Delayless Block Individual-Weighting-Factors Sign Subband Adaptive Filters With an Improved Band-Dependent Variable Step-Size

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ABSTRACT Delayless individual-weighting-factors sign subband adaptive filter (IWF-SSAF) algorithms with a band-dependent variable step-size (BDVSS) were recently introduced to achieve a robust convergence performance against the impulsive interference and to avoid an undesirable signal path delay in subband systems. In this paper, we develop a block implementation of the delayless IWF-SSAF algorithm designed for an active impulsive noise control (AINC) system. With the block-processing approach, the proposed delayless block IWF-SSAF algorithm can be implemented more efficiently than the original delayless algorithm regardless of number of subbands, which is verified through the computational analysis. Furthermore, an improved BDVSS version (I-BDVSS) is also proposed by using the multiple auxiliary past gradients, which are given for each band by the block-processing. Finally, the simulation results illustrate that the proposed delayless block IWF-SSAF algorithm with the I-BDVSS, even requiring less computational burden, can achieve a better convergence performance than the original delayless algorithm with the BDVSS under severe impulsive noise control environment.

INDEX TERMS Delayless structure, individual-weighting-factors sign subband adaptive filter, block implementation, active impulsive noise control, band-dependent variable step-size.

I. INTRODUCTION
Adaptive filter (AF) algorithms have been utilized in numerous applications such as system identification, signal prediction, and array processing [1]–[8]. Some applications such as acoustic echo cancellation (AEC) and wideband active noise control (ANC), demand very long AF with high computational complexity, which restricts its use in small and low-cost audio devices, e.g., earbuds. In addition, the AF with many taps also suffers from slow convergence for highly correlated signals. Subband AF (SAF) has received much attention for low computational complexity and fast convergence, whereby whitening signals are processed with lower order subfilters at a lower decimated sampling rate.

However, traditional SAF techniques accompany undesirable band-edge and aliasing effects [8]. As an attractive approach to addressing both issues, a novel SAF algorithm, called a normalized SAF (NSAF), was introduced by employing subband input signals without decimation into fullband weight update to alleviate the aliasing effect and by using a critically sampled structure to mitigate the band-edge effect [9]–[11]. The NSAF yields faster convergence than the normalized least-mean-square (NLMS) algorithm, but requires almost the same number of multiplications.

Several variants of the NSAF have been proposed under different backgrounds. Firstly, when impulsive interference occurs, the performance of the NSAF can be seriously deteriorated due to its $\ell_2$-norm based nature. To resolve the problem, a sign SAF (SSAF) was introduced by incorporating a $\ell_1$-norm based minimization into the NSAF.
structure [12]. Furthermore, the convergence performance of the SSAF can be enhanced by adopting various variable step-size (VSS) schemes [13]–[17], and by fully utilizing the decorrelating property of the SSAF which leads to an individual-weighting-factors SSAF (IWF-SSAF) [18]. In addition to the SSAF based algorithms, several M-estimate based NSAF algorithms and their variable step-size (VSS) schemes have been also presented to improve the robustness of the NSAF against the impulsive noise [19], [20]. Secondly, the NSAF structure has an undesirable signal path delay caused by analysis and synthesis filters, which may lead to restrictive usage of the NSAF in real-time applications. To tackle the issue, two novel delayless structures (i.e., open-loop and closed-loop schemes) were proposed for the NSAF and they have been successfully applied in various real-time systems [21]. Recently, by associating the robust IWF-SSAF [18] with the delayless NSAF structures [21], the delayless IWF-SSAF algorithms [22] were presented to overcome both aforementioned difficulties and their efficacy was verified in several impulsive interference environments including active impulsive noise control (AINC) applications.

