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Review of active noise control algorithms for impulsive noise control

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Abstract

Active noise control is gaining popularity in recent years. Especially, active control of impulsive noise is of great interest. Due to specific nature of such noise, standard approach to active control is not satisfying. This paper reviews existing algorithms specifically developed for impulsive noise control. Performance of the algorithms is verified using computer simulations and several noise signals.

Keywords: active noise control, impulsive noise, FxLMS, FxLMP, FxLogLMS.

Przegląd algorytmów aktywnej redukcji hałasu impulsowego

Streszczenie

Aktywna redukcja hałasu zyskuje na popularności w ostatnich latach. Z powodu specyfiki hałasu impulsowego, standardowe podejście do aktywnej redukcji nie jest zadawalające. Niniejsza praca przedstawia algorytmy stworzone specjalnie na potrzeby redukcji hałasu impulsowego, który ze względu na swoją specyfikę nie jest poprawnie tłumiony przez klasyczne algorytmy redukcji hałasu. W pierwszym punkcie przedstawiona jest ogólnie idea aktywnej redukcji hałasu. W drugim punkcie opisany jest hałas impulsowy: charakterystyka, wpływ na człowieka oraz technika modelowania. W trzecim punkcie przedstawiony został podstawowy algorytm aktywnej redukcji hałasu oraz jego modyfikacje stworzone do aktywnej redukcji hałasu impulsowego. W czwartym punkcie przedstawione zostały wyniki porównujące przedstawione algorytmy. Porównanie algorytmów wykonane zostało za pomocą symulacji komputerowej z wykorzystaniem modeli rzeczywistych torów akustycznych oraz dwóch rodzajów hałasu: modelowanego i rzeczywistego nagrania. W ostatnim punkcie zostały przedstawione wnioski z prezentowanej pracy.

Słowa kluczowe: aktywna redukcja hałasu, hałas impulsowy, FxLMS, FxLMP, FxLogLMS.

1. Introduction

Active Noise Control (ANC) requires introducing secondary noise sources. An acoustic wave generated by those sources interferes with the primary noise in the acoustic field. If the secondary noise is generated properly, destructive interference between both waves, resulting in lowering noise level in the so-called quiet zone, occurs [1]. The filtered-reference least mean squares (FxLMS) algorithm is the most popular one for ANC applications. It is based on minimization of the variance of the error signal. Its main advantages are simplicity and low computational effort. However, there are many applications, for which the standard FxLMS algorithm does not perform satisfactorily. One of such cases is occurrence of impulsive noise. This paper reassesses adaptive algorithms designed for active control of impulsive noise.

2. Impulsive noise

It is difficult to define impulsive noise precisely. There are many definitions, which have been created for different purposes. The most general description says that it is a noise with low probability and large amplitude sample. Polish labour law classifies impulsive noise as one or more acoustic events with duration less than 1s [2].

In simulations it is common to model impulsive noise using the symmetric alpha stable distribution with a characteristic function given as:

$$\varphi(t) = \exp(jat - \gamma \, | \, t \, |^{\alpha}) \, , \tag{1}$$

where α is a stability parameter, a is a location parameter and γ is a scale parameter. Parameter α should be within the range from 0 to 2, with higher value resulting in less impulsive signal. To model impulsive noise, the standard distribution is used, i.e. $a = 0$ and $\gamma = 1$.

Real impulsive noise occurs in many environments, where heavy industry hardware is used, like: pumps, gas jets, grinders, engines, jackhammers, pile drivers and many others. Another sources of impulsive noise are explosions and gunfire.

Due to its nature, impulsive noise is exceptionally dangerous, since exposition to it can lead to temporary or permanent hearing damage. The stapedius reflex, which prevents high levels of noise from being transmitted to the cochlea, has too long contraction time and does not secure human ear from impulsive noise.

3. Impulsive noise control

The most popular structure for ANC systems is feedforward control with secondary path model, as presented in Fig. 1.

