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Intelligent Adaptive Active Noise Control in Non-stationary Noise Environments

비정상 잡음환경에서의 지능형 적응 능동소음제어

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ABSTRACT: The famous filtered-x least mean square (FxLMS) algorithm for active noise control (ANC) systems may become unstable in non-stationary noise environment. To solve this problem, Sun's algorithm and Akhtar's algorithm are developed based on modifying the reference signal in update of FxLMS algorithm, but these two algorithms have dissatisfactory stability in dealing with sustaining impulsive noise. In proposed algorithm, probability estimation and zero-crossing rate (ZCR) control are used to improve the stability and performance, at the same time, an optimal parameter selection based on fuzzy system is utilized. Computer simulation results prove the proposed algorithm has faster convergence and better stability in non-stationary noise environment.
Keywords: ANC, FxLMS, Non-stationary noise, Zero-crossing rate, Fuzzy system.
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초 록: 능동소음제어에서 널리 사용되는 FxLMS 알고리즘은 비정상 잡음환경에서 불안정하게 동작하는 경우가 있다. 이와 같은 문제를 해결하기 위하여, Sun과 Akhtar는 FxLMS 알고리즘의 갱신 과정에서 기준신호를 수정하는 방법을 제안하였다. 그러나 이들의 방법은 임펄스 노이즈가 발생할 경우 만족스러운 안정성을 보여주지 못하였다. 본 논문에서 제안된 알고리즘은 확률추정과 영교차율을 이용하여 능동소음제어의 안정성과 성능을 개선하였다. 또한 최적의 파라미터 선정을 위하여 퍼지 추론을 사용하였다. 제안된 방법의 실험결과 비정상 잡음환경에서 기존의 방법에 비하여 우수한 안정성과 빠른 수렴속도를 보여줬다.
핵심용어: 능동소음제어, FxLMS, 비정상잡음, 영교차율, 퍼지 시스템

I. Introduction

Acoustic noise problems become more and more evident. But the passive techniques in acoustic noise control such as enclosures, barriers, are relatively large, costly, and ineffective at low frequencies. ANC based on cancellation of acoustic waves [1] can efficiently attenuate low frequency noise with benefits in size and cost.

The famous FxLMS algorithm[2] is shown in Fig. 1. Essentially, ANC system cancels the primary noise by generating and combining an anti-noise (with equal amplitude but opposite phase).[1,3] For generating this anti-noise, we use adaptive filter $W(z)$ to estimate the

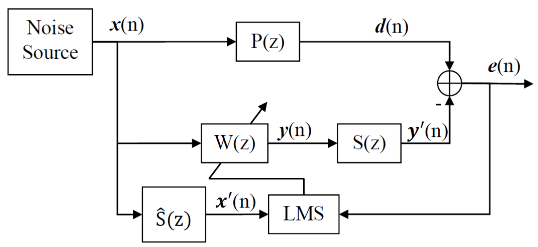

Fig. 1. Block diagram of ANC system using the FxLMS algorithm.

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unknown primary transfer function $P(z)$ by minimizing the mean square error $e(n)$; the reference signal $x(n)$ is received by microphone; and then, we generate digital anti-noise signal $y(n)$; this digital signal is transformed to a real anti-noise $y'(n)$ in an acoustic domain after passing through the secondary path $S(z)$. The update equation of adaptive filter $W(z)$ is

$$w(n+1) = w(n) + \mu x'(n) e(n), \qquad (1)$$

where μ is the step size, $x'(n)$ is the filtered $x(n)$ signal by $S(z)$, but $S(z)$ is unknown and must be estimated by an additional filter $\hat{S}(z)$.[2]

The FxLMS algorithm may become unstable, especially in a non-stationary impulsive noise environment.[4] To solve this problem, Sun proved that the samples of the reference signal should be treated probabilistically.[4]

Sun's algorithm and Akhtar's algorithm[5] used the assumption that the noise has a uniform distribution within a certain range, then they ignored (or clipped) the noise out of this range. In their experiments, they selected the threshold parameters offline and improved the stability for a special impulsive noise environment. But these two algorithms have dissatisfied performance and stability in huge magnitude or sustaining impulsive noise environment.

