A novel Adaptive Sub-Band Filter design with BD-VSS using Particle Swarm Optimization

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Abstract – *A delayless Sign Subband Adaptive Filter algorithm with Individual Weighting Factors (IWF-SSAF) and Band-Dependent Variable Step-Sizes (BD-VSS) approach is recently proposed to control noise for impulsive noise environments. However, such approaches have slow convergence rate and high computation complexity for real-time applications. To address these issues, Particle Swarm Optimization (PSO) algorithm delayless closed loop IWF-SSAF with BD-VSS is proposed. The proposed algorithm is applied for Active Impulsive Noise Control (AINC) technique to suppress the impulsive noise. The proposed algorithm attains better convergence performance by employing the* l_1*-norm minimization approach to sub-bands and decorrelating properties of SSAF. Furthermore, the proposed algorithm has achieved more computational efficiency with the aid of PSO algorithm. The experimental result shows that the proposed algorithm obtained better performance than the conventional SSAF algorithms in terms of computational complexity.*

Key words – *Sign Subband Adaptive Filter, Particle Swarm Optimization, Active Impulsive Noise Control, Variable Step-Sizes.*

1. INTRODUCTION

Normalized Least Mean Square (NLMS) is one of the fundamental approaches in adaptive filtering techniques which has been broadly used in several real-time applications including channel estimation, system identification and Active noise cancellation (ANC) [1]. However, NLMS approach has the disadvantage of slow converges for the colored input signals. An innovative approach which is used in the Sub-band Adaptive Filter (SAF) for resolving the disadvantage of NLMS approach [2]. It splits the coloured input signal into the equally divided multiple sub-band signals, where each sub-band signal is almost white. Then, the Normalized Sub-band Adaptive Filter (NSAF) approach is introduced which converges the NLMS for the coloured input signals owing to the inherent decorrelating features of SAF in a faster manner [3], [4].

In addition, NSAF approach has the same computational complexity of the NLMS approach for the applications of echo cancellation [5]. Also, the traditional NLMS approach and NSAF approach has a trade-off between the rate of convergence and steady-state error for the selection step size. Then, more variable step size NSAF approaches were established to attain both low steady-state error and fast convergence rate [6]. However, these approaches may deviate for the presence of impulsive noises. A Sign Sub-band Adaptive Filter (SSAF) approach is developed for reducing the L1-norm of the a posteriori error vector of Sub-band filter to mitigate the impulsive interferences [7]. Also, Variable Regularization Parameter with SSAF is presented for lower the steady-state error of the SSAF [8].

Then, some variable step size SSAF approaches were presented from diverse principles of the step size update to alleviate the trade-off problem of the SSAF [9]. But, these convergence rates of several variable step size SSAF approaches are not reasonable [8]. To address this concern, a novel SAF approach is developed from Huber's cost function using the gradient descent technique [10]. This approach offers an automatic scheme to adjustment between the NSAF and SSAF approaches by iteratively updating the cut-off metrics and provides good robustness to the impulsive noises. Hence, this approach is called as the robust variable step size NSAF (RVSS-NSAF) [11].

Moreover, SSAF approach with Individual Weighting Factors (IWF-SSAF) approach is presented to improve the convergence rate of SSAF approach [12], [13]. An improved proportionate IWF-SSAF is proposed for sparse system to further improve the convergence rate of the IWF-SSAF algorithm. Two delayless structures for NSAF were proposed to alleviate the concern of undesirable signal path delay since this is essential for the different real-time applications such as AEC and ANC [14]. SSAF approaches have an inherent signal path delay issue for real-time systems. Hence, a delayless IWF-SSAF with band-dependent variable step-sizes (BD-VSS) algorithm is developed which offers more robustness under impulsive noise conditions [14].

2. RELATED WORKS

M-Estimator based approach is developed to control the context of active impulse noise where M-Estimator aims to minimize the effect of outliers [15], [20]. This result proved the better efficiency of the M-Estimator than the existing algorithms based on noise control performance. However, its complexity is lower than the other conventional approaches. A BD-VSS based SSAF is presented using the concept of mean-square deviation (MSD) minimization [10]. In this, the filter performance is improved based on the assign of different step size to each band. From the results, this approach performs better than the conventional techniques based on the steady-state estimation error and convergence rate.

