, and are summarized in Table 1. For each case, 25 realizations of the process are considered. It is worth mentioning, that, up to Authors' best knowledge this is first extensive simulation study of ANC for impulse noise.

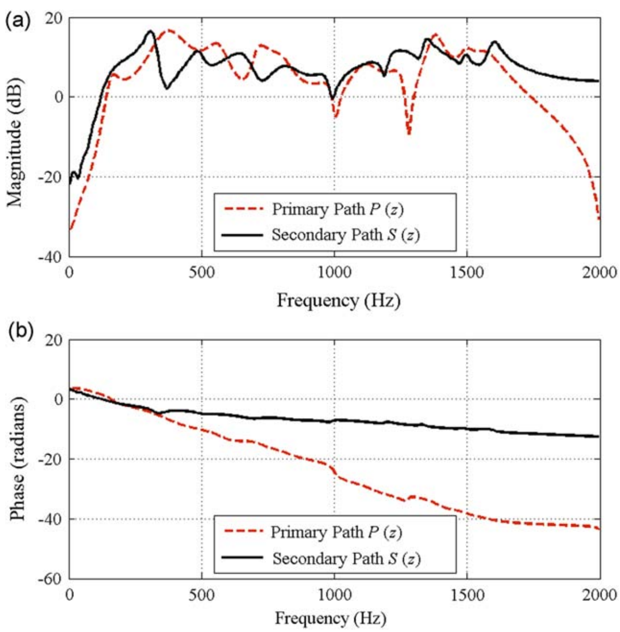


**Fig. 6.** Frequency response of acoustic paths used in computer simulations. (a) Magnitude response and (b) phase response.

**Table 1**
Simulation parameters for computer experiments.

| | Case 1 ($\alpha = 1.3$) | Case 2 ($\alpha = 1.5$) | Case 3 ($\alpha = 1.7$) |
|---|---|---|---|
| FxLMS algorithm | $\mu = 1 \times 10^{-6}$ | $\mu = 1 \times 10^{-6}$ | $\mu = 1 \times 10^{-6}$ |
| FxLMP algorithm | $p = 1.29,\ \mu = 1 \times 10^{-6}$ | $p = 1.49,\ \mu = 1 \times 10^{-6}$ | $p = 1.69,\ \mu = 5 \times 10^{-6}$ |
| Sun's algorithm | $\mu = 1 \times 10^{-6}$ | $\mu = 1 \times 10^{-6}$ | $\mu = 5 \times 10^{-6}$ |
| Proposed algorithms | $\mu = 1 \times 10^{-6}$ | $\mu = 5 \times 10^{-6}$ | $\mu = 1 \times 10^{-5}$ |

### *4.1. Case 1*

The simulations results for Case 1, which represents S$\alpha$S process with heavy tail, are presented in Fig. 7. Here the thresholding parameters $[c_1, c_2]$ are selected on the basis of percentile values for reference noise. Since we have assumed symmetric distribution for the reference noise, a large percentile value, for example above 90 percentile, would give value for upper threshold $c_2$ and small percentile value, for example below 10 percentile, would give lower threshold $c_1$. Extensive simulations are carried out to determine suitable values for the thresholding parameters $[c_1, c_2]$ in Sun's algorithm and the proposed modified algorithms, and those values are selected that give fast and stable convergence. In Sun's algorithm, the parameters $[c_1, c_2]$ are experimentally selected as [0.5, 99.5] percentile of the reference noise $x(n)$, and in proposed algorithms, $[c_1, c_2]$ are selected as [0.1, 99.9] percentile of the $x(n)$.

In Fig. 7, each row represents signals for each realization of the process, as marked by circled number. The sub-figures in column (a) show the disturbance signal $d(n)$ at the error microphone. The sub-figures in columns (b), (c), (d), (e), and (f) show the residual error signal $e(n)$ in the FxLMS algorithm, FxLMP algorithm, Sun's algorithm, modified-Sun's algorithm, and the proposed algorithm, respectively. We see that the FxLMS algorithm is unstable for all realizations of the process. Sun's algorithm is unstable for about 20% realizations and the FxLMP algorithm is unstable for a couple of realizations. As compared with the other algorithms, the proposed algorithms are stable for all realizations. The curves for averaged NR for Case 1 are shown in Fig. 8, where Fig. 8(a) shows results averaged over all realizations. We have seen that FxLMP algorithm and Sun's algorithm are not stable for all realizations. The NR curves obtained by averaging only stable realizations for FxLMP algorithm and Sun's algorithm are shown in Fig. 8(b). This figure clearly shows that the proposed algorithms give the best performance than the other methods, in both stability and the convergence speed.