To improve the performance, we propose an estimated probability density function (PDF) of reference signal; to improve the stability, we control the adaptive filter's step size according zero-crossing rate; and to select optimal threshold in various noise environments, we develop an online parameter selection method based on fuzzy system.

The organization of this paper is as follows. Sun's algorithm and Akhtar's algorithm are briefly described in Section II. Section III introduces the proposed algorithm. In Section IV, the simulation results are illustrated comparing with the existing algorithms. Conclusions are drawn in section V.

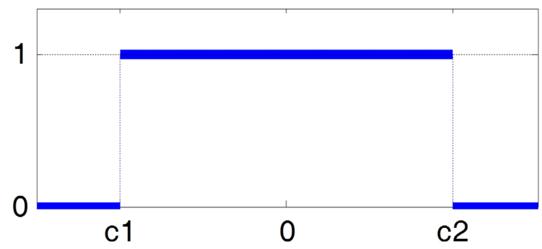

Fig. 2. PDF employed in Sun's algorithm.

II. Modified FxLMS algorithm

FxLMS algorithm may become unstable in non-stationary impulsive noise environment. Some algorithms have been researched to solve this problem. One is based on minimizing least mean pth-power (FxLMP) of the error signal[6]; the others are based on modifying the reference signal during the update of FxLMS algorithm. Sun's algorithm and Akhtar's algorithm are the later approach.

2.1 Sun's algorithm

Sun proved that the samples of the reference signal $x(n)$ should be treated probabilistically as follow

$$w(n+1) = w(n) + \mu e(n) \hat{s}(n) * [P(n) x(n)], \qquad (2)$$

where * denotes linear convolution, $P(n)$ is the PDF of reference signal. This PDF can not be calculated, so the assumed one in Fig. 2 is used. The thresholds c_1 and c_2 are obtained in offline operation. Thus $x(n)$ is modified as

$$x''(n) = \begin{cases} x(n), & \text{if } x(n) \in [c_1, c_2], \\ 0, & otherwise \end{cases}. \qquad (3)$$

After this modification, Sun's algorithm is given as

$$w(n+1) = w(n) + \mu e(n) [\hat{s}(n) * x''(n)]. \qquad (4)$$

2.2 Akhtar's algorithm

Akhtar's algorithm[2] is a modified and extended version of Sun's algorithm, the reference signal is modified as

$$x'''(n) = \begin{cases} c_1, & x(n) \le c_1, \\ c_2, & x(n) \ge c_2, \\ x(n), & otherwise. \end{cases} \quad (5)$$

He also extended this idea to error signal $e(n)$ as shown

$$e'''(n) = \begin{cases} c_1, & e(n) \le c_1, \\ c_2, & e(n) \ge c_2, \\ e(n), & otherwise. \end{cases} \quad (6)$$

Akhtar's algorithm is given below

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

III. Intelligent ANC SYSTEM

Although Sun's algorithm and Akhtar's algorithm increase the robustness, the stability and performance are still not satisfied, especially, when they deal with sustaining impulsive noise. To solve this problem, we develop probability estimation and zero-crossing rate control; and to eliminate the effect of impulsive noise, an optimal parameter selection based on fuzzy control is also utilized.

3.1 Probability estimation

In Sun's and Akhtar's algorithms, they assumed the noise has a uniform distribution within the range $[c_1, c_2]$ and then ignored the noise out of this range. However, the proposed algorithm is different, we use the range $[-c, c]$ instead of $[c_1, c_2]$. Then we assume that the probability of the noise beyond this range exists but decreases rapidly,[7] as

$$P_{x(n)} = \frac{1}{1 + (\frac{x(n)}{c})^K}, \quad (8)$$

where K $(K = 0, 2, 4, 6 \cdots)$ is the attenuation factor and controls the attenuation speed. In proposed algorithm, we experimentally choose K equals 6. The estimated PDF of $K = 6$ is shown in Fig. 3. To compare the attenuation