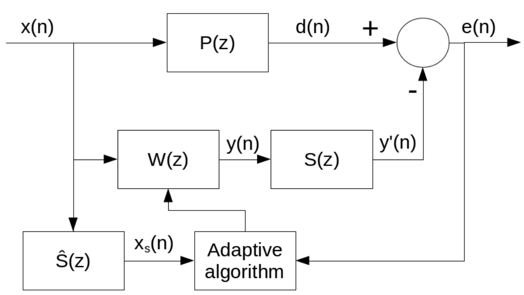

Fig. 1. Block diagram of feedforward single channel ANC system with secondary path model.
Rys. 1. Schemat blokowy jednokanałowego systemu aktywnej redukcji hałasu z modelem ścieżki wtórnej.

The primary noise x, also called reference signal, is propagating through acoustic path P to the error microphone located where a quiet zone is demanded. The ANC system should generate such signal y that after propagating through secondary acoustic path S interferes with the primary noise. Residual noise e is measured by the error microphone and is used to adapt the control filter W. Ŝ is a model of secondary path S. In Fig. 1 n stands for the discrete time sample, and z is a complex variable in the Z-transform. It is common to use an FIR filter for W with order of Lw:

$$\mathbf{w}(n) = [w_0(n), w_1(n), ..., w_{Lw-1}(n)] \, . \tag{2}$$

The filtered reference signal is defined as:

$$\mathbf{x_s}(n) = \hat{S}(n) * \mathbf{x}(n)\,, \tag{3}$$

where Ŝ (n) denotes impulse response of the secondary path model, * is linear convolution operation and

$$\mathbf{x}(n) = [x(n), x(n-1), ..., x(n-Lw+1)]\,. \tag{4}$$

The most popular adaptive algorithm for ANC systems is FxLMS with update equation as follows:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x_s}(n)\,, \tag{5}$$

where μ is step size parameter. Since there may be very big values of reference signal in case of impulsive noise, FxLMS may become unstable [3].

To cope with this problem, a modification was proposed by Sun in [4]. It consists in stopping adaptation impulses are detected. This effect is acquired by modifying the reference signal in the following manner:

$$x'(n) = \begin{cases} x(n), & \text{if } x(n) \in [c_1, c_2] \\ 0 & \text{otherwise} \end{cases}, \tag{6}$$

and the update equation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x'_s}(n)\,, \tag{7}$$

where

$$\mathbf{x'_s}(n) = \hat{S}(n) * \mathbf{x'}(n) \tag{8}$$

and

$$\mathbf{x'}(n) = [x'(n), x'(n-1), ..., x'(n-Lw+1)]\,. \tag{9}$$

Parameters c1 and c2 are thresholding parameters, which can be estimated offline, prior to ANC system operation, or online, simultaneously with the ANC system [5]. Sun's modification improves stability of the FxLMS algorithm, but it deals only with peaks in the reference signal, while those peaks may propagate to the error signal via the acoustic path. In order to eliminate this problem, another modification was proposed in [6]. Similar procedure as in Sun's modification was proposed for the error signal, resulting in a new error signal definition:

$$e'(n) = \begin{cases} e(n), & \text{if } e(n) \in [c_1, c_2] \\ 0 & \text{otherwise} \end{cases}, \tag{10}$$

and the update equation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e'(n)\mathbf{x'_s}(n)\,. \tag{11}$$

When using this modification, adaptation of the ANC system is stopped when a large amplitude sample is present in either reference or error signal. However, the convergence rate is decreased comparing to the standard FxLMS for non-impulsive noise. Another improvement to the FxLMS algorithm proposed by Akhtar is to saturate both reference and error signal at some level, instead of removing them [5]. The resulting update equation takes the following form:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e''(n)\mathbf{x''_s}(n)\,, \tag{12}$$

where

$$\mathbf{x''_s}(n) = \hat{S}(n) * \mathbf{x''}(n) \tag{13}$$

and

$$\mathbf{x''}(n) = [x''(n), x''(n-1), ..., x''(n-Lw+1)] \tag{14}$$

and

$$x''(n) = \begin{cases} x(n), & \text{if } x(n) \in [c_1, c_2] \\ c_1, & \text{if } x(n) < c_1 \\ c_2, & \text{if } x(n) > c_2 \end{cases}, \tag{15}$$

The error signal in (12) is modified according to:

$$e''(n) = \begin{cases} e(n), & \text{if } e(n) \in [c_1, c_2] \\ c_1, & \text{if } e(n) < c_1 \\ c_2, & \text{if } e(n) > c_2 \end{cases}. \tag{16}$$

Saturating large samples instead of ignoring them increases speed of convergence of the adaptive algorithm, without destabilizing it. In all of the aforementioned algorithms, a proper choice of the thresholding parameters is crucial for proper operation of the ANC system.

