



DWT- SVD BASED CONTRAST ENHANCEMENT OF SATELLITE IMAGES WITH OPTIMAL SHAPE TUNING AND THRESHOLDING PARAMETERS USING ANT LION OPTIMIZATION ALGORITHM

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Abstract: Satellite images often have inferior perceptual quality due to environmental and altitude factors of the region it characterizes. Because of insufficient enlightenment the image acquisition system of the satellite captures poor contrast noisy images which need to be processed for better visualization, interpretation and subsequent digital analysis. The discrete wavelet (DWT) coefficients of these images are denoised on the basis of optimal thresholding and shape tuning parameters. The desired thresholding and shape tuning parameters are searched by the nature inspired Ant Lion Optimization (ALO) algorithm in the direction of minimizing the mean squared error risk of the coefficients for better estimation of thresholded DWT coefficients. The illumination information in the denoised thresholded DWT coefficients is uncorrelated by the Singular Value Decomposition (SVD) technique for scaling the intensity of the image. The contrast enhanced image is realized by rebuilding the image using inverse discrete wavelet transformation. The effectiveness of the proposed ALO based methodology has been validated on several low contrast satellite images in terms of visual quality and quantitative performance measures. The superiority of this method is exhibited by comparing the results with state-of-the-art methods.

Keywords: Contrast enhancement, Ant Lion Optimizer, DWT, SVD, shape tuning parameters, satellite images.

I. INTRODUCTION

Remotely sensed satellite images comprise wavelength intensity information attained by gathering electromagnetic radiation of the object and its intensity. This information are often distorted due to poor detector sensitivity, weak signal from the object, similarity in reflectance of several objects and environmental condition such as haze, pollution, poor lightening etc., at the time of capturing result in low contrast images [1, 2]. For this reason contrast enhancement is required for better visual perception and information extraction, which is considered as a key processing step prior to any further image analysis like segmentation, feature extraction and classification [3-5].

Classical histogram equalization and its variants are the most common and basic methods adopted in image enhancement. These technologies cannot be generalized and automated due to their inherent nature of image dependent for enhancement that result in a number of image artifacts [6,7]. Having inherent qualities like decomposition and sparsity, wavelet domain image enhancement based methods have gained popularity for the last few decades [8-11]. The noise present in the image which is embedded with DWT coefficient can be effectively eliminated by the localized character of wavelet transform [12-15].

Zhang extended soft thresholding functions for denoising and proposed a neural network based methodology to denoise the wavelet coefficient [16, 17]. Shape turning parameters are embedded in the thresholding function by Nasri and Pour to achieve better flexibility and capability to remove the noise in the wavelet coefficients. These parameters were estimated by employing Least Mean Square (LMS) algorithm with steepest gradient of mean

square risk [18]. To overcome the dependency of initial values for proper convergence and to reduce the computational burden in LMS algorithm, Bhutada et. al proposed a novel Particle Swarm Optimization (PSO) based approach [19] for denoising. Recently proposed approaches are simultaneously intended to eliminate the noise elements and to modify the intensity information in DWT coefficients for contrast enhancement [20, 21]. Population based Meta-heuristic optimization algorithms such as Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, Artificial Bee Colony Optimization and Cuckoo Search are used effectively for solving various image processing problems [22-24].

In this proposed methodology low contrast satellite image is decomposed into sub-bands by DWT coefficients. The coefficients are modified to eliminate the noise associated with the image. The successful noise elimination of the wavelet coefficient depends on the effective searching of optimum shape tuning parameters guided in the direction of minimizing the mean squared error risk (MSE-Risk) of the DWT coefficients. This requires a global, reliable, computational efficient algorithm for achieving optimal solution by exploring various alternatives. Recently published, nature inspired meta-heuristic Ant Lion Optimizer (ALO) has successfully solved several benchmark optimization problems in various fields. It possesses the inherent property of gradient free with minimum algorithmic parameter [25]. ALO algorithm has been employed in this methodology to search the optimal shape tuning parameters for denoising wavelet coefficient of the image. The illumination information contained in the denoised wavelet coefficient is scaled on the application of singular value decomposition for enhancing the input image.

Image reconstruction is performed using inverse wavelet transform on the noise free scaled wavelet coefficient.

The structure of this article is as follows. Section 2 presents a thresholding function model for estimating the thresholded wavelet coefficients for suppressing the noise associated with the image. Section 3 proposes ALO based approach for effective searching of optimal thresholding, shape tuning and asymptotic parameters as a problem of minimization of the MSE-Risk. Section 4 describes the proposed contrast enhancement strategy for illumination correction and noise elimination. Section 5 enumerates the quantitative performance measures related to the image enhancement for the purpose of analyzing the applicability of the proposed strategy and for comparing with existing methodologies. Section 6 presents the simulation results of proposed approach to the low contrast noisy multiband input satellite images. Finally the inferences are concluded in Section 7.