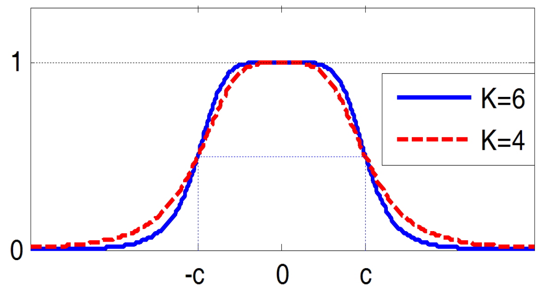

Fig. 3. PDF employed in proposed algorithm (K=6).

speed, the PDF of $K = 4$ is also shown in this figure.

Actually, in proposed algorithm, we utilize a forgetting factor λ $(0.9 < \lambda < 1)$ to smooth the probability of adjacent samples.

$$\frac{1}{P_{x(n)}} = \lambda \frac{1}{P_{x(n-1)}} + (1-\lambda)(1 + (\frac{x(n)}{c})^K). \quad (9)$$

Using this probability estimation, the update equation of FxLMS algorithm is modified as

$$w(n+1) = w(n) + \mu e(n)[\hat{s}(n) * [P_{x(n)} x(n)]]. \quad (10)$$

3.2 Zero-crossing rate control

During experimental implementation, we observe that the coefficients of adaptive filter are sensitive and change rapidly when the ZCR of current signal is relatively high as around 0.9 s and 3.8 s in Fig. 4.

This phenomenon has dual characters. It may help adaptive filter converge quickly at about 0.9 s; or it may lead to a crash after the algorithm has converged at approximately 3.8 s.

According to this phenomenon, zero-crossing rate control is employed after the algorithm has converged.

$$\mu'(n) = \begin{cases} \frac{\mu z_{mean}}{z_x(n)}, & \text{if } converge, \\ \mu, & otherwise \end{cases} . \quad (11)$$

where $z_x(n)$ is the zero-crossing rate around current sample and z_{mean} is the mean zero-crossing rate of the noise.

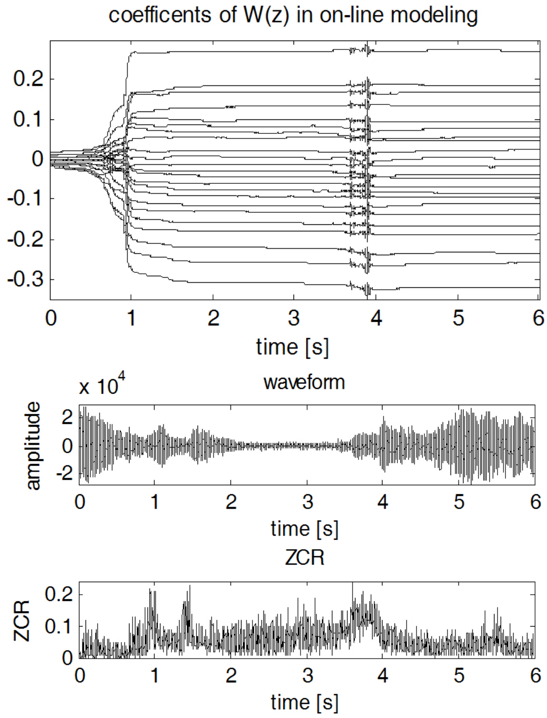

Fig. 4. Coefficients and zero-crossing rate comparisons.

The update equation of FxLMS algorithm is modified to

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

3.3 Optimal parameter selection based on fuzzy control

The threshold parameter c in (8) controls the estimated probability of the reference signal. A small c will treat normal noise as low probability signal, likewise, a large c can not reduce the mischief of impulsive noise, so the choice of c have much more effect on the performance. Our idea is that when impulsive noise appears we shrink c to reduce the effects of this impulsive noise. We propose fuzzy control to utilize this idea. The simulation results in next section show that we successfully eliminate the effects of impulsive noise with a relatively small threshold and preserve the information of normal noise with a relatively large threshold.