### *4.2. Cases 2 and 3*

As in Case 1, extensive simulations are carried out to determine suitable values for the parameters $[c_1, c_2]$, and those values are selected that give fast and stable convergence. In both, Cases 2 and 3, the parameters $[c_1, c_2]$ are experimentally found as [0.05, 99.95] and [0.1, 99.9] percentile of the reference noise $x(n)$, in Sun's algorithm and proposed algorithms, respectively. For the sake of space, only averaged results are presented in these cases.

Fig. 9 shows curves of averaged NR for various methods in Case 2. Here the FxLMP and Sun's algorithms become unstable for a couple of realizations, and the proposed algorithms are stable for all realizations. From Fig. 9(b) it is evident that the performance of the proposed algorithm is better than the other algorithms considered in this paper. Figure 10 shows curves of averaged NR for various methods in Case 3. As stated earlier, this case corresponds to $\alpha = 1.7$, and hence process is close to Gaussian. Therefore, FxLMS algorithm is also considered for comparison. We have observed that the FxLMS, FxLMP, and Sun's algorithms are unstable for a couple of realizations, and only the proposed algorithms are stable for all realizations. From Fig. 9(b) it is evident that the performance of the proposed algorithms is better than the other algorithms considered in this paper.

### *4.3. Discussion*

From the simulation results (presented in Figs. 7–10) for ANC of impulsive noise modeled by non-Gaussian standard S$\alpha$S process, we observe that:

- The FxLMS algorithm is unstable for small values of $\alpha$, and has a very poor convergence for $\alpha \to 2$.
- Sun's algorithm, which is a modified-reference FxLMS algorithm where reference signal is modified by ignoring large magnitude samples in the update equation, shows better robustness as compared with the FxLMS algorithm. However, stability cannot be guaranteed for S$\alpha$S process with $\alpha \to 1$.
- The FxLMP algorithm has better robustness as compared with Sun's algorithm.
- The performance of Sun's algorithm can be greatly improved by freezing the adaptation when a large amplitude is detected in the error signal $e(n)$ (modified-Sun's algorithm).