An active control of impulsive noise with symmetric α-stable (SαS) distribution is developed ANC system [16]. A common step-size normalized filtered-x Least Mean Square (FxLMS) approach is derived based on the Gaussian distribution function is used to regularize the step size. The results demonstrate that the developed approach has good performance for SαS impulsive noise attenuation. Then, the filtered-x state-space recursive least square (FxSSRLS) is presented for active noise control (ANC) [17]. From the results, FxSSRLS approach is more effective in exterminating high-peaked impulses than other approaches for ANC applications.

SAF approach is developed for reducing impulsive noises using Huber's cost function [12]. In general, this approach operates in the normalized SAF mode and it performs like SSAF approach. The sub-band cut-off metrics are derived in a recursive manner for enhancing the robustness of the approach against impulsive noises. For impulsive ANC, an altered bi-normalized data-reusing (BNDR) based adaptive approach is developed [18]. The approach is resulting from a adapted cost function and it is based on reusing the past and present data samples. The results demonstrates the effectiveness of the BNDR-based adaptive approach with a rational increase in the complexity. Delayless SSAF approaches were derived with IWF-SSAF and BD-VSS in impulsive noise conditions for real-time applications [14]. In this, two delayless filter structures implemented for the $\ell 2$-norm based SAF are applied together with IWF-SSAF. Finally, the performance of the approach is proved efficiency in different impulsive interference situations.

3. PRELIMINARIES

3.1 Sign Subband Adaptive Filter Algorithms with Individual Weighting Factors (IWF-SSAF)

Subband adaptive filter (SAF) is an attractive option to minimize the computational complexity problem of the Least Mean Squares (LMS). Fig.1 shows the structure of SAF algorithm.

The desired signal $d(n)$ is expressed as (1),

$$d(n) = w_{opt}^T u(n) + v(n) \qquad (1)$$

Where, $u(n)$ is the input signal that is represented by $u(n) = [u(n), u(n-1), u(n-2), \ldots, u(n-L+1)]^T$, w_{opt} is the weight vector of the unknown system with L-length and $v(n)$ includes an impulsive noise $i(n)$ and the background noise $b(n)$.

The sub-band signals are represented by $d_i(n)$ and $u_i(n)$ which are attained by filtering the $d(n)$ and $u(n)$ using filter examination $H_i(z)$ for i=1,2,3,...,N is the number sub-bands. In addition, $d_{i,D}(k)$ is obtained by decimating $d_i(n)$ by a factor of N, the decimated sequence is represented as k. The error vector of decimated sub-band $e_D(k)$ is calculated as (2),

$$e_D(k) = d_D(k) - U^T(k) w(k) \qquad (2)$$

Where, $w(k)$ is the calculate of w_{opt} at k-number of iterations,

$$U(k) = [u_1(k), u_2(k), \ldots, u_N(k)]$$
$$d_D(k) = [d_{1,D}(k), d_{2,D}(k), \ldots, d_{N,D}(k)]^T$$
$$u_i(k) = [u_i(kN), \ldots, u_i(kN-L+1)]^T$$

The coefficient vector is attained by reducing the cost function using a stochastic gradient decent [12]:

$$J(k) = \sum_{i=1}^{N} \lambda_i \left| e_{i,D}(k) \right| \qquad (3)$$

Where, $d_{i,D}(k)$ is the i^{th} element of $e_D(k)$ in (2) and λ_i represents the weighting feature. Besides, the updated equation for the coefficient vector derived as follows in the IWF-SSAF,

$$\begin{aligned} W(k+1) &= w(k) - \mu \frac{\partial J(k)}{\partial w(k)} \\ &= w(k) + \mu \sum_{i=1}^{N} \lambda_i u_i(k) \operatorname{sgn}(e_{i,D}(k)) \end{aligned} \qquad (4)$$

Where, $sgn(\cdot)$ is denotes the sign function and μ is a step-size to make sure that the coefficient vector does not change rapidly and sgn(•) represents the sign function. When δ is derived as a small positive constant to keep away from dividing by zero, $\lambda_i = \frac{1}{\sqrt{\sum_{i=1}^{N} u_i^T(k) u_i(k) + \delta}}$ is employed as the weighting feature in the original SSAF [5]. Also, the individual weighting feature λ_i for IWF-SSAF is considered in all sub-bands:

$$\lambda_i = \frac{1}{\sqrt{u_i^T(k) u_i(k) + \delta}}, \qquad i = 1, 2, \ldots, N \qquad (5)$$

