Abstract—Satellite image denoising is essential for enhancing the visual quality of images and for facilitating further image processing and analysis tasks. Designing of self-tunable 2-D finite-impulse response (FIR) filters attracted researchers to explore its usefulness in various domains. Furthermore, 2-D FIR Wiener filters which estimate the desired signal using its statistical parameters became a standard method employed for signal restoration applications. In this paper, we propose a 2-D FIR Wiener filter driven by the adaptive cuckoo search (ACS) algorithm for denoising multispectral satellite images contaminated with the Gaussian noise of different variance levels. The ACS algorithm is proposed to optimize the Wiener weights for obtaining the best possible estimate of the desired uncorrupted image. Quantitative and qualitative comparisons are conducted with 10 recent denoising algorithms prominently used in the remote-sensing domain to substantiate the performance and computational capability of the proposed ACSWF. The tested data set included satellite images procured from various sources, such as Satpalada Geospatial Services, Satellite Imaging Corporation, and National Aeronautics and Space Administration. The stability analysis and study of convergence characteristics are also performed, which revealed the possibility of extending the ACSWF for real-time applications as well.

Index Terms—2-D finite-impulse response (FIR) Wiener filter, adaptive cuckoo search (ACS) algorithm, metaheuristic optimization algorithms, satellite image denoising.

I. INTRODUCTION

MULTISPECTRAL imagery (MSI) is steadily growing in its popularity as a digital means for remote sensing, terrain analysis, and detecting thermal signature. It is often used as a viable alternative for mapping applications when standard mapping and geodesy product become inadequate or outdated. The first and foremost attribute of the MSI is its capability to record spectral reflectance in different portions of the electromagnetic spectrum, which makes it useful in various applications [1], [2]. MS images embed the amount of reflectance and illumination of the scene procured, in a wide stretch of much narrower frequency bands than RGB images. The MSI system records such MS signal with the aid of multispectrum arrays of sensors. MS images thus convey an authentic representation of real-world scenes, and hence the performance measures of remote-sensing operations get enhanced. Compared with hyperspectral images (with 100–200 bands which record the acquired signal in a wide spectral range), MS images generally possess a less number of distinct spectral bands (i.e., 4–7) and hence is less bulky to process.

However, the MSI is often affected by noisy signals, thereby corrupting the original image. Such noise sources range from system calibration errors, recording equipment limitations, varying sensitivity of sensors, photon effects, and interfering natural phenomena [3]. Moreover, narrow-bandwidth and limited-radiance energy obtained via sensors increases the probability of thermal noises getting affected on the image pixels significantly. Such noises are inevitable in the satellite-based remote-sensing environment.

The characteristics of such interfering noises depend on the acquisition system as well as the type of the images to be processed. Mostly, this type of noise can be represented as a random process following the normal distribution (Gaussian) with zero mean. MS imaging systems consist of a large spectral redundancy, which implies that the obtained image with a range of frequency bands is correlated with each other. Hence, the noise removal task results in the elimination of minor spectral components. Thus, denoising of MS images remains as a challenging task because of lack of a robust approach.

The simplest way of denoising is to utilize the conventional 2-D denoising techniques to reduce noise in the MS image pixel-by-pixel or band-by-band. Such filtering approaches include the use of 2-D IIR and finite-impulse response (FIR) filters and adaptive filtering algorithms, such as 2-D least mean square (2-D-LMS) algorithm [4]–[6], 2-D normalized LMS (2-D-NLMS) algorithm [7], [8], and 2-D affine projection algorithm (2-D-APA) [6], [9]. Later, 2-D FIR adaptive Wiener filters were also developed which guaranteed an optimal trade-off between noise smoothing and inverse filtering [10]. The optimization of 2-D adaptive filter coefficients for the aforementioned algorithms was performed using conventional optimization algorithms [7], [8].
Consequently, the advent of evolutionary and swarm intelligence-based algorithms paved the way to use its potential to solve similar iterative optimization problems [11]–[16]. For instance, Tzeng [14] proposed a 2-D adaptive FIR digital filter design using the genetic algorithm for filter coefficient optimization. Boudjelaba et al. conducted a comprehensive comparative study highlighting the merits and demerits of using evolutionary algorithms for designing 2-D adaptive FIR digital filters [15]. Such stochastic algorithms were then widely found use in the medical domain [17] as well as for denoising natural images [12], [13], [18], [19]. Recently, Bhandari et al. [20] extended the use of evolutionary algorithms for wavelet-domain-based MS satellite image denoising application. The authors used the adaptive differential evolution (JADE) algorithm to find the optimal subband thresholds to separate noise from image [20]. Although the authors claimed the algorithm to be superior compared with others, but it was less efficient in preserving the edges and other textural features.