In this paper, we develop a block implementation of the delayless closed-loop IWF-SSAF algorithm [22], designed for the AINC systems. In the proposed algorithm, the block-processing with the overlap-save technique is employed to update the weight, which reduces the required computational complexity. Especially in the block-processing, multiple auxiliary past gradients are available for each subband, which leads to an opportunity to introduce an improved BDVSS algorithm (I-BDVSS) than the original BDVSS one [22], in terms of the averaged noise reduction (ANR) performance. The effectiveness of the proposed delayless block algorithm is validated using a symmetric alpha stable (SαS) distribution, whose real impulsive noise examples include heavy machinery in industrial setup, traffic noise, gun shot and explosion, noise in MRI room, and so on. Therefore, the proposed delayless block algorithm can be employed to reduce such various impulsive noises.

This paper is organized as follows: We first present a review of related work in the context of AINC in Section II. Then, the modified delayless closed-loop IWF-SSAF for the AINC is briefly introduced in Section III. In Section IV, its block implementation and improved BDVSS (I-BDVSS) algorithm are proposed along with the computational analysis. In Section V, several simulation results are provided under impulsive noise control environments to verify the convergence performance. Finally, concluding remarks are given in Section VI.

II. RELATED WORK

Several modified filtered-x least mean squares (FxLMS) algorithms have been presented for the AINC application. There are two main approaches. First, since the second order moment does not exist for the SαS distribution, the widely used FxLMS algorithm cannot give a stable convergence performance [23], [24]. Therefore, the problem of minimizing the lower fractional order moment \( p < \alpha \) has been introduced for the AINC system to improve the robustness of the FxLMS, which results in filtered-x least mean \( p \)-power (FxLMP) algorithms [23]. Here, \( \alpha \) controls the impulsive nature. Second, the peaky reference/error signals are truncated with a threshold value because the weight can be largely fluctuated by the peaky samples during the weight update due to the modelling error, which finally degrades the convergence performance [25]. However, the aforementioned two approaches should estimate the value of \( \alpha \) or the reference/error signal statistic to determine the threshold value, which may not be available in practice.

Recently, the delayless IWF-SSAF algorithm with the BDVSS [22] was proposed for the AINC application. Unlike the aforementioned two approaches, the delayless IWF-SSAF was derived by adopting the robust \( \ell_1 \)-norm based optimization criterion. Furthermore, from the experiments performed in [22], the improved ANR performance was also obtained when compared with that of the above two conventional AINC approaches and their combinations. In this paper, the efficient implementation of the delayless IWF-SSAF [22] is developed by using the block-processing, which can be applied especially for small and low-cost devices such as earbuds.

![FIGURE 1. Delayless closed-loop IWF-SSAF structure modified for the AINC applications.](image-url)

III. MODIFIED DELAYLESS CLOSED-LOOP IWF-SSAF FOR AINC APPLICATIONS

Fig. 1 illustrates the delayless closed-loop IWF-SSAF modified for the AINC systems [22]. The desired signal \( d(n) \) is the output of the primary path \( P(z) \) with the reference signal \( u(n) \) as its input. In addition, \( N \) is number of subbands and \( k \) is a decimated sequence of \( n \) by a factor of \( N \). Then, if \( W(z) \) is modelled by a finite impulse response (FIR) filter \( w(k) \) of the length \( L \), its output \( y(n) \) can be written as \( y(n) = w^T(k)u(n) \) and error \( e(n) \) can be expressed as follows:

\[
e(n) = d(n) - s(n) * y(n),
\]

where

\[
d(n) = \alpha \sum_{k=-\infty}^{\infty} w(k) u(n-k),
\]

\[
s(n) = \sum_{k=-\infty}^{\infty} s(k) u(n-k),
\]

\[
y(n) = \sum_{k=-\infty}^{\infty} w(k) u(n-k),
\]

\[
e(n) = \alpha \sum_{k=-\infty}^{\infty} w(k) u(n-k) - \sum_{k=-\infty}^{\infty} s(k) \sum_{k=-\infty}^{\infty} w(k) u(n-k),
\]

\[
e(n) = \sum_{k=-\infty}^{\infty} w(k) [\alpha u(n-k) - s(n-k)],
\]