Form the outcome, IWF-SSAF completely uses the decorrelating possessions of SSAF and provides speedy convergence. At last, the coefficient vector update in IWF-SSAF is,

$$w(k+1) = w(k) + \mu \sum_{i=1}^{N} \frac{u_i(k) \operatorname{sgn}(e_{i,D}(k)}{\sqrt{u_i^T(k) u_i(k) + \delta}} \qquad (6)$$

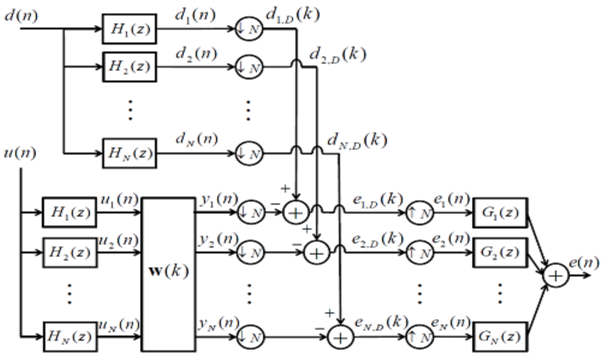

Fig.1 Sub-band adaptive filter structure [12].

3.2 Delayless IWF-SSAF

IWF-SSAF approach [12] enhances the convergence rate of the conventional SSAF approach [5]. In [17], developed two delayless IWF-SSAF namely-loop and closed-loop designs by applying the new delayless configurations in the NSAF. In the delayless open-loop based IWF-SSAF, the obtained convergence performance is same as the IWF-SSAF. Besides, the error signal $e(n)$ in the proposed approach is developed without delay and estimated in a supplementary loop, although the signal path delay can be produced in IWF-SSAF because it is recreated by the combination filter bank.

In addition, a delayless closed-loop based IWF-SSAF is achieved based on configuration of closed-loop shown in Fig.2. In this, sub-band error signal derived by d $e(n)$ using the examination of filter $H_i(z)$. Then, by decimating it based on a factor of N and update the adaptive filter $w(k)$. Therefore, it is adjusted based on prior data of the error signal due to the interruption of the analysis filters $H_i(z)$.

In delayless closed-loop IWF-SSAF, the results show that the upper bound of the step size is reduced for fixed convergence [19]. To address this drawback, the delayless closed-loop structure is used in some beneficial application called as active impulsive noise control (AINC) while only the error signal is obtainable and it is considered as impulsive interference.

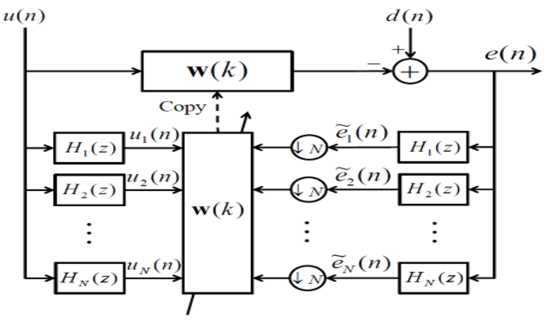

Fig.2 Delayless closed-loop NSAF structure [14]

The delayless closed loop IWF-SSAF algorithm as follows,

Algorithm: 1 Delayless Closed-Loop IWF-SSAF algorithm [14]

Input: $u(n)$ – *input signal vector*, $e(n)$ – *error signal*,
Output: *update equation for the coefficient vector* $w(k)$

1. *For* $n = 1,2,3,....,$
2. $e(n) = d(n) - w^T(k)u(k)$
3. $u_i(n) = h_i^T a(n), \quad i = 1,2,...,N$
4. *For* $k = 1,2,3,....,$ *when* $n = kN$
5. $\tilde{e}_{i,D}(k) = h_i^T e(kN) \quad i = 1,2,...,N$
6. $\sigma_i(k) = \sqrt{u_i^T(k)u_i(k)}$
7. $w(k+1) = w(k) + \mu \sum_{i=1}^{N} \frac{u_i(k)\,\mathrm{sgn}(\tilde{e}_{i,D}(k))}{\sigma_i(k)}$
8. *end*
9. *end*

3.3 BD-VSS based delayless IWF-SSAF

Besides, a BD-VSS approach is introduced to enhance the open-loop convergence rate and closed-loop delayless IWF-SSAF approach. In this, the l_1 normalization is integrated into each subband of the delayless IWF-SSAF [9]. This provides the robustness against impulsive interferences. Hence, to achieve the expected convergence rate, variable step sizes are arranged to be considered to corresponding subbands. Some VSS subband approaches have been proposed [8]. Although, most of these algorithm needs the past information which may be basically unavailable and a priori knowledge is not required in ℓ1-norm based VSS approach.