The statistical estimation of the desired signal from the noisy signal using 2-D FIR adaptive Wiener filters is found to perform well, provided the filter coefficients are fine-tuned. The recent advancements in the field of artificial intelligence and the proven potential of metaheuristic algorithms motivated us to use the same for finding the optimal adaptive Wiener weights. A prior analytical study comparing the performance of different metaheuristic algorithms for solving nonlinear optimization problems was conducted before choosing cuckoo search (CS) algorithm in modeling the proposed denoising method [1], [21]. The CS algorithm was adopted accounting for its implementation simplicity and efficient solution exploitation and exploration strategies along its run. So as to further enhance the solution exploration strategy, with a commendable improvement in the algorithm’s convergence capability, a computationally efficient adaptive CS (ACS) algorithm is proposed. Therefore, in this paper, an efficient 2-D FIR adaptive Wiener filtering method using the ACS algorithm (ACSWF) is proposed for denoising satellite images contaminated with additive white Gaussian noise (AWGN). The noise is assumed to be uniform in every band and the low-spectral correlations between bands are treated as self-evident. The major contributions of this paper are as follows.

1) A computationally efficient ACS algorithm is proposed by remodeling self-ACS (SACS) algorithm that was put forward by Li et al. for optimizing the weight vectors of an adaptive Wiener filter [22].

2) A robust ACS-based adaptive Wiener filtering (ACSWF) for denoising MS satellite images corrupted with the Gaussian noise is proposed.

Visual and numerical results highlight the superiority of the proposed method in restoring images corrupted with the Gaussian noise of different variance levels consistently. Performance stability and improved convergence capability of the proposed filter make it adaptable for other signal processing applications.

The rest of this paper is organized as follows. Section II presents a detailed study of various denoising techniques found in the literature for MS image denoising. Section III gives the details of the theory and implementation steps of the proposed ACSWF. Section IV presents the simulation results and discussions. Finally, Section V draws the conclusion.

II. RELATED WORK

Unfortunately, the presence of noise in MS images not only affects the human interpretation but also limits the accuracy of the computational methods. The poor image quality also makes various quantitative measurements and computer-aided analysis challenging and unreliable. Hence, quality enhancement of such images by employing proper denoising methods becomes a prerequisite for all practical applications. In the last few decades, a large number of methods have been proposed for denoising MS and hyperspectral images. Focusing on the works done over the past decade for MS image denoising, we come across techniques using transform-domain-based schemes [23]–[26], nonlocal sparse models [27]–[30], anisotropic diffusion scheme [31], partial differential equations (PDEs) [28], nonlocal tensor based models [32], [33], and bilateral filtering [34], [35].

Scheunders and De Backer [23] proposed a Bayesian wavelet-based method for denoising MS satellite images using a prior noise-free image. The authors claimed that the proposed method is performing better compared with other MS image denoising algorithms. Chaux et al. put forward a nonlinear Stein-based estimator for wavelet denoising of multichannel data [24]. Experiments performed for denoising MS remote-sensing images significantly outperformed other wavelet-based methods. A wavelet-based MS image restoration technique was proposed by Duijster et al. based on an iterative expectation maximization algorithm, applying deconvolution and denoising steps alternately [36]. Experiments on Landsat and AVIRIS images highlighted the denoising efficiency of the proposed method over bandwise method [36]. Despite the aforementioned merits, wavelet-based methods are computationally complex because of domain transformation, and an inappropriate selection of basis functions or subband thresholds for denoising can cause blurring and ringing artifacts around edges.

Mairal et al. [27] introduced a new image restoration model combining the nonlocal means and sparse coding approaches. Quantitative and qualitative experiments on images corrupted with synthetic or real noise showed the effectiveness of the proposed model compared with other state-of-the-art denoising methods, in the expense of computational complexity. Prasath and Singh [31] proposed an MS image denoising scheme using coupled PDEs with anisotropic diffusion. The well posedness of the scheme guaranteed its stability with efficient prefiltering capacity, whereas the increased computational complexity made the scheme practically difficult to process images of bigger size and more than three channels [31]. A similar remote-sensing image denoising method using PDEs and auxiliary image priors (PDE-AIP) was proposed by Liu et al. [28] in 2012. Visual results and quantitative indicators proved the proposed method to be particularly suited for denoising images corrupted with high-variance noise. In 2014, Peng et al. [32] proposed a decomposable
nonlocal tensor-based dictionary learning technique for MS image denoising. The proposed method ameliorated the image quality considerably but failed to preserve the structural details compared with others. Recently, Xie et al. [33] proposed a new MSI denoising model using a newly designed tensor-based sparsity measure. Experimental results substantiated the superiority of the proposed denoising scheme beyond the state of the art in recovering the fine and course grained structures. At the same time, all tensor-based image processing techniques account for an increased computation time and memory. Peng et al. [34] used optimized vector bilateral filtering for MS image denoising which provided fair tradeoff between noise filtering and edge degradation. The authors selected the image-dependent filter parameters by optimization procedure based on Steins principle. In 2017, Papari et al. [35] introduced a bilateral filtering scheme for 3-D images. The filtering scheme was computationally efficient, but it resulted in reasonable image artifacts particularly near edges. Similarly, a plethora of literature is available on hyperspectral image denoising which can be roughly categorized as transform-based methods [37], filter-based methods [38], regularization-based methods [39]–[41], and kernel based methods [42].