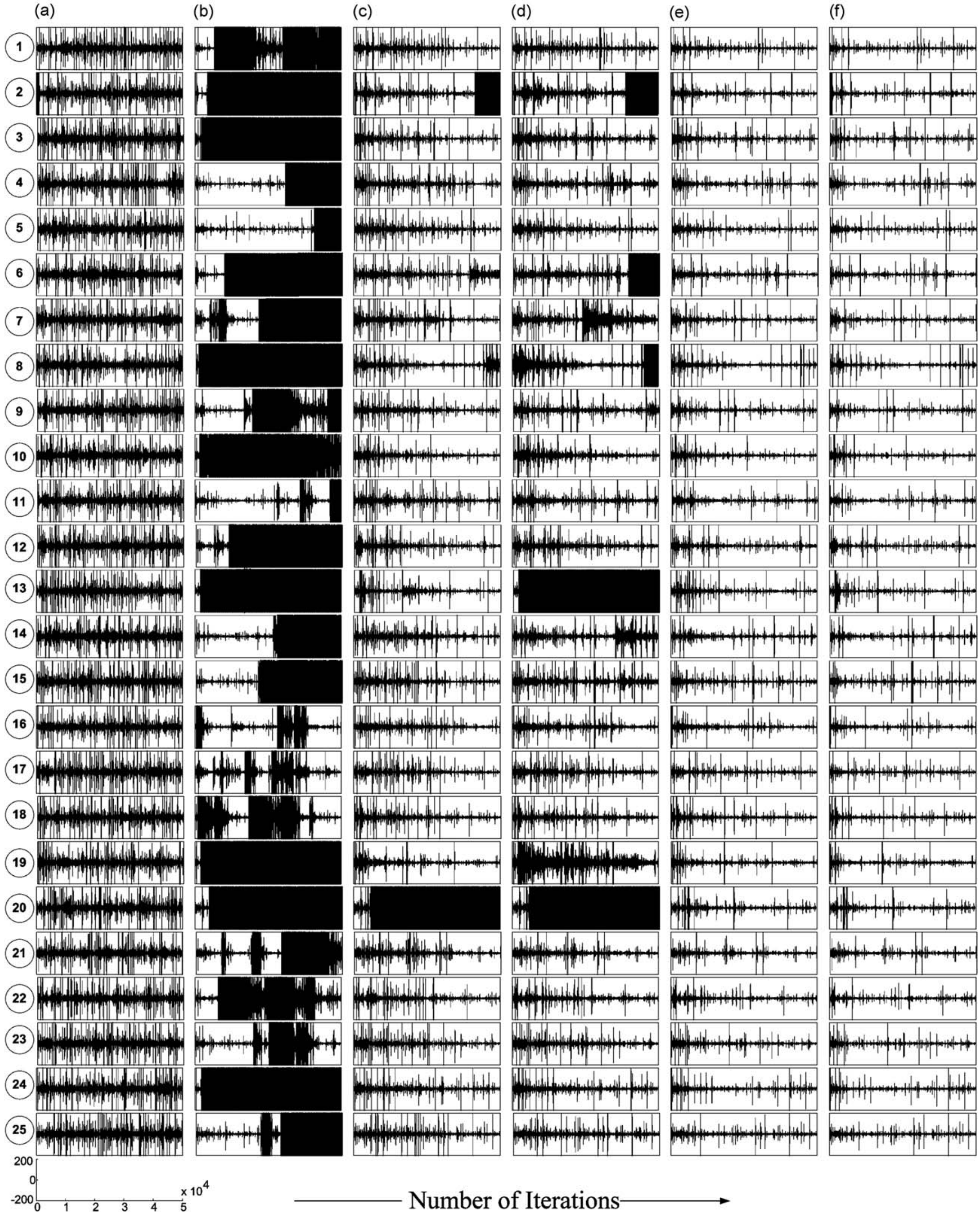


**Fig. 7.** Simulation results for reference noise with $\alpha = 1.3$ (Case 1). Each row represents one realization of the process. Sub-figures in column (a) show the disturbance signal $d(n)$ at the error microphone. Sub-figures in columns (b), (c), (d), (e), and (f) show the residual error signal $e(n)$ in FxLMS algorithm, FxLMP algorithm, Sun's algorithm, modified-Sun's algorithm, and proposed algorithm, respectively.

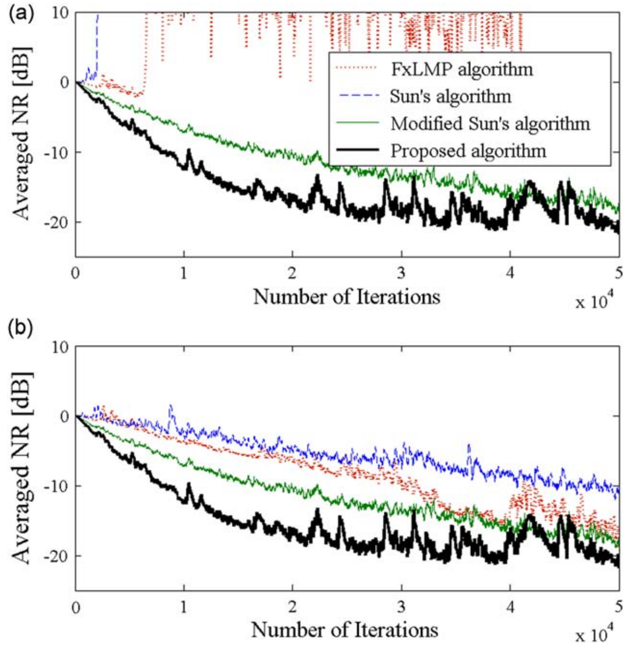


**Fig. 8.** Curves for averaged noise reduction (NR) in Case 1 ($\alpha = 1.3$). (a) Averaged over all realizations and (b) averaged considering stable realizations for FxLMP, and Sun's algorithms.