Our fuzzy logic controller has two inputs and one output. For fuzzification, the isosceles triangle and max-min method are used.[8] For defuzzification, the center of area method is used.

The first fuzzy input variable x_{mag} is defined as the ratio between current signal magnitude $x(n)$ and mean magnitude value x_{mean} of stationary noise.

$$x_{mag}=|\frac{x(n)}{x_{mean}}|. \tag{13}$$

Second fuzzy input variable x_{dur} is defined as the duration (in samples) of current signal magnitude.

The output of fuzzy controller is x_{coe}, it is the coefficient of x_{mean}. The threshold c can be calculated as follow

$$c=x_{coe}\,x_{mean}. \tag{14}$$

Table 1. Linguistic variable in x_{mag}, x_{dur} and x_{coe}.

	Linguistic variable in $x_{mag}, x_{dur}, x_{coe}$
VS	Very Small, Very Short, Very Small
S	Small, Short, Small
M	Medium
L	Large, Long, Large
VL	Very Large, Very Long, Very Large

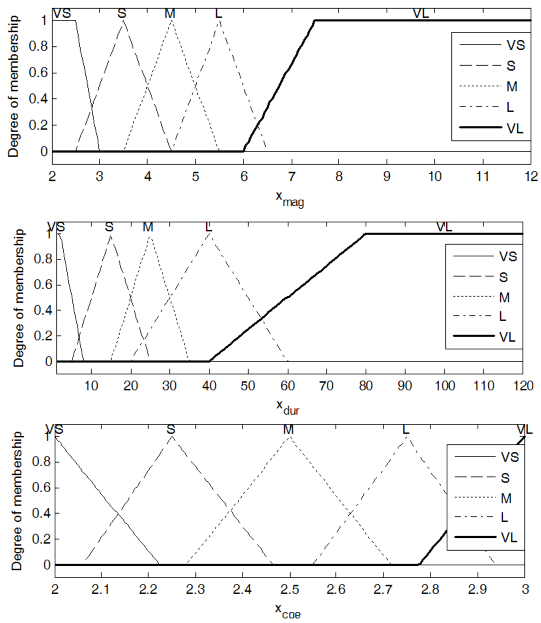

Fig. 5. Membership functions of x_{mag}, x_{dur} and x_{coe}.

Table 2. Fuzzy rules.

$x_{dur} \backslash x_{mag}$	VS	S	M	L	VL
VS	VL	VL	L	M	S
S	VL	L	M	S	VS
M	VL	L	M	S	VS
L	L	L	M	VS	VS
VL	L	M	S	VS	VS

The linguistic variable in x_{mag}, x_{dur} and x_{coe} are shown in Table 1 and the membership functions are shown in Fig. 5.

Fuzzy approximation uses IF ~ Then rule. Our rules are decided based on experiments and shown in Table 2. The block diagram of proposed algorithm is shown as follow

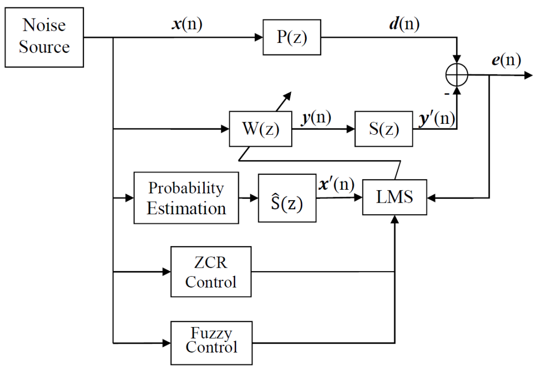

Fig. 6. Block diagram of proposed ANC algorithm.

IV. Computer Simulation

This section provides the simulation results to verify the effectiveness of the proposed algorithm comparing with Sun's algorithm and Akhtar's algorithm.

