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Binormalized data-reusing adaptive filtering algorithm for active control of impulsive sources

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A B S T R A C T

The main objective of active noise control (ANC) is to provide attenuation for the environmental acoustic noise. The adaptive algorithms for ANC systems work well to attenuate the Gaussian noise; however, their performance may degrade for non-Gaussian impulsive noise sources. Recently, we have proposed variants of the most famous ANC algorithm, the filtered-x least mean square (FxLMS) algorithm, where an improved performance has been realized by thresholding the input data or by efficiently normalizing the step-size. In this paper, we propose a modified binormalized data-reusing (BNDR)-based adaptive algorithm for impulsive ANC. The proposed algorithm is derived by minimizing a modified cost function, and is based on reusing the past and present samples of data. The main contribution of the paper is to develop a practical DR-type adaptive algorithm, which incorporates an efficiently normalized step-size, and is well suited for ANC of impulsive noise sources. The computer simulations are carried out to demonstrate the effectiveness of the proposed algorithm. It is shown that an improved performance has been realized with a reasonable increase in the computational complexity.

1. Introduction

Active noise control (ANC) is based on the principle of the destructive interference of acoustic waves. The primary noise generated by the noise source is canceled around some desired location by generating and combing an antiphase canceling noise [1]. The block diagram for a single-channel feedforward ANC system is shown in Fig. 1. As shown, a single-channel ANC system comprises one reference microphone 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 system is called 'feedforward' as a reference signal is available before the cancelation point. The definitions for various quantities shown in Fig. 1, together with vector definitions for various signals, are summarized in Table 1 for the sake of clarity of presentation. The most famous adaptation algorithm for ANC systems is the filtered-x least mean square (FxLMS) algorithm [1], which is a modified version of the LMS algorithm [2]. The FxLMS algorithm is a popular ANC algorithm due to its robust performance, low computational complexity, and ease of implementation [1]. The FxLMS algorithm [1] is obtained by minimizing the mean-square-error cost function; $J(n) = \mathbb{E}\{e^2(n)\} \approx e^2(n)$, where $\mathbb{E}\{.\}$ is the expectation operator; and is given as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu e(n)\boldsymbol{x}_f(n), \tag{1}$$

where μ is the step size parameter. As shown in Fig. 1, we consider the noise source being of impulsive nature. The FxLMS algorithm may become unstable for such type of impulsive noise sources, as rigorously shown in [3, Section 2.1].

1.1. Impulsive noise and existing ANC algorithms

In practice, the impulsive noises are often due to the occurrence of noise disturbance with low probability but large amplitude, for example punching and stamping machines in the manufacturing plants, presses, combustion engines, pile drivers, IV pump sounds in the hospitals [4,5]. In this paper, we consider impulsive noise modeled by stable non-Gaussian distribution [7]; essentially, we consider standard symmetric α-stable (SαS) distribution $f(x)$ having characteristic function of the form $\varphi(t) = e^{|t|^{\alpha}}$, where $0 < \alpha < 2$ is the shape parameter called as the characteristics exponent. If a stable random variable has a small value for α, then distribution has a very heavy tail. It is Gaussian distribution for $\alpha = 2$ and Cauchy distribution for $\alpha = 1$. Modeling the impulsive noise as SαS process is fairly a good choice. For example, the road traffic noise or office noise are more accurately represented by SαS processes rather than Gaussian ones [6].

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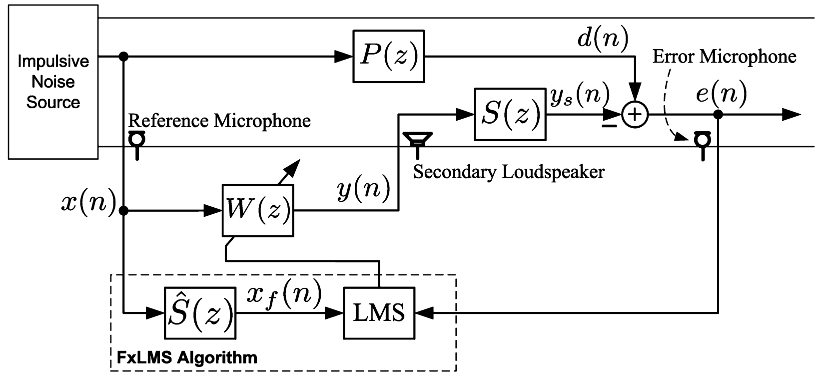

Fig. 1. Block diagram of FxLMS algorithm-based single-channel feedforward ANC systems.

Table 1
Listing of various mathematical quantities used in this paper for description of ANC algorithms.