III. ADAPTIVE CUCKOO SEARCH-BASED WIENER FILTER (ACSWF)

A. Theory Behind the Proposed ACSWF

This section presents the theory and fundamental concepts of the proposed ACS algorithm-based Wiener filtering for the denoising of satellite images corrupted with the AWGN. The key idea of the proposed method is to find the best possible estimate of the original image using 2-D FIR Wiener filtering. The 2-D FIR Wiener filter is modeled to adaptively modify its window weights, to minimize the mean square error (MSE) between the desired image and the filter output. The proposed denoising method uses the ACS algorithm for optimizing those filter weights ensuring the least possible mean squared error as compared with other similar metaheuristic algorithms. The block schematic of the proposed ACSWF for satellite image denoising is shown in Fig. 1.

The Wiener filtering theory assumes the signals to be stationary. The 2-D FIR Wiener filters are block-adaptive, wherein it calculates the filter coefficients periodically for a predefined block size of \(n \times n\) samples [43].

Let \(x_{i,j}\) be the original uncorrupted image pixel located at spatial location \(i, j\) and \(y_{i,j}\) be its noisy counterpart contaminated with signal independent AWGN, \(\eta_{i,j}\). Modeling a 2-D FIR Wiener filter for denoising this image, to obtain a linear estimate \(\hat{x}_{i,j}\), requires minimizing the MSE value between \(\hat{x}_{i,j}\) and \(x_{i,j}\). It can be mathematically formulated as in

\[
\text{MSE} = \sum_{i=1}^{M} \sum_{j=1}^{N} (\hat{x}_{i,j} - x_{i,j})^2
\]

where \(M\) and \(N\) denote the dimension of the input image to be processed. The linear estimate \(\hat{x}_{i,j}\) of the desired signal obtained using Wiener filtering can be evaluated using [44], [45]

\[
\hat{x}_{i,j} = \frac{\sigma_{\eta_{i,j}}^2}{\sigma_{\eta_{i,j}}^2 + \sigma_{\eta_{i,j}}^2} \left( y_{i,j} - \mu_{x_{i,j}} \right) + \mu_{x_{i,j}}
\]

where

\[
y_{i,j} = x_{i,j} + \eta_{i,j}.
\]

Parameters \(\mu\) and \(\sigma^2\) indicate the mean and variance of the signal, assuming \(x_{i,j}\) to be a white Gaussian process and the noise mean to be zero. For estimating the linear estimate \(\hat{x}_{i,j}\), we assume that the mean and variance values of the AWG noise \((\mu_{\eta_{i,j}}, \sigma_{\eta_{i,j}}^2)\) are known [46], [47]. Hence, the prime focus is on estimating the mean and variance of the desired input signal, \(\mu_{x_{i,j}}\) and \(\sigma_{x_{i,j}}^2\), respectively. In our proposed method, the mean and variance measures of \(x_{i,j}\) are usually estimated using the method devised by Kuan et al. [45]. The local signal statistics estimation using adaptive weight factors formulated by Kuan et al. [45] overcame the severe blurring around the edges of the images introduced using the local linear minimum MSE [44].

The authors proposed using monotonically decreasing functions such as the Gaussian function for calculating the filtering window weights, by asserting more confidence on variance estimate at the center of the window used. The use of adaptive window weights, rather than deterministic weights by Kuan et al. [45], seemed to be more appropriate and reliable for image filtering. Hence, we propound the use of adaptive Wiener weights in our proposed denoising method driven by the ACS algorithm (ACSWF). The optimal weights thus obtained are used for estimating the local statistics of the linear estimate of the desired signal. The estimated mean and variance measures using adaptive Wiener weights are formulated as given in

\[
\hat{\mu}_{x_{i,j}} = \frac{\sum_{a=i-n}^{i+n} \sum_{b=j-n}^{j+n} w_{i,j,a,b} y_{a,b}}{(i+n)(j+n)}
\]

\[
\hat{\sigma}_{x_{i,j}}^2 = \frac{\sum_{a=i-n}^{i+n} \sum_{b=j-n}^{j+n} (w_{i,j,a,b} (y_{a,b} - \hat{\mu}_{x_{i,j}}))^2}{(i+n)(j+n)}
\]

where \(w_{i,j,a,b}\) is the adaptive Wiener weight vector.