All reference signals we used are actual noise. In our simulations, the primary path $P(z)$ and the secondary path $S(z)$ in Fig. 1 are IIR filter and the filter parameters can be found in the disk attached to with Ref.[2]. The length of adaptive filter we selected is 256. We use noise ratio(NR) as performance measure. NR is defined as

$$NR(n) = 10\log_{10}\frac{P_e(n)}{P_d(n)}, \tag{15}$$

where $P_e(n)$ and $P_d(n)$ are the powers of residual error signal $e(n)$ and disturbance signal $d(n)$.

4.1 Case 1

The reference noises for Case 1 are car noises. We pick out 19 car noise signals with lots of instantaneous and sustaining impulses. The average length of these noise signals is 20 seconds. After implementation with these signals, Sun's algorithm is unstable for 10 realizations, Akhtar's algorithm is unstable for 6 realizations, as compared with them, the proposed algorithm is stable for all realizations.

One of the noise signal is shown in Fig. 7. The results given in Figs. 8 and 9 demonstrate that the proposed algorithm gives the best performance, stability and convergence speed.

4.2 Case 2

In this case, factory noises are recorded as reference noises. We pick out 20 noise signals, one of them is shown in Fig. 10. These factory noises have few impulses, but the noise magnitude is changing quickly. Dealing with this kind of noise, Sun's algorithm and Akhtar's algorithm are stable, but their convergence speed are quite slow.

The average length of these noise signals is only 6 seconds, but the sampling frequency is higher than in Case 1. The results of noise signal in Fig. 10 are shown in Fig. 11 and Fig. 12.

From Case 1 and Case 2, Sun's algorithm and Akhtar's algorithm are relatively unstable and have dissatisfactory stability in dealing with sustaining impulsive noise, the proposed algorithm has much more better performance, stability and convergence speed in non-stationary noise environment.

V. Conclusions

The proposed algorithm is based on modification of FxLMS algorithm. We proposed probability estimation and zero-crossing rate control to improve the stability and

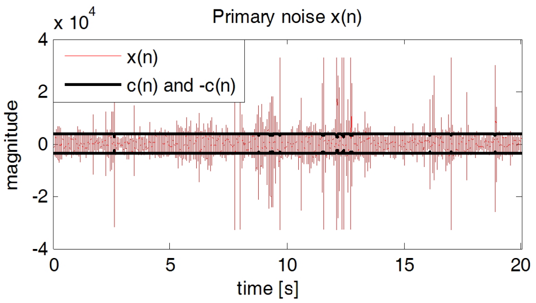

Fig. 7. Primary noise in Case 1 (a car noise 16-bit, 11025 Hz).

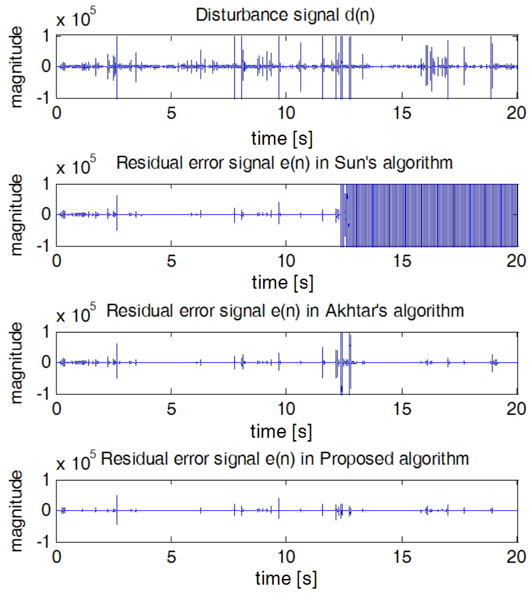

Fig. 8. Simulation results in Case 1: Sub-figures in column show disturbance signal and residual error signals in Sun's algorithm ($\mu=1\times10^{-11}$), Akhtar's algorithm ($\mu=1\times10^{-11}$), and proposed algorithm ($\mu=1\times10^{-10}$, $\lambda=0.999$) respectively.