\[
e(n) = \sum_{k=-\infty}^{\infty} w(k) [\alpha u(n-k) - \sum_{k=-\infty}^{\infty} s(k) u(n-k)].
\]
where \( \mathbf{u}(n) = [u(n), u(n - 1), \ldots, u(n - L + 1)]^T \), \( s(n) \) is the impulse response of the secondary path \( S(z) \) with the length \( M \), and \( * \) denotes the linear convolution operation. The filtered-x signal \( \hat{u}(n) \) is obtained by filtering \( u(n) \) through the estimated secondary path \( \hat{S}(z) \). Then, \( \hat{u}(n) \) and \( e(n) \) are split into subbands via the analysis filter \( H_i(z) \), which leads to the subband signals, \( \hat{u}_i(n) \) and \( \tilde{e}_i(n) \), respectively. The IWF-SSAF weight update [18] is given as

\[
w(k + 1) = w(k) + \mu \sum_{i=1}^{N} \hat{u}_i(k) \text{sgn}(\hat{e}_i,D(k)) ,
\]

where \( \mu \) is a step-size, \( \hat{u}_i(k) = [\hat{u}_i(kN), \ldots, \hat{u}_i(kN-L+1)]^T \), \( \hat{e}_i(k) \) is a decimated sequence of \( \tilde{e}_i(n) \) by a factor of \( N \), and \( \text{sgn}(\cdot) \) represents the sign function.

**IV. PROPOSED BLOCK IMPLEMENTATION WITH AN IMPROVED BDVSS**

**A. BLOCK IMPLEMENTATION OF MODIFIED DELAYLESS IWF-SSAF**

Fig. 2 depicts a block implementation of Fig. 1. We employ a block-processing with an overlap-save method to update the weight. Here, the overlap rate is 0.5; thus, the weight is updated in every \( L \) fullband samples.

**Algorithm 1** Summary of the Proposed Block Implementation. \( e(k) = [e(kN), e(kN-1), \ldots, e(kN-Q+1)]^T \)

For \( n = 0, 1, 2, \ldots \),

\[
e(n) = d(n) - w^T(m)u(n)
\]

For \( k = 0, 1, 2, \ldots \), where \( kN = n \),

\[
\hat{e}_i(k) = \mathbf{h}_i^T e(k), \quad i = 1, \ldots, N
\]

End

For \( m = 0, 1, 2, \ldots \), where \( mL = n \),

\[
\mathbf{u}'(n) = \text{FFT}([u(n-2L+1), \ldots, u(n)]^T)
\]

\[
\hat{u}(n) = \mathbf{u}'(n) \odot \hat{s}'(n)
\]

\[
[\hat{u}(n-L+1), \ldots, \hat{u}(n)]^T = \text{IFFT}(\hat{u}'(n))(L + 1: 2L)
\]

\[
\hat{u}_i(n-l) = \mathbf{h}_i^T \hat{u}(n-l), \quad l = 0, \ldots, L-1
\]

\[
w(m + 1) = w(m) + \mu \sum_{i=1}^{N} \sum_{j=0}^{L/N-1} \frac{\hat{u}_i(k-j) \text{sgn}(\hat{e}_i,D(k-j))}{\sqrt{\hat{u}_i^2(k-j) + \delta}}
\]

End

**B. IMPROVED BAND-DEPENDENT VARIABLE STEP-SIZE**

An \( \ell_1 \)-norm based band-dependent variable step-size (BDVSS) algorithm [22] was introduced to improve the convergence of the original closed-loop IWF-SSAF. In this section, its improved BDVSS version (I-BDVSS) is proposed by exploiting the several past gradients for each subband, as shown in (6).
The proposed I-BDVSS algorithm is derived by extending the $\ell_1$-norm based minimization criterion [22], [27] to the multiple past gradients. Initially, the $i$-th subband a posteriori error $e_{i,p}(k-j)$ is defined as follows:

$$e_{i,p}(k-j) = d_i(k-j) - \tilde{u}_i(k-j)w_i(m+1) \tag{7}$$

$$w_i(m+1) = w(m) + \mu_i(m)\frac{\tilde{u}_i(k-j)\text{sgn}(\epsilon_i(k-j))}{\sqrt{\tilde{u}_i^2(k-j)\hat{u}_i(k-j)}}, \tag{8}$$