B. Proposed Adaptive Cuckoo Search Algorithm

The CS is a stochastic metaheuristic algorithm evolved mimicking the obligate brood parasitic behavior shown by some cuckoo species [48]. The use of Lévy flight strategy rather than Brownian random walks for solution space exploration and its implementation simplicity because of the use of a
single control parameter $p_a$ (switching parameter) are the key factors which make it superior compared with others. The flow of the CS algorithm is based on three idealized rules, wherein the single control parameter ($p_a$) denotes the probability of discovering alien eggs by the host species. Practical implementation of this scenario includes replacing $p_a$ proportion of the current solution set with new ones [48]. Similarly, Lévy flight strategy for random walks follows variable step sizes ensuring least chances for oversampling, which eventually improved the convergence rate of the algorithm. Thus, the CS algorithm uses a balanced combination of local and global random walks controlled by a “switching parameter” $p_a$ [48].

In order to further improve the solution searching capability of the CS algorithm, many CS variants were proposed for different optimization problems. A prior extensive study was undertaken comparing the potential of various ACS variants in the literature, for implementing the above-defined satellite image denoising [22], [49]–[52]. The SACS algorithm was developed by modifying and combining the mutation strategies used by two common variants of differential evolution (DE) algorithm [53]. The structure of any DE variants is generalized by denoting them as DE/x/y/1, where $x$ is the mutation vector, $y$ is the number of vectors used for mutation, and $z$ indicates the crossover scheme [binomial (bin) or exponential (exp)] employed [2], [54]. The authors used a scale factor “$\phi$” to control the pace of the algorithm to reach optimality. The scale factor “$\phi$” was drawn in each iteration from a Gaussian distribution of mean 0.5 and standard deviation 0.1 [22].

Further investigations proved that the random initialization of “$\phi$” values repeatedly in each iteration did not help in improving the convergence rate or enhancing the performance. At the same time, it resulted in an unwanted increase in the computational complexity of the algorithm. Hence, we remodelled the above-mentioned approach by replacing the scale factor “$\phi$” with the switching parameter “$p_a$.”

The mutation strategies used by two DE variants given in (4) are modified and adopted in the proposed ACS algorithm [22]

\[
\begin{align*}
\text{DE/rand/1/bin}: w_{k,G+1} & = w_{r_1,G} + F \cdot (w_{r_2,G} - w_{r_3,G}) \\
\text{DE/best/1/bin}: w_{k,G+1} & = w_{\text{best},G} + F \cdot (w_{r_1,G} - w_{r_2,G}) \\
& + w_{r_3,G} - w_{r_4,G}
\end{align*}
\]

where $k \in \{1, \ldots, N_p\}$, $r_1, r_2, r_3,$ and $r_4$ are random integer indices selected from $k \in \{1, \ldots, N_p\}$, $x_{\text{best}}$ is the mutation vector, $N_p$ is the population size, and $F$ is the scaling factor used in the DE algorithm. $F \in [0, 1]$ helps in avoiding search stagnation of the algorithm by controlling the effect of the difference vector in mutation operation [54]. Equation (5) gives the modified form of (4) included in the proposed ACS algorithm

\[
\begin{align*}
\text{CS/rand/1/bin}: w_{k,G+1} & = w_{r_1,G} + p_a \cdot (w_{r_2,G} - w_{r_3,G}) \\
\text{CS/best/1/bin}: w_{k,G+1} & = w_{\text{best},G} + p_a \cdot (w_{r_1,G} - w_{r_2,G}) \\
& + w_{r_3,G} - w_{r_4,G}
\end{align*}
\]

where $p_a$ is the “switching parameter” in the CS algorithm. The pseudocode of this phase is as given in the following.

```plaintext
if rand$_k$ $\geq 1 - \frac{G}{G_{\text{max}}}$ then
  CS/best/1/bin;
else
  CS/rand/1/bin;
end
```

In this pseudocode, $\text{rand}_k$, $k = \{1, \ldots, N_p\}$ is a random number drawn from a uniform probability distribution, whose value lies within the range $[0, 1]$. The parameter $G$ indicates the current iteration (generation) count and $G_{\text{max}}$ denotes the total number of iterations included. Thus, in the ACS algorithm, the discovery and randomization stages of the CS algorithm are modified by adopting the two mutation strategies following the pseudocode given above. The randomization stage selects any of the two strategies by comparing the value of $(1 - (G/G_{\text{max}}))$ with the $\text{rand}_k \in [0, 1]$ value, generated in each iteration for the entire population. It indicates that the probability of selecting any of the two search strategies is a function of the iteration count $G$. Hence, if $\text{rand}_k$ is less than $(1 - (G/G_{\text{max}}))$, CS/rand/1/bin is chosen, or else CS/best/1/bin is selected as the randomization strategy for the ACS algorithm. The selection between these two mutation strategies ensures an increased probability of exploration during the initial iterations and increased exploitation toward the final iterations. It can be easily analyzed, since it is evident that the value of $(1 - (G/G_{\text{max}}))$ decreases from 1 to 0 as it proceeds through the iterations. Thus, the probability of selecting CS/rand/1/bin is more in the initial set of iterations, whereas the probability of choosing CS/best/1/bin increases toward the end. Hence, based on two new search strategies controlled by a linear decreasing probability rule, the ACS algorithm does a better balancing of its exploration and exploitation phases [22].