1.	$W(z)$ = Transfer function for ANC adaptive filter
2.	$\boldsymbol{w}(n) = [w_0(n), w_1(n), \cdots, w_{L-1}(n)]^T$ (Coefficient vector for $W(z)$)
3.	$P(z)$ = Transfer function for primary path
4.	$p(n)$ = Impulse response of primary path $P(z)$
5.	$S(z)$ = Transfer function for secondary path
6.	$s(n)$ = Impulse response of secondary path $S(z)$
7.	$\hat{S}(z)$ = Transfer function for secondary path modeling filter
8.	$\hat{s}(n)$ = Impulse response of secondary path modeling filter $\hat{S}(z)$
9.	$x(n)$ = The reference signal picked-up by the reference microphone
10.	$\boldsymbol{x}(n) = [x(n), x(n-1), \cdots, x(n-L+1)]^T$ (Reference signal vector)
11.	$y(n) = \boldsymbol{w}^T(n)\boldsymbol{x}(n)$ (output of ANC filter $W(z)$)
12.	$d(n) = p(n) * x(n)$ (Disturbance at the error microphone)
13.	$y_s(n) = s(n) * y(n)$ (Secondary canceling signal at the error microphone)
14.	$e(n) = d(n) - y_s(n)$ (Error signal picked-up by the error microphone)
15.	$x_f(n) = \hat{s}(n) * x(n)$ (Filtered-reference signal)
16.	$\boldsymbol{x}_f(n) = [x_f(n), x_f(n-1), \cdots, x_f(n-L+1)]^T$ (Filtered-reference signal vector)

In [3], Sun et al. have proposed a simple variant of the FxLMS algorithm for ANC of impulsive noise. The basic idea here is to ignore the sample of the reference signal $x(n)$ if its amplitude is above a certain value set by its statistics, and thus the reference signal is modified as

$$x'(n) = \begin{cases} x(n), & \text{if } x(n) \in [c_1, c_2] \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

and the update equation is modified as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu e(n)\boldsymbol{x}'_f(n), \tag{3}$$

where $\boldsymbol{x}'_f(n) = [x'_f(n), x'_f(n-1), \cdots, x'_f(n-L+1)]^T$, and where T denotes transposition and $x'_f(n) = \hat{s}(n) * x'(n)$ is the modified-filtered-reference signal where $*$ represents the convolution. Effectively, Sun's algorithm [3] assumes the same probability density function (PDF) for $x'(n)$ with in $[c_1, c_2]$ as that of $x(n)$, and simply neglects the tail beyond $[c_1, c_2]$. As compared with the FxLMS algorithm, this algorithm gives stable and robust performance. However, the stability cannot be guaranteed, and algorithm might become unstable particularly when α is small. In [8], we suggested thresholding-based FxLMS (ThFxLMS) algorithm, which gives improved performance as compared with the Sun's algorithm. The main problem is that these algorithms [3,8] require estimation of appropriate thresholding parameters. In [9], we have proposed a normalized-step-size FxLMS (NSS-FxLMS) algorithm that does not use modified reference and/or error signals, and hence does not require choosing the thresholding parameters. The NSS-FxLMS algorithm is summarized below [9]:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu(n)e(n)\boldsymbol{x}_f(n), \tag{4}$$

$$\mu(n) = \frac{\tilde{\mu}}{\|\boldsymbol{x}_f(n)\|^2 + E_e(n) + \delta}, \tag{5}$$

$$E_e(n) = \lambda E_e(n-1) + (1-\lambda)e^2(n), \tag{6}$$

where $\tilde{\mu}$ is the fixed step-size, δ is a small positive constant to avoid division by zero, λ is the forgetting factor, and $\|\cdot\|$ denotes Euclidean norm of the quantity inside.

1.2. Proposed algorithm and paper organization

Many data-reusing (DR) adaptive algorithms have been proposed in the literature [10–13], where the main objective is to improve the convergence of the initial algorithm. In [14], we have attempted to investigate whether DR can be adopted to develop an efficient strategy for ANC of impulsive noise sources. The work in [14] is based on Schnaufer and Jenkins DR-NLMS (SJ-DR-NLMS) algorithm [12], and the step-size in each data-reuse is being normalized using (filtered-) reference as well as error signals. We observe an improved performance; however, relatively a large order of data-reuse is required, which might result in a computational complexity formidable for practical ANC applications. In this paper, we investigate modifying and employing binormalized DR (BNDR) [15] type algorithm for ANC of impulsive noise sources. The main objective is to realize an improved convergence performance while keeping the computational complexity within reasonable limits. This is indeed achieved as BNDR algorithm requires only past and present data samples, and thus the order of data-reuse is only 2.

The rest of the paper is organized as follows. Section 2 describes derivation of the proposed algorithm. A detailed computational complexity analysis is also included in this section. A few remarks on the performance analysis are also provided. Section 3 presents the simulation results and discussion, and the concluding remarks are given in Section 4.

2. Details of proposed algorithm

The basic idea in any DR-type adaptive algorithm is to "re-use" the present (and/or past) data samples while updating the coefficients of the adaptive filter [10]. In the case of ANC systems being implemented using FxLMS algorithm (see Fig. 1), the signals $d(n)$ and $e(n)$ are generated acoustically with only $e(n)$ being accessible via error microphone. This problem can be solved by adapting the ANC filter $W(z)$ using a modified-structure FxLMS algorithm,[1] where the disturbance signal $d(n)$ can be indirectly estimated as explained below. Consider the bock diagram for a modified structures single-channel ANC as shown in Fig. 2, which comprises two

[1] For details on modified FxLMS (MFxLMS) algorithm, see [16] and references there in.