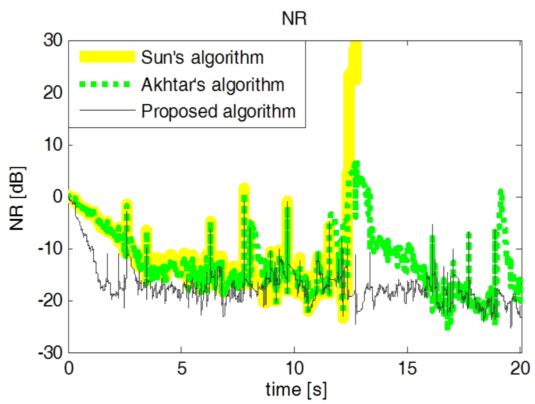

Fig. 9. Curves for noise ratio (NR) in Case 1.

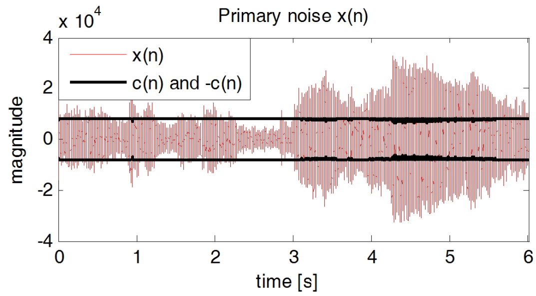

Fig. 10. Primary noise in Case 2 (a factory noise 16-bit, 44100 Hz).

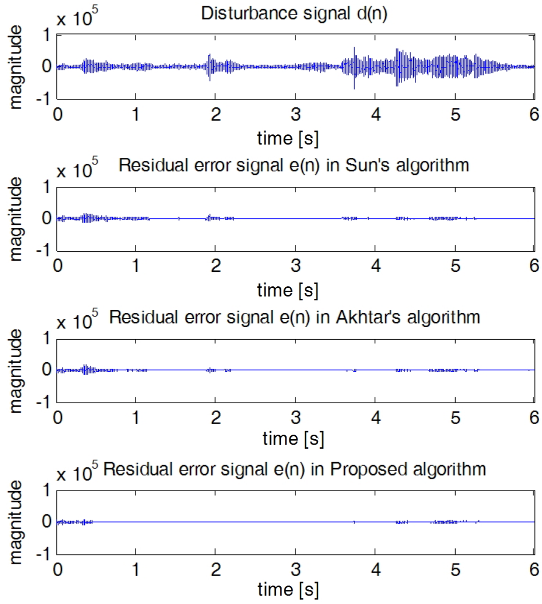

Fig. 11. Simulation results in Case 2: Sub-figures in column show disturbance signal and residual error signals in Sun's algorithm($\mu=1.5\times10^{-12}$), Akhtar's algorithm($\mu=2\times10^{-12}$), and proposed algorithm ($\mu=1\times10^{-11}$, $\lambda=0.999$) respectively.

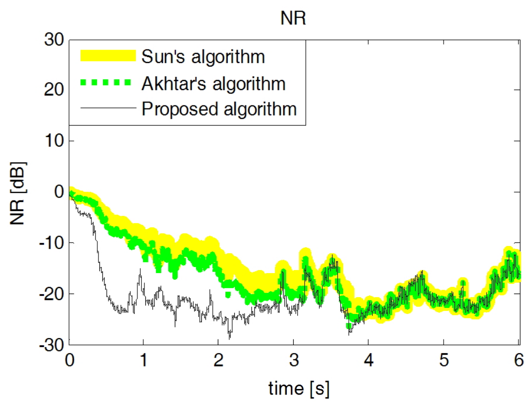

Fig. 12. Curves for noise ratio (NR) in Case 2.

performance. In Sun's and Akhtar's algorithm, they used a special noise environment and estimate the threshold parameters offline. To ameliorate it, we developed an online parameter selection method based on fuzzy control. Comparative simulation results demonstrated the proposed algorithm has improved the stability, performance and convergence speed.

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