Another adaptive algorithm is FxLMP, which does not minimize the variance of the error signal, but its pth-power. The structure of the system is the same as for FxLMS, but the update equation takes the form:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu p|e(n)|^{p-1}\,\mathrm{sgn}(e(n))\mathbf{x_s}(n)\,, \tag{17}$$

where parameter p must satisfy $0<p<\mu$, and sgn denotes the signum function:

$$\mathrm{sgn}(e(n)) = \begin{cases} 1, & \text{if } e(n) > 0 \\ 0, & \text{if } e(n) = 0 \\ -1, & \text{if } e(n) < 0 \end{cases}. \tag{18}$$

The FxLMP algorithm is much more robust with respect to impulsive noise. However, a proper selection of parameter p is then crucial.

Another approach for impulsive noise control is presented in [7]. The authors observed that α stable processes, which were used to model impulsive noise had finite logarithmic moments. Minimization of the logarithmic transformation of the error variance yields the following update equation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\,\mathrm{sgn}(e_l(n))\frac{\log|e_l(n)|}{|e_l(n)|}\mathbf{x_s}(n)\,, \tag{19}$$

where the error signal is modified to avoid the logarithmic function diverging to infinity:

$$e_l(n) = \begin{cases} e(n), & \text{if } |e(n)| > 0 \\ 1 & \text{otherwise} \end{cases}. \tag{20}$$

There are also several algorithms basing on the previously mentioned ones, but with a variable step size. The value of the step size parameter is normalized with respect to the reference signal or both reference and error signals. The update equation of the Normalized FxLMS (NFxLMS) takes the form:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)e(n)\mathbf{x_s}(n)\,, \tag{21}$$

where

$$\mu(n)=\frac{\widetilde{\mu}}{\|\mathbf{x_s}(n)\|_2^2+\delta}, \tag{22}$$

δ is a small number to avoid division by zero and $\widetilde{\mu}$ is the constant step size [8]. Similarly, the Normalized FxLMP algorithm can be defined:

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mu(n)p|e(n)|^{p-1}\operatorname{sgn}(e(n))\mathbf{x_s}(n), \tag{23}$$

where

$$\mu(n)=\frac{\widetilde{\mu}}{\|\mathbf{x_s}(n)\|_p^p+\delta} \tag{24}$$

and $||x_s(n)||_p^p$ is p-th norm of the vector.

Like in case of the Sun's algorithm, neither NFxLMS nor NFxLMP algorithm takes into account impulses occurring in the error signal. Extending normalization of the step size with respect to the error signal results in the update equation, like in (21) for the Modified NFxLMS, or (23) for the Modified NFxLMP, but the step size parameter is calculated as:

$$\mu(n)=\frac{\widetilde{\mu}}{\|\mathbf{x_s}(n)\|_2^2+E_e(n)+\delta} \tag{25}$$

for MNFxLMS [9] and

$$\mu(n)=\frac{\widetilde{\mu}}{\|\mathbf{x_s}(n)\|_p^p+E_e(n)+\delta} \tag{26}$$

for MNFxLMP [10], where

$$E_e(n)=\lambda E_e(n-1)+(1-\lambda)e^2(n) \tag{27}$$

and λ is the forgetting factor and $E_e(0)=0$.

4. Simulations and comparison

In order to compare the presented algorithms, extensive computer simulations were carried out. Acoustic paths P and S were modelled using FIR filters and data from [1]. Their frequency responses are shown in Figs. 2 and 3.