where $d_i(k)$, defined for the open-loop scheme, is obtained by filtering $d(m)$ through the analysis filter and further decimating it by a factor of $N$. $\mu_i(m)$ is an $i$-th band variable step-size, and $e_{i,D}(k-j) = d_i(k-j) - \tilde{u}_i^T(k-j)w_i(m)$. In addition, (7) can be rewritten as follows:

$$e_{i,p}(k-j) = \tilde{e}_i(k-j) - \mu_i(m)g_i(k-j), \tag{9}$$

$$g_i(k-j) = \frac{\tilde{u}_i^T(k-j)\hat{u}_i(k-j)\text{sgn}(\epsilon_i(k-j))}{\sqrt{\tilde{u}_i^2(k-j)\hat{u}_i(k-j)}}. \tag{10}$$

Note that in (9), $e_{i,D}(k-j)$ is replaced with $\tilde{e}_i(k-j)$ to suit the proposed closed-loop scheme [22].

Then, the I-BDVSS can be derived by minimizing the $\ell_1$-norm of the a posteriori error as follows:

$$\mu_i^*(m) = \arg\min_{\mu_i(m)} \|\tilde{e}_i(k-j) - \mu_i(m)g_i(k-j)\|_1$$

subject to $\mu_L \leq \mu_i(m) \leq \mu_U$, \tag{11}

where $\mu_L$ and $\mu_U$ are defined by the lower and upper bounds of the step-size, respectively. By observing that (11) is a piecewise linear convex problem as in [22], [27], its optimal solution $\mu_i^*(m)$ can be obtained by utilizing a similar numerical procedure to [22] as follows:

(i) $\mu_{i,j}^*(m) = \tilde{e}_i(k-j)/g_i(k-j)$

(ii) $\mu_{i,j}^*(m) = \begin{cases} \mu_U, & \text{if } \mu_{i,j}^*(m) > \mu_U \\ \mu_L, & \text{if } \mu_{i,j}^*(m) < \mu_L \\ \mu_{i,j}^*(m), & \text{otherwise}. \end{cases}$

However, $\mu_{i,j}^*(m)$ may be increased due to the effect of the impulsive noise as discussed in [22], [27], which degrades the convergence. To prevent this possibility, the final step-size $\mu_i(m)$ is scheduled to be monotonically decreasing by merging $L/N$ number of $\mu_{i,j}^*(m)$ for each subband as follows:

(i) $\mu_{i,0}(m-1) = \mu_i(m-1)$

$\mu_{i,j+1}(m-1) = \beta\mu_{i,j}(m-1) + (1 - \beta)$

(ii) $\min(\mu_{i,j}^*(m), \mu_{i,j}(m-1)), \ j = 0, \ldots, L/N - 1$

(iii) $\mu_i(m) = \mu_{i,L/N}(m-1)$,

where $\beta$ is a smoothing parameter. When the proposed I-BDVSS $\mu_i(m)$ is combined with the proposed weight update (6) including the averaged gradient close to the true gradient, the proposed I-BDVSS algorithm can yield the enhanced convergence, which is demonstrated in the simulation results.

### C. COMPUTATIONAL ANALYSIS

In Table 1, the computational cost of the proposed delayless block IWF-SSAF algorithm is analyzed in terms of number of real multiplications and additions per one fullband input sample.

| Operations   | Multiplications | Additions |
|--------------|-----------------|-----------|
| Filtered-x   | $2 \times 2L \log_2(2L)$ | $2 \times 2L \log_2(2L)$ |
| Subband      | $\frac{Q \times N \times L}{2L} = Q \times N$ | $(Q-1) \times N \times L = (Q-1) \times N$ |
| Weight       | $\frac{2L \times L}{2L} = 2L$ | $2L \times (L-1) \times L = 2L(L-1)$ |
| I-BDVSS      | $N \times \frac{(1/L)}{N} = 1$ | $N \times \frac{(1/L)}{N} = 1$ |

FIGURE 3. (a) Primary path and (b) secondary path used for the AINC system.
FIGURE 4. ANR performance obtained by the original delayless algorithm with the BDVSS [22] and the proposed delayless block algorithm with the I-BDVSS when (a) $\alpha = 1$, (b) $\alpha = 0.8$, (c) $\alpha = 0.6$, and (d) $\alpha = 0.4$.