4. PROPOSED METHODOLOGY

The proposed IWF-SSAF with BD-VSS and Particle Swarm optimization (PSO) [21] is assigned and its closed-loop design is developed. Fig.3 shows the structure of proposed approach with PSO for the AINC.

We proposed methodology incorporates AINC technique into the Filtering technique to suppress the noises. The posteriori error of i^{th} sub-band is derived as,

$$e_{i,p}(k) = d_{i,D}(k) - u_i^T(k)w_i(k+1) \quad (7)$$

Where, $w_i(k+1) = w(k) + \mu_i(k)\dfrac{u_i(k)\,\mathrm{sgn}(e_{i,D}(k))}{\sqrt{u_i^T(k)u_i(k)+\delta}}$,

$\mu_i(k)$ is

The step size of the i^{th} subband and $e_{i,p}(k)$ is rewritten as follows,

$$e_{i,p}(k) = e_{i,D}(k) - u_i(k)g_i(k) \quad (8)$$

Where, $g_i(k) = \dfrac{u_i(k)u_i^T(k)\,\mathrm{sgn}(e_{i,D}(k))}{\sqrt{u_i^T(k)u_i(k)+\delta}}$.

Also, the BD-VSS for $i = 1, 2, \ldots, N$, optimum in the l_1-norm regularization control [8], is derived by minimizing l_1-norm of $e_{i,p}(k)$ as,

$$\mu_{i,sol}(k) = \begin{cases} \underset{\mu_i(k)}{\arg\min} & \left\| e_{i,D}(k) - u_i(k) g_i(k) \right\| \\ subject\ to & \mu_L \le \mu_i(k) \le \mu_U \end{cases} \quad (9)$$

In (9), the positive constraints, the lower and upper bounds for $u_i(k)$ are represented as μ_L and μ_U respectively. The μ_U is chosen to be adjacent to zero and μ_U is considered as less than one for constancy of the adjusted l_1-norm approach. Moreover, diverse numbers for μ_L and μ_U are considered for every sub-band. Nevertheless, the identical μ_L and μ_U are employed in every sub-bands. From (9), we examine that the l_1-norm regularization that is a one-dimensional linear curved constraint. Therefore, the result of $\mu_{i,sol}(k)$ is expressed from the l_1-norm regularization approach. This should be derived as,

$$\mu_{i,sol}(k) = \frac{e_{i,D}(k)}{g_i(k)+\varepsilon}, \quad i = 1, 2, \ldots, N \quad (10)$$

Where, ε is used to evade dividing by zero and developing the convexity of l_1-norm, the optimum result (9) is derived.

$$\mu_{i,sol}(k) = \begin{cases} \mu_U, & \text{if } \mu_{i,sol}(k) > \mu_U \\ \mu_L, & \text{if } \mu_{i,sol}(k) < \mu_L \\ \mu_{i,sol}(k), & \text{otherwise} \end{cases} \quad (11)$$

Further, the convergence performance of the BD-VSS approach is assuming the consequence of the impulsive interference in step size control. However, from equation (10), when the impulsive noise works on few sub-band which controls the impulsive noise and the convergence behaviour is weakened.

To prevent this, in the BD-VSS $\mu_i(k)$ is achieved by applying the time average method as follows,

$$\mu_i(k) = \beta\mu_i(k-1) + (1-\beta)\min\left\{\mu_{i,opt}(k), \mu_i(k-1)\right\} \quad (12)$$

Where, β is the smoothing parameter that is expressed, $\beta = \dfrac{1-N}{\xi . L}$ and $\xi \in \{1, 2, \ldots, 10\}$ is a variable which is based the input signal and coefficient vector $w(k)$ correlation.