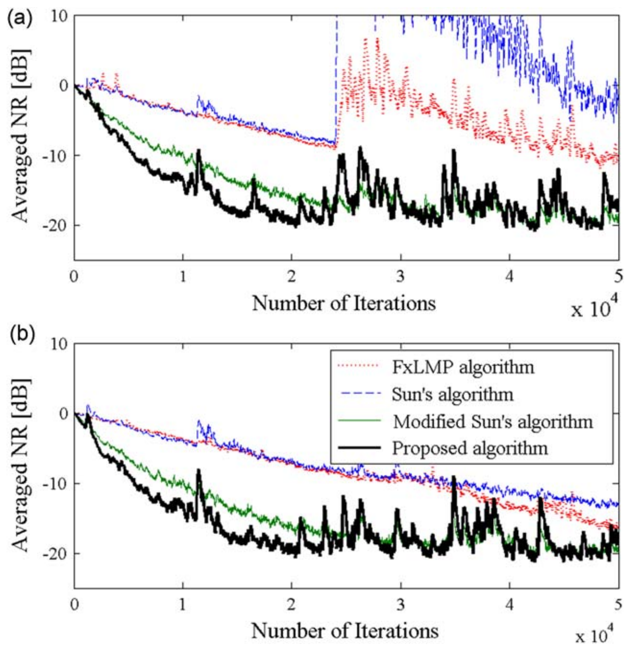


**Fig. 9.** Curves for averaged noise reduction (NR) in Case 2 ($\alpha = 1.5$). (a) Averaged over all realizations and (b) averaged considering stable realizations for FxLMP, and Sun's algorithms.

- The proposed algorithm, which is a modified FxLMS algorithm where large valued samples in the reference signal $x(n)$ and error signal $e(n)$ are replaced by appropriate threshold values, achieves a very fast convergence speed and stable performance, and hence best overall performance than the other methods considered in this paper.

## 5. Concluding remarks

In this paper we have presented new results for ANC of impulsive noise. It is shown that the proposed algorithm has very fast convergence and good stability for ANC of impulse noises. The main idea to modify the reference and/or error

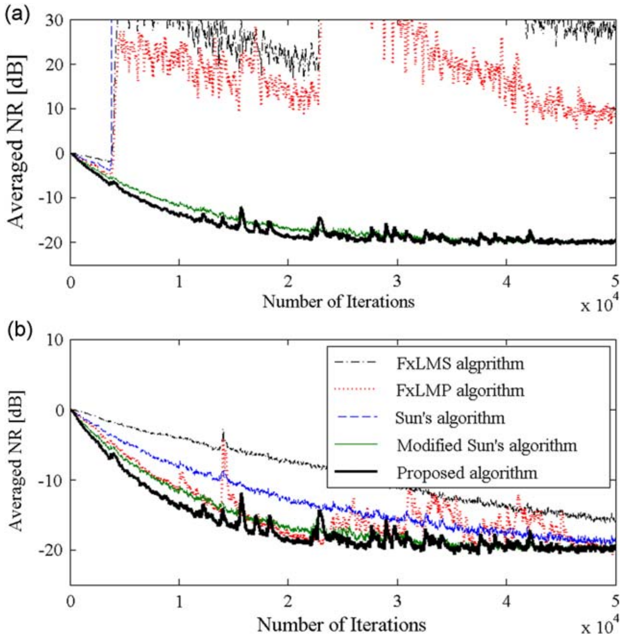


**Fig. 10.** Curves for averaged noise reduction (NR) in Case 3 ($\alpha = 1.7$). (a) Averaged over all realizations and (b) averaged considering stable realizations for FxLMS, FxLMP, and Sun's algorithms.

signal in the FxLMS algorithm on the basis of appropriate threshold parameters $c_1$ and $c_2$. In this paper these parameter values are assumed to be available offline. It would be interesting to explore the estimation of these parameters in online fashion during the operation of ANC systems.

In this paper extensive computer simulations are carried out to demonstrate the effectiveness of proposed algorithm, and performing real-time experiments is a future task. Beside stable processes, the impulsive noise may be of transient sinusoids type, as considered in [10]. In future it would be interesting to investigate the adaptive filtering algorithms for ANC of impulsive noise that are not $\alpha$-stable.

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