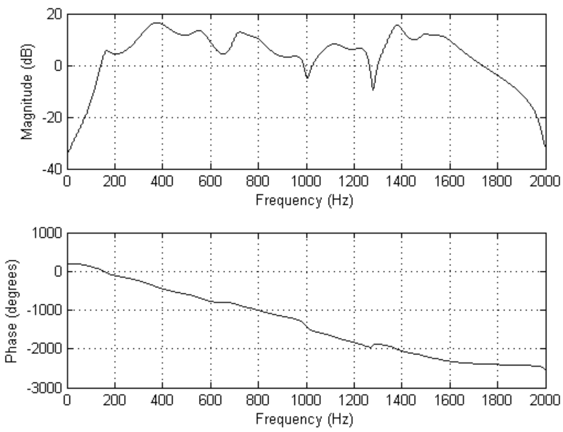

Fig. 2. Frequency response of the primary acoustic path P
Rys. 2. Charakterystyka częstotliwościowa pierwotnego toru akustycznego P

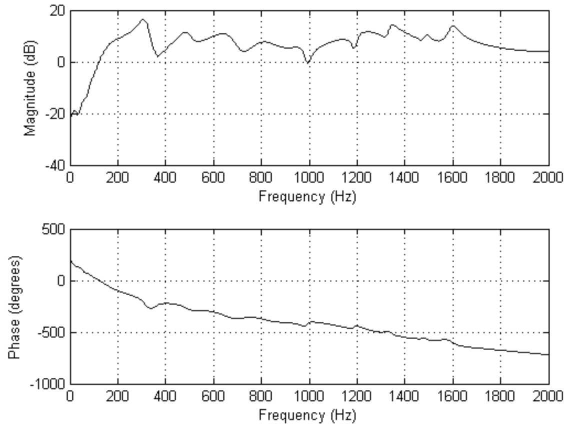

Fig. 3. Frequency response of the secondary acoustic path S
Rys. 3. Charakterystyka częstotliwościowa wtórnego toru akustycznego S

The order of the control filter W was chosen as 128. The average noise reduction (ANR) performance index was used as:

$$ANR(n)=20\log_{10}\frac{A_e(n)}{A_d(n)}, \tag{28}$$

where

$$A_q(n)=\lambda A_q(n-1)+(1-\lambda)\,|\,q(n)\,| \tag{29}$$

and $A_q(0)=0$.

Several noise signals were used to compare the algorithm performance, and two most representative cases are presented below: the noise modelled using the α stable distribution with stability parameter equal to 1.6, and the recorded noise of hammering. Exemplary time plots of these signals are presented in Figs. 4 and 5. In the case of the modelled noise, the experiment results were averaged over 20 realizations in order to reduce randomness of the obtained results. The step size parameter values were chosen by the trial and error method to obtain stable operation and the convergence speed as high as possible. The ideal modeling was assumed, i.e. Ŝ=S.

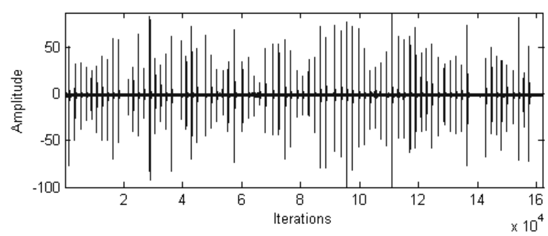

Fig. 4. Time plot of the hammer noise
Rys. 4. Przebieg czasowy hałasu uderzania młotem

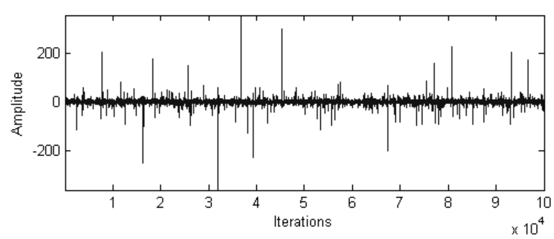

Fig. 5. Time plot of the modelled noise
Rys. 5. Przebieg czasowy hałasu modelowanego

In Figs. 6 to 9, the plots of the ANR index are presented for each algorithm. To increase readability of the plots, the algorithms were divided into two groups: with a fixed step size and with a variable step size.