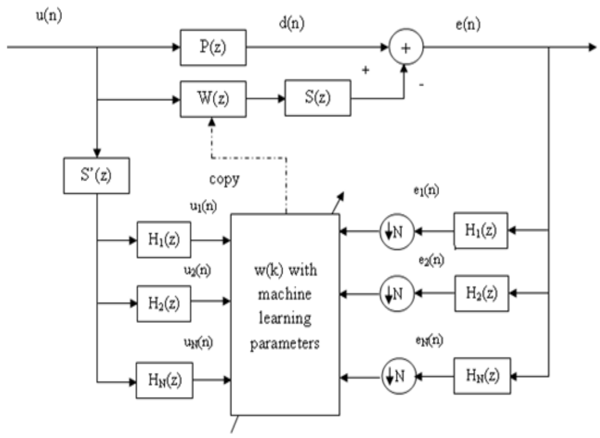

Fig.3 The proposed structure of delayless closed-loop IWF-SSAF approach with BDVSS and PSO for the AINC

Algorithm: 2 Proposed IWF-SSAF algorithms with BDVSS and PSO

Input: $g_k(k), u_i(k), c1$ & $c2$ *are acceleration coefficients* $0 \le c1, c2 \le 2$,
$r1, r2$ *are random values* $(0 \le r1,\ r2 \le 1)$, g *is the swarm's best solution*
x_i *is the particle position*, $\hat{x}_i$ *is the particle's individual best solution.*

Output: *optimal* $\mu_i(k)$, *update* $w(k)$

1. *For each particle* i, $i = 1, 2, \ldots, N$
2. *For each* dimension $k = 1, 2, 3, \ldots$
3. *update step-size* $\mu_i(k), i = 1, 2, \ldots, N$

   i. $g_i(k) = \dfrac{u_i(k)u_i^T(k)\,\mathrm{sgn}(e_{i,D}(k))}{\sqrt{u_i^T(k)u_i(k)+\delta}}$

   ii. $\mu_{i,sol}(k) = \dfrac{\tilde{e}_{i,D}(k)}{g_i(k)+\varepsilon}$

   iii. $\mu_{i,sol}(k) = \begin{cases} \mu_U, & \text{if } \mu_{i,sol}(k) > \mu_U \\ \mu_L, & \text{if } \mu_{i,sol}(k) < \mu_L \\ \mu_{i,sol}(k), & \text{otherwise} \end{cases}$

   iv. $\mu_i(k) = \beta\mu_i(k-1) + (1-\beta)\min\left\{\mu_{i,opt}(k), \mu_i(k-1)\right\}$
4. *Update* $w(k)$ *and velocity* $v_i(k)$

   i. $w_i(k+1) = w(k) + \mu_i(k)\dfrac{u_i(k)\,\mathrm{sgn}(e_{i,D}(k))}{\sqrt{u_i^T(k)u_i(k)+\delta}}$

   ii. $v_i(k) = v_i(k)\ w_i(k+1) + c_1 r_1[\hat{x}_i - x_i] + c_2 r_2[g - x_i]$
5. *end*
6. *end*

The equation (12) expresses the BD-VSS approach is derived from the aforementioned step size $\mu_i(k-1)$ where the impulsive interferences influence the i^{th} subband that provides heftiness in contradiction of impulsive noise. Else, the algorithm is performed with the time normalized optimal step size as follows,

$$\mu_i(k) = \beta\mu_i(k-1) + (1-\beta)\mu_{i,opt}(k) \quad (13)$$

Moreover, the computational complexity is diminished using proposed approach with PSO.

5. RESULTS AND DISCUSSION

In this, we present the results of computational complexity and convergence operation of the proposed algorithm. Initially, we have considered the input signal in time domain which includes the noise signal Fig.4 shows the input signal in time domain representation.

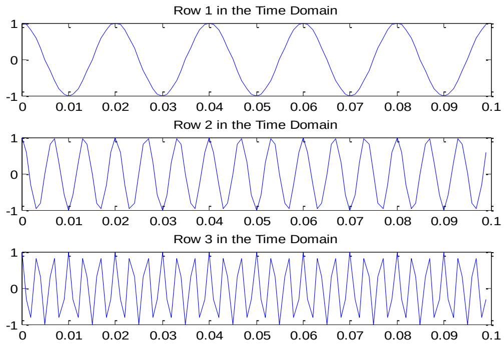

Fig.4 Input signal in time domain

Then, the signal is switched into frequency domain from time domain using FFT transformation. Fig.5 illustrates the input signal in frequency domain representation.