C. Implementation of Proposed ACSWF

The pseudocode and stepwise implementation details of the proposed ACSWF are given in the following.

**Step 1**: Initialize the solution space randomly using

\[
w_{k,l} = w_{k,l}^{\text{min}} + \text{rand} \cdot (w_{k,l}^{\text{max}} - w_{k,l}^{\text{min}})
\]

where $w_{k,l}$ denotes weights allotted for 2-D FIR Wiener filter. The subscripts $k = \{1, \ldots, N_p\}$, where $N_p$ is the population size, and $l = \{1, \ldots, d\}$, where $d = n^2$ is the total number of coefficients required to form the filter weight matrix. The boundary constraints $[w_{\text{min}}, w_{\text{max}}]$ are set to $[-1, 1]$.  

**Step 2**: The $n \times n$ weight matrix for 2-D FIR Wiener filtering is formed by the 2-D lexicographic conversion of each of the candidate solution vector from the entire population using

\[
[w_{k,1}, w_{k,2}, \ldots, w_{k,n}, w_{k,n+1}, \ldots, w_{k,2n}, w_{k,(n+1)n+1}, \ldots, w_{k,d}] \Rightarrow \left[ \begin{array}{cc}
w_{k,1} & \cdots \n_{k,n} \\
\cdots & \cdots & \cdots \\
w_{k,n(n-1)+1} & \cdots & w_{k,d} \end{array} \right].
\]
Algorithm 1: Proposed ACSWF

// Initialization
Population initialization: \( w_{k,1} \) where \( k = 1, 2, ..., N_p; 1 = 1, 2, ..., d; N_p = \text{population size}; d = \text{dimensionality}; \\
1 Parameter initialization: Switching parameter \((p_a)\), \\
Maximun number of iterations \((G_{max})\).
// 2D FIR Wiener filtering and MSE calculation
2 2D lexicographic ordering of weight vectors \( w_k \) using equation \((8)\);
3 Estimate \( \hat{y}_{i,j} \) using equations \((2)\) and \((3)\) with \( w_{i,j,a,b} = w_k \);
4 Calculate fitness (MSE) values \((F_k)\) using equation \((1)\);
5 Record the best fitness (MSE) value and the corresponding solution set \((w_{best})\).
// Adaptive Cuckoo Search algorithm
6 for \((G \leq G_{max})\) do
7 Lévy flight modeling of random walks to generate new solution sets following equation \((9)\);
8 Estimate \( \hat{y}_{i,j} \) using updated solution set and compute their respective fitness values.;
9 for all \(k\) do
10 if \( F_{k}^{new} > F_{k} \) then
11 \( F_{k} = F_{k}^{new}; \)
12 \( w_{best} = w_{new}; \)
13 end
14 for all \(k\) do
15 if \( \text{rand}_k \geq 1 - \frac{\alpha}{G_{max}} \) then
16 CS/best/1/bin: \\
17 \( w_{k,G+1} = w_{r_1,G} + \alpha \cdot (w_{r_2,G} - w_{r_3,G}); \)
18 else
19 CS/rand/1/bin: \( w_{k,G+1} = w_{best,G} + \alpha \cdot (w_{r_1,G} - w_{r_2,G} + w_{r_3,G} - w_{r_4,G}); \)
20 end
21 end
22 Output estimation and fitness value computation following equations \((2)\) and \((3)\);
23 Comparison of newly generated fitness values with the earlier set and recording the best \((w_{best})\) so far;
24 end
25 Estimate \( \hat{y}_{i,j} \) using the optimal adaptive Wiener weight vector as \( w_{best} \) following equations \((2)\) and \((3)\);

Step 3: Estimate the linear estimate of the desired signal \( \hat{y}_{i,j} \) following \((2)\) and \((3)\) using the adaptive Wiener weight vector as \( w_k \).

Step 4: Compute the fitness (MSE) values of the estimated filter outputs obtained using each possible weight matrix formed in Step 2 using \((1)\). Repeat if number of iterations \( G < G_{max} \).

Step 5: Retain the best possible weight matrix (solution) in the previous iteration and generate new random solutions by Lévy flights around the previous solution set [48]. The new population set thus formed follows:

\[
\begin{align*}
    w_{k,G+1} &= w_{k,G} + \alpha L(s, \beta) \quad (0 < \beta < 2, \alpha = 0.01) \\
    L(s, \beta) &= \frac{\beta \Gamma((\beta\sin(\frac{\pi s}{\beta})^2))}{\pi (s+1)^{\beta}} \\
    \text{where } s &= \text{the step size, } \beta = \text{the smallest step size (typically 0.1–1) and } \alpha = \text{the scaling factor for step size, } G = \text{the iteration/generation count, } w_{k,G} = \text{the weight vectors generated, } w_{k,G+1} = \text{the weight vectors formed for the } G^{th} \text{ generation of the ACS algorithm.}
\end{align*}
\]

Step 6: Estimate \( \hat{y}_{i,j} \) using the new set of weight matrices formed, and compute the fitness value of the newly generated solutions using \((1)\). Memorize the best solution.