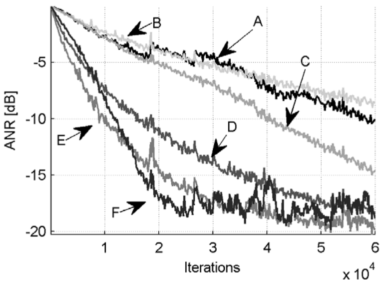

Fig. 6. ANR curves for the modelled noise: A – FxLMS, B – Sun's FxLMS, C – Mod. Sun's FxLMS, D – Akhtar's FxLMS, E – FxLMP, F - FxLogLMS

Rys. 6. Wykresy wskaźnika ANR dla hałasu modelowanego: A – FxLMS, B – Sun's FxLMS, C – Mod. Sun's FxLMS, D – Akhtar's FxLMS, E – FxLMP, F - FxLogLMS

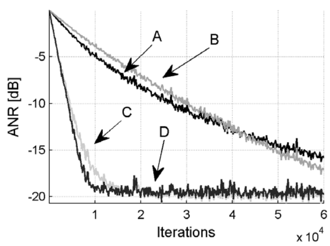

Fig. 7. ANR curves for the modelled noise: A – NFxLMS, B –NFxLMP, C- MNFxLMS, D - MNFxLMP

Rys. 7. Wykresy wskaźnika ANR dla hałasu modelowanego: A – NFxLMS, B –NFxLMP, C- MNFxLMS, D – MNFxLMP

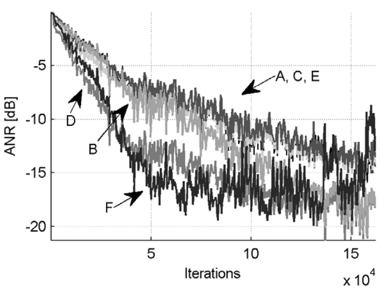

Fig. 8. ANR curves for the hammer noise: A – FxLMS, B – Sun's FxLMS, C – Mod. Sun's FxLMS, D – Akhtar's FxLMS, E – FxLMP, F - FxLogLMS

Rys. 8. Wykresy wskaźnika ANR dla hałasu uderzania młotem: A – FxLMS, B – Sun's FxLMS, C – Mod. Sun's FxLMS, D – Akhtar's FxLMS, E – FxLMP, F - FxLogLMS

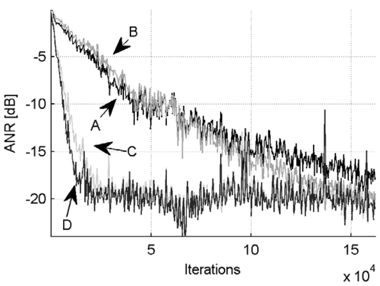

Fig. 9. ANR curves for the hammer noise: A – NFxLMS, B –NFxLMP, C- MNFxLMS, D - MNFxLMP

Rys. 9. Wykresy wskaźnika ANR dla hałasu uderzania młotem: A – NFxLMS, B –NFxLMP, C- MNFxLMS, D – MNFxLMP

In the case of the modelled noise it can be observed that the ANR curves tend to form groups of similar performance algorithms. The first group consists of FxLMS and Sun's FxLMS, the second one of Akhtar's FxLMS, FxLMP and FxLogLMS, the third one of NFxLMS and NFxLMP and the last group of MNFxLMS and MNFxLMP. The performance of the first group is the poorest, while the third group is similar to the second one, with a much better performance. The group of Modified Normalized algorithms has the best performance.

A bit different results are obtained for the hammer noise. In this case, MNFxLMS and MNFxLMP algorithms show much faster convergence speed than any other algorithm. The rest of the algorithms exhibit similar performance.

5. Conclusions

Several algorithms dealing with impulsive noise control have been presented in this paper. After carrying out simulations using both modelled and real noise several conclusions can be drawn. The MNFxLMS and MNFxLMP algorithms outperform other algorithms in both investigated cases. The MNFxLMP shows even better performance than the MNFxLMS, however for proper operation it requires the tuning of additional parameter *p*, which may be difficult in practice. Further work should be directed to the analysis of the algorithm computational complexity. If, for some applications, the adaptive control is unable to respond to the impulsive noise with a sufficient rate, the fixed control, and particularly the analogue approach, is recommended as in [11]. Furthermore, in this paper the ideal modelling has been assumed, $\hat{S}=S$. However, in reality it may not be satisfied, causing poor performance of an ANC system. To overcome this, issue algorithms without the secondary path modelling are being developed.

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