TABLE 2. Computational complexity of the original delayless IWF-SSAF algorithm, in terms of number of real multiplications and additions per one fullband input sample.

| Operations          | Multiplications | Additions          |
|---------------------|-----------------|--------------------|
| Filtered-x          | $\hat{u}(n)$    | $M$                | $M - 1$            |
| Subband signals     | $\tilde{u}_i(n)$| $Q \times N \times N = Q \times N$ | $\frac{(Q-1) \times N \times N}{N} = (Q - 1) \times N$ |
|                     | $\tilde{e}_{i,D}(k)$ | $\frac{M \times N}{N} = M$ | $\frac{(Q-1) \times N \times N}{N} = (Q - 1) \times N$ |
| Weight update       | (2)             | $2 \times N \times L = 2L$ | $2 \times (L - 1) \times N = 2(L - 1)$ |

input sample. In the proposed delayless algorithm, there are three main computational parts, i.e., (i) generating the filtered-x signal $\hat{u}(n)$, (ii) subband signals (i.e., $\tilde{u}_i(n)$ and $\tilde{e}_{i,D}(k)$), and (iii) the weight update.

To generate $\hat{u}(n)$, the proposed algorithm demands $2L$-point FFT, its inverse FFT, and $2L$ complex multiplications for (3), which leads to $8 \log_2(2L) + 8$ multiplications and $8 \log_2(2L)$ additions in total. In addition, $QN$ multiplications and $(Q - 1)N$ additions are required for $\tilde{u}_i(n)$, and $Q$ multiplications and $(Q - 1)$ additions are required for $\tilde{e}_{i,D}(k)$. Also, the weight update needs $2L$ multiplications and $2(L - 1)$ additions.

On the other hand, the original delayless algorithm demands the same computational burden as in the proposed delayless algorithm except generating the filtered-x signal $\hat{u}(n)$, as described in Table 2. The original algorithm should
require $M$ multiplications and $(M-1)$ additions to compute $\hat{u}(n)$ since $\hat{u}(n)$ is directly filtered through the long fullband path $\hat{S}(z)$. Therefore, the proposed delayless algorithm can be more efficiently realized than the original delayless algorithm regardless of $N$ since $M \gg 8 \log_2(2L) + 8$, e.g., $1024 \gg 8 \log_2(2 \times 2048) + 8 = 104$ for $M = 1024$ and $L = 2048$ (when considering the number of multiplications only).

Furthermore, additional computational burden required by the proposed I-BDVSS algorithm is briefly analyzed in Table 1. Initially, $g_i(k-j) = \sqrt{\tilde{u}_i^T(k-j)\tilde{u}_i(k-j) \times \text{sgn}(\hat{e}_{i,p}(k-j))}$ can be computed without any further multiplications. Furthermore, as investigated in [13], $\mu_{i,j}^*(m)$ and the time-average scheme can be implemented with 1 and 2 multiplications, respectively. Therefore, the proposed I-BDVSS algorithm requires additional 3 multiplications in total, which is the same computational burden as required by the BDVSS [22].