Step 7: Apply mutative randomization to the existing solution set as explained in Section II-B and update the new solution set using \((5)\).

Step 8: Compute the estimated output using the updated solution set and evaluate their respective fitness values.

Step 9: Increment the iteration count by 1, i.e., \( G = G + 1 \).

Step 10: Obtain the optimal filter weights \( w_{best,G_{max}} \) and denoise \( y_{i,j} \) using them to get the best possible estimate of the desired signal.

D. Illustration of Proposed ACSWF for Image Denoising

Experiments were conducted for denoising test images corrupted with the Gaussian noise of three different noise variance levels using 2-D adaptive Wiener filter (2-D AWF), CS-based AWF (CSAWF), SACS-based AWF (SACS-AWF), and the proposed ACSWF. The results obtained were compared to substantiate the effect of ACS algorithm in optimizing Wiener weights compared with the other. The qualitative and quantitative results obtained for denoising images contaminated with the Gaussian noise is presented in Fig. 2 and Table I, respectively. The quantitative metrics compared include MSE [55], peak signal-to-noise ratio (PSNR) [56], feature similarity index (FSIM) [57], universal quality index (UQI) [58], normalized absolute error (NAE) [59], and CPU running time. Lower MSE and NAE values along with higher PSNR, FSIM,
Fig. 2. Simulation results of denoising test images corrupted with Gaussian noise of 30% variance level using 2-D AWF, CSAWF, SACSAWF, and ACSWF. (a)–(f) Image 1. (g)–(l) Image 2. Best zoomed on screen.

and UQI values are the preferable conditions for evaluating the performance of the denoising algorithms. The quantitative analysis given in Table I provides two major inferences: 1) with weight search algorithms, such as CS and SACS [22], the image denoising performance can be improved and 2) as compared with the other search algorithms, such as CS and SACS [22], our proposed ACS can achieve superior performance, demonstrating its effectiveness. The visual results also indicate that the use of ACS algorithm in optimizing Wiener weights has a great impact in estimating the desired image. The ACSWF proved to be very efficient in removing the AWGN from the corrupted image, preserving the relevant edges and other features of the image.

The 2-D AWF selects the weight vectors for a pixel \((i, j)\) adaptively by biasing the estimated statistical measures in favor of pixels with values similar to \(y_{i,j}\)

\[
w(i, j, a, b) = \frac{A(i, j)}{1 + \xi (\max\{\epsilon^2, (y_{i,j} - y_{a,b})^2\})}
\]

\[
A(i, j) = \left\{ \sum_{a,b} 1 + \xi (\max\{\epsilon^2, (y_{i,j} - y_{a,b})^2\}) \right\}^{-1}
\]

where \(\xi > 0\), \(\epsilon = 2.5\sigma_{r, w(i, j, a, b)} = 0\), and \(A(i, j)\) is the normalization constant. Parameter \(\xi\) was chosen such that \(\xi \epsilon^2 \gg 1\) so as to limit outliers [60]. Since our test images are complex scenes with profound edge and textual information, this adaptive weight selection constraint will tend to fuse the closely laid edges. It reflects as blurring along the edges and minor textural features for such images, whereas this approach works effectively for preserving edges of less complex scenes.

The use of the metaheuristic algorithm effectively enhances this adaptive weight vector selection problem. The use of the CS algorithm for optimizing the weights (CSAWF) works well in preserving the edges, since the selection of weight factors are solely based on the fitness function, which is to reduce the MSE value between the estimated pixels and the original image. The use of uncorrupted image prior helps in optimizing the wiener weights to estimate a close enough approximation of the original image. The proposed ACSWF approach includes a better balance between solution exploration and exploitation strategies, which efficiently explores every single possibility for the optimal weight vectors which reduces the calculated MSE value. It eventually reduces the chances of getting clogged in a near optimal solution set as seen using the CS algorithm [2]. Hence, the selection of the best possible Wiener weight vector using the proposed ACSWF approach results in a better denoising result with less image artifacts.