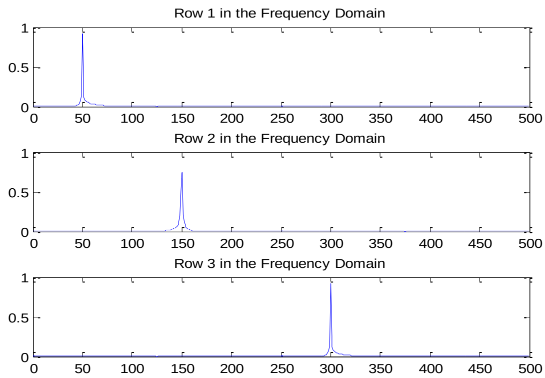

Fig.5 Input signal in frequency domain

The analysis of IWF-SSAF with BD-VSS with PSO approach was proved in ANIC, which is assigned as an impulsive noise situation of the closed-loop structure.

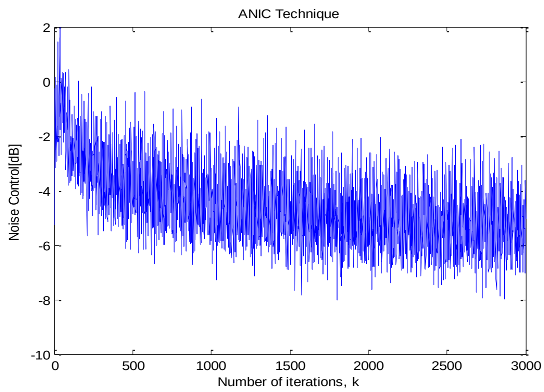

Fig.6 Noise suppression using AINC technique

To analyze the performance enhancement by the proposed closed-loop algorithm, this is better than without optimization algorithm. Fig.6 shows the noise suppression of proposed method. Simultaneously, the input signal is divided into multiples subband using Mexican Hat Wavelet transformation. Fig.7 shows the Mexican Hat wavelet,

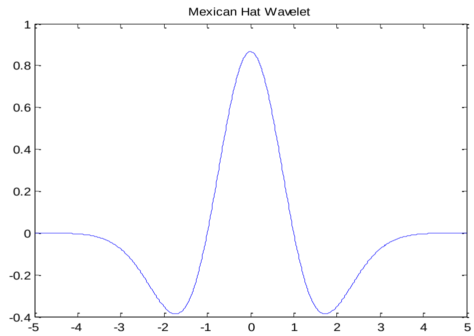

Fig.7 Mexican Hat Wavelet

Now, there are two signals are achieved, one from output of FFT and another from Mexican Wavelet result. These signals are undergone with analysis of ROC and the results are obtained. Then, the Machine learning algorithms are incorporated to analyse on the best values of ROC in the Mexican wavelet transformation and FFT and the best values are collected in a structured array. Moreover, the evaluation factors are analysed to have an concept on the signal accuracy and strength. This evaluation parameter gives an idea on the extension of the signals.

In Fig.8 show that the Averaged Noise Reduction (ANR) performances achieved by the proposed approach with Particle Swarm Optimization (PSO) algorithm. This demonstrates the approach produced the effective ANR operation.

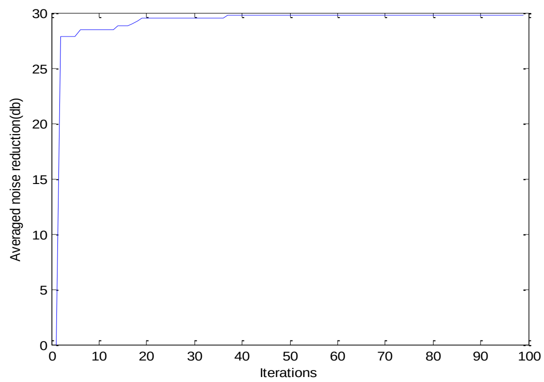

Fig.8 ANR performance of proposed algorithm

The closed-loop l_1-norm achieved a effective performance under the same environments and high impulsive noise control compared to other existed algorithms. In addition, the impulsive noises by all assigned algorithms which prove that the algorithm accomplished a efficient noise control than other approches.

6. CONCLUSION

In this paper, BD-VSS based delayless closed-loop IWF-SSAF approach is proposed. The impulsive noise is successfully suppressed using AINC technique. The proposed approach has better convergence performance based on the l_1-norm minimization technique and decorrelating properties of SSAF algorithm. PSO technique is applied together with IWF-SSAF algorithm for reducing the computational complication. The performance evaluation verifies the proposed algorithm has improved convergence rate with condensed complexity compared to the other SSAF algorithms.

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