V. EXPERIMENTS
In this section, the performance of the proposed delayless block IWF-SSAF algorithm was verified by simulations. In the simulations, similar settings as in [22] were used. Specifically, $u(n)$ was modelled as the $\alpha$, $\phi$ distribution with $\alpha = 0.4$–1. Its characteristic function can be expressed as

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

where $\gamma$ is a dispersion parameter and $0 < \alpha < 2$ is the characteristic exponent. If $\gamma = 1$, the corresponding distribution is called standard. In the standard distribution, $\alpha$ controls the impulsive nature. That is, the lower $\alpha$ means the higher impulsive noise, and vice versa. $P(z)$ and $S(z)$ were respectively modelled as FIR filters with orders 512 and 192, as shown in Fig. 3 [28]. Note that $\hat{S}(z)$ was exactly the same as $S(z)$. $W(z)$ was modelled by an FIR filter of order 288. The averaged noise reduction (ANR) was adopted as a performance measure [22], which is defined as

$$\text{ANR} = E\{\sigma_d(n)/\sigma_e(n)\},$$

where

$$\sigma_d(n) = \lambda \sigma_d(n-1) + (1-\lambda)\hat{d}(n),$$

$$\sigma_e(n) = \lambda \sigma_e(n-1) + (1-\lambda)\hat{e}(n).$$

For a fair comparison, the same optimally tuned parameters were used for the original BDVSS [22] and proposed I-BDVSS, as listed in Table 3.

| Algorithms            | Parameters                      |
|-----------------------|---------------------------------|
| Original [22], Proposed | $\mu = 0.01, \delta = 0.01, N = 8$ |
| Original BDVSS [22], Proposed I-BDVSS | $\mu_i(0) = \mu_e = 0.05, \mu_c = 10^{-5}$, $\delta = 0.01, \beta = 1 - \frac{1}{2L}, N = 8$ |

Fig. 4 shows the ANR performance of the original delayless algorithm with the BDVSS [22] and the proposed delayless block one with the I-BDVSS when $\alpha = 0.4$–1. For the fixed step-size scheme, both algorithms yielded almost the same ANR performance for all cases as expected (see green and black lines of Fig. 4). Note that smaller $\alpha$ means more severe impulsive noise control environment. Therefore, both algorithms experienced a gradual performance degradation as $\alpha$ is decreased. For the BDVSS scheme, the proposed I-BDVSS algorithm, even with less computational burden, achieved a better ANR performance in the steady-state for all considered $\alpha$ when compared with the original BDVSS algorithm (see blue and red lines of Fig. 4). Especially for smaller $\alpha$, i.e., more severe impulsive noise control environment, the proposed I-BDVSS algorithm achieved higher performance gain over the original BDVSS [22].

In Fig. 5, the ANR performance of the proposed delayless block algorithm with the I-BDVSS was compared with that of
some conventional algorithms aimed at impulsive noise control when $\alpha = 0.8, 1$. The performance when $\alpha = 0.4, 0.6$ was not included in Fig. 5 since the conventional AINC algorithms exhibited unstable convergence performance. In the simulations, two existing AINC algorithms, i.e., modified normalized filtered-$x$ least mean $p$-power (MNFxLMP) [23] and fractional FxLMS algorithm with a modified tanh thresholding function (MTanh-Th-FrLMS) [25], were considered. In the MNFxLMP, the parameter $p$ was set to $\alpha = 0.01$ as recommended. In the MTanh-Th-FrLMS, the fractional order was set to 0.65. Furthermore, in the modified tanh function, the thresholding parameters were determined by [1, 99] percentile of the reference signal and the tuning slope parameter was set to 2, as suggested. As a result, the MTanh-Th-FrLMS obtained a better ANR performance than the MNFxLMP for both cases. On the other hand, the proposed delayless block algorithm with the I-BDVSS yielded a superior ANR performance relative to the MTanh-Th-FrLMS.

VI. CONCLUSION

In this paper, a delayless closed-loop IWF-SSAF with an improved BDVSS (I-BDVSS) is designed for AINC systems, and its block implementation was developed. A computational complexity analysis was also performed, which reveals that the proposed delayless block IWF-SSAF algorithm is more efficiently implemented than the original delayless algorithm regardless of number of subbands. Finally, it was illustrated from the simulations that the proposed delayless algorithm with the I-BDVSS, requiring less computational complexity, can achieve the better ANR performance than the original delayless algorithm with the BDVSS. As a future work, we will consider the convergence analysis of the proposed delayless algorithm to investigate the effect of the averaged gradient under the AINC environment.

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