IV. RESULTS AND DISCUSSION

A. Data Set Description and System Specifications

The tested data set includes satellite images procured from various sources, such as Satpalka Geospatial Services, Satellite Imaging Corporation, and NASA. All the test images included in the study are MS images with four bands (blue: 430–550 nm; green: 500–620 nm; red: 590–710 nm; near IR: 740–940 nm). The three images included in this paper are referred as Image 1: landslide in Zhouqu, China, 1263 × 1261, WorldView-2, MS-4 50 m Res. (http://earthobservatory.nasa.gov), Image 2: Madrid, Spain, 1000 × 1000, WorldView-3, MS-4 40 cm Res. (http://www.satimagingcorp.com), Image 3: real noisy image, Sentinel-2, 1034 × 1030, (computed noise variance 19.88%), (https://eros.usgs.gov/sentinel-2). Two more images with their simulation results are included in the Supplementary Material. Simulations were carried out using MATLAB R2015a software running on an Intel Core i7-3770.
B. Simulation Results

This section includes experimental results obtained using three high-spatial resolution MS satellite images of which one is a real noisy image obtained. Two more such MS images with their qualitative and quantitative results are provided in Fig. 3 and Tables II–IV of the Supplementary Material. The performance analysis of the proposed ACSWF is carried out by comparing it with basic 2-D adaptive filtering methods, such as 2-D-NLMS algorithm [19], [61] and 2-D-APA [19], [62]. We have also included most recent state-of-the-art denoising methods used with MS satellite images which employs the principal component analysis combined with block-matching 3-D (BM3-D-PCA) [63], [64], PDE-AIP [28], nonlocal cosine integral images (CII-NLM) [25], discrete shearlet transform (DST) [26], and spatiotemporal total variation (SSTV) [30]. For ensuring a fair comparison, we have included comparison with recent denoising algorithms using metaheuristics, such as the JADE algorithm [20] and the 2-D artificial bee colony (ABC) system with 3.40-GHz CPU, 8-GB RAM, and 64-bit operating system. The optimal value for the “switching parameter” ($p_d$) used in the proposed algorithm is fixed as 0.5, by conducting a prior empirical study [2]. This value ensures a proper balancing between the exploitation and exploration stages of the optimization algorithm.

Fig. 3. Simulation results of denoising Images 1 and 2 corrupted with Gaussian noise of variance 30% using state-of-the-art denoising algorithms. (a) Original. (b) Noisy. (c) 2-D-NLMS. (d) 2-D-APA. (e) BM3-D-PCA. (f) PDE-AIP. (g) CII-NLM. (h) DST. (i) SSTV. (j) 2-D ABC adaptive filtering. (k) JADE. (l) Proposed ACSWF.
adaptive filtering algorithm [19]. The aforementioned metaheuristic-based denoising algorithms and the proposed ACSWF were executed for 31 independent trials, and the best results among them are furnished.

Experiments were conducted for denoising images corrupted with three different Gaussian noise variance levels, i.e., 10%, 20%, and 30%, to substantiate the efficiency of the proposed algorithm. Since satellite images are most prone to the Gaussian noise of small variance levels, we have fixed the window size to be $3 \times 3$ for the entire set of experiments. Parameter initialization phase of the proposed algorithm includes manual assignment of parameter values for $N_p$, $w_{\text{min}}$, $w_{\text{max}}$, and $G_{\text{max}}$. We have fixed their values to be $50$, $-1$, $1$, and $100$, respectively. The dimensionality $d$ of the optimization problem denotes the total number of elements included as filter coefficients for the defined filter. Since we have chosen the filter window size $n \times n$ to be $3 \times 3$, the value of $d = n^2$ is set as 9. All other parameters used in the algorithms compared are chosen from their respective references.

### TABLE II

<table>
<thead>
<tr>
<th>Image</th>
<th>Algo.</th>
<th>2D-MLMS</th>
<th>2D-APA</th>
<th>BM3D-PCA</th>
<th>PDF-AIP</th>
<th>CH-NLM</th>
<th>DST</th>
<th>SSTV</th>
<th>2D ABC</th>
<th>JADE</th>
<th>ACSWF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>138.16e4</td>
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<td>261.00e2</td>
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<td>288.36e2</td>
<td>168.91e3</td>
<td>176.03e8</td>
<td>196.05e9</td>
<td>78.22e8</td>
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</tr>
<tr>
<td>PSNR</td>
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<td>23.64e2</td>
<td>23.96e2</td>
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<tr>
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### TABLE III

<table>
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<th>Image</th>
<th>Algo.</th>
<th>2D-MLMS</th>
<th>2D-APA</th>
<th>BM3D-PCA</th>
<th>PDF-AIP</th>
<th>CH-NLM</th>
<th>DST</th>
<th>SSTV</th>
<th>2D ABC</th>
<th>JADE</th>
<th>ACSWF</th>
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<tr>
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<td>274.18e7</td>
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<tr>
<td>PSNR</td>
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<td>23.65e0</td>
<td>24.36e0</td>
<td>24.09e0</td>
<td>23.53e0</td>
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### TABLE IV

<table>
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<tr>
<th>Image</th>
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<th>2D-APA</th>
<th>BM3D-PCA</th>
<th>PDF-AIP</th>
<th>CH-NLM</th>
<th>DST</th>
<th>SSTV</th>
<th>2D ABC</th>
<th>JADE</th>
<th>ACSWF</th>
</tr>
</thead>
<tbody>
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<td>341.29e7</td>
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<tr>
<td>PSNR</td>
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<tr>
<td>FSIM</td>
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<tr>
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<tr>
<td>Time (s)</td>
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<td>12.31e0</td>
<td>15.35e0</td>
<td>18.42e0</td>
<td>16.58e0</td>
<td>11.52e3</td>
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</tr>
</tbody>
</table>
Tables II–VI present the quantitative results obtained by comparing the 10 algorithms for denoising test images corrupted with the Gaussian noise of three different variance levels. The test images are processed band-by-band, assuming the noise to be uniform in every band and finally combined to form the denoised image. The quantitative metrics are computed by averaging the bandwise metric values and are reported in Tables II–VI. The proposed ACSWF yielded the least possible MSE value with a minimum NAE factor. These measures indicate the closeness of denoised images to the original uncorrupted image. A high value of PSNR, FSIM, and UQI for the proposed algorithm among the compared set highlights the visual quality of the estimated output image.

Subjective evaluation of denoised images obtained for 30% Gaussian noise variance level case using different algorithms compared is presented in Figs. 3 and 4. The proposed ACSWF proved to be very effective in preserving the information bearing structures like terrain edges and other significant textural features, especially for high noise variance levels.

It also resulted in very less blurring effect to the estimated image compared with others for all the three noise variance levels investigated.

The stability and converging capability of the three metaheuristic-based denoising algorithms were analyzed by...
investigating their box-and-whisker plots, statistical parameters, and convergence characteristics plots. Stability analysis was carried out by comparing the box-and-whisker plots of the three metaheuristic-based denoising algorithms. The random initialization phase followed by metaheuristic algorithms, such as JADE, 2-D ABC, and the proposed ACSWF used for image denoising, lead to slight discrepancies in the final optimal solutions.

Box-and-whisker plots give a graphical representation of the fitness value obtained in each repetition of the same experiment. Hence, it helps in assessing the repeatability of an algorithm over time, subject to the same experimental conditions. A highly stable algorithm gives more or less the same experimental results on each repetition and hence can be used for real-time applications as well. Figs. 5 and 7(a) present the box-and-whisker plots comparing the three metaheuristic algorithms included in our study, by repeating each experiment for 31 independent trials. The red line across each box indicates their respective median value and is shown on the top of each box. Comparison of the statistical parameters, such as standard deviation, mean, best value, and worst value of the fitness function (MSE) obtained, after 31 trials of each experiment is presented in Table VI. The comparison also proves the stability and efficiency of the proposed ACSWF for denoising satellite images.

The test images were denoised using all the three algorithms by fixing the maximum number of iterations to be 100. The fitness values obtained in each run were plotted against the iteration count to analyze the convergence characteristics of each. The random population initialization phase and the solution exploration and exploitation strategies followed by different metaheuristic algorithms have a high impact on governing its convergence characteristics. Figs. 6 and 7(b) show the convergence plots, wherein the proposed ACSWF emerged to be converging fast to the least possible fitness (MSE) value. The reasonably fast convergence rate makes ACSWF adaptable for real-time applications too.

V. CONCLUSION

In this paper, a 2-D FIR Wiener filter based on the ACS algorithm (ACSWF) was proposed for denoising satellite images corrupted with AWGN. The ACS algorithm was proposed to optimize the adaptive Wiener filter weights to obtain the best possible estimate of the desired input image. Performance assessment included quantitative and qualitative comparisons with most studied and state-of-the-art denoising algorithms, such as 2-D NLMS, 2-D-APA, BM3-D-PCA, PDE-AIP, CII-NLM, DST, SSTV, JADE, and 2-D-ABC. Simulation experiments were conducted for denoising satellite images corrupted with three different Gaussian noise variance levels to substantiate the performance of the proposed filter. Robustness of the proposed filter was evaluated by testing it across a wide range of MS satellite image data set.

Comparisons between the evaluated performance metrics quantify the efficiency of the proposed filter in preserving significant image features with the LMS error. Subjective comparisons between the resultant images also highlight the filtering capability of the proposed ACSWF in denoising satellite images with reasonably fewer image artifacts. Stability and convergence capability analysis performed between JADE, 2-D-ABC, and ACSWF using box-and-whisker plots, statistical parameters, and convergence characteristics plots also highlights the performance of the proposed denoising filter. The ACSWF emerged with the least MSE value in a less number of iterations among the three. Substantial improvement in the quantitative and qualitative results along its stable nature makes it highly adaptable for other real-time image processing applications.
As a part of the future study, the performance of the proposed filter can be assessed for other 2-D signal processing applications, such as channel estimation and system identification.

ACKNOWLEDGMENT

The authors would like to thank the editors and anonymous reviewers for their valuable suggestions and comments which helped to improve the quality of this paper.

REFERENCES


This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.


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