II. MODELING OF THRESHOLDING FUNCTION AND PARAMETERS FOR DENOISING THE WAVELET COEFFICIENTS

Enhancing a low contrast noisy satellite image in wavelet domain involves 2-D wavelet decomposition of the original image by applying 1-D DWT along the rows of the image first and then along the columns. The Daubechies wavelet transform such as db4 which has slightly longer support for scaling and wavelet coefficients than Haar wavelet has been applied. The DWT coefficients (LL, LH, HL & HH) contain frequency and noise elements. Optimal thresholding approach is applied for reducing the noise elements and SVD based approach is employed for correction of illumination information in the frequency elements.

The denoising problem of the satellite image is formulated as an optimization problem of minimizing the non-linear objective function with bound constraints. The original signal 'x' is contaminated by the unwanted noise 'n' that is embedded during the image acquisition stages. Image denoising is aimed for better estimation of noise free original signal \tilde{x} by suppressing the noise signal. This can be achieved by selecting suitable thresholding values and functions which preserve the signal energy and suppress the noise energy.

Thresholding functions reported in the literature based on hard, soft, semisoft and garrote functions have some advantages over others. In general their over dependency on the functions selected and their inability of differentiable up to higher order makes the function rigid and affect its functionality. The effective denoising requires flexible thresholding function that can fine-tuned depends on the thresholding value.

The observed data vector of the input satellite image $y = [y_0, y_1, \dots, y_{N-1}]$ is the sum of original signal vector $x = [x_0, x_1, \dots, x_{N-1}]$ and noise vector $n = [n_1, n_2, \dots, n_{N-1}]$.

$$i.e \quad y = x + n \quad (1)$$

The estimate of the original signal vector \tilde{x} is obtained from the observed signal y by reducing the noise to achieve the estimate close to the original signal vector x. The criteria

used for the best estimate is to minimize the mean squared error risk associated with original signal energy.

$$MSE(\tilde{x}, x) = \frac{1}{2} E \|\tilde{x} - x\|^2 = \frac{1}{2} \sum_{i=0}^{N-1} E(\tilde{x}_i - x_i)^2 \quad (2)$$

In wavelet domain, the energy of the original signal vector is concentrated in few large important coefficients and the noise energy is distributed in every coefficients. The estimate \tilde{x} is obtained from the thresholding function and threshold value. The soft threshold function presented in ref. [15] has weak second order derivate while the function in Ref.[16] possesses infinite differentiable property with higher order derivatives are given by

$$\tilde{x} = f(x, \lambda, k) = \begin{cases} x + \lambda - \frac{\lambda}{2k+1} & x < -\lambda \\ \frac{1}{(2k+1)\lambda^{2k}} x^{2k+1} & |x| \leq \lambda \\ x - \lambda + \frac{\lambda}{2k+1} & x > \lambda \end{cases} \quad (3)$$

$$\tilde{x} = f(x, \lambda, p) = x + 0.5(\sqrt{(x-\lambda)^2 + p} - \sqrt{(x+\lambda)^2 + p}) \quad (4)$$

Where λ is threshold value and k is asymptote determination variable and p is derivative order determination constant.

Combining these two equations, Nasri presented a new function for simultaneous adjustment of thresholding function and value with infinite differentiability is

$$\tilde{x} = f(x, \lambda, k, s) = \begin{cases} x - 0.5 \frac{k\lambda^s}{x^{s-1}} + (k-1)\lambda & x > \lambda \\ 0.5 \frac{k|x|^{s+\frac{2-k}{k}}}{\lambda^{s+\frac{2-k}{k}}} \text{sign}(x) & |x| \leq \lambda \\ x + 0.5 \frac{k(-\lambda)^s}{x^{s-1}} - (k-1)\lambda & x < -\lambda \end{cases} \quad (5)$$

The proposed parameter s fine tunes the function f thereby altering the shape of the thresholding function which is sensitive to the changes in λ . Here the estimate \tilde{x} is thresholded wavelet coefficient, x is the wavelet coefficient of the input, λ is threshold value, k is asymptote determination variable and s is shape tuning parameter.

The thresholded wavelet coefficient is estimated with optimal λ , k and s which are searched in the direction to minimize the MSE-Risk. This can be formulated as optimization problem as follows

Minimize

$$MSE - Risk(x, \tilde{x}, \lambda, k, s) = \frac{1}{N} \sum_{i=1}^N (x(i) - \tilde{x}(i))^2 \quad (6)$$

Subject to $\lambda_{min} \leq \lambda \leq \lambda_{max}$

$$0 < k < 1$$

$$s_{min} < s < s_{max}$$

By adjusting k in the interval $[0, 1]$, the thresholding function nature changes between hard and soft thresholding. The parameter s adds more flexibility in function performance. The objective of this methodology is to improve the estimation of the thresholded wavelet

coefficients by solving the above objective and in this methodology ALO algorithm is used to search the optimum thresholding and shape tuning parameters.

III. ALO BASED OPTIMAL SEARCHING OF THRESHOLDING AND SHAPE TUNING PARAMETERS

ALO developed by Mirjalili is a nature-inspired optimization algorithm mimicking the food capturing mechanism of antlions and their food ants in their habitat [25]. ALO copies this mechanism for searching optimal solution in multidimensional search space and this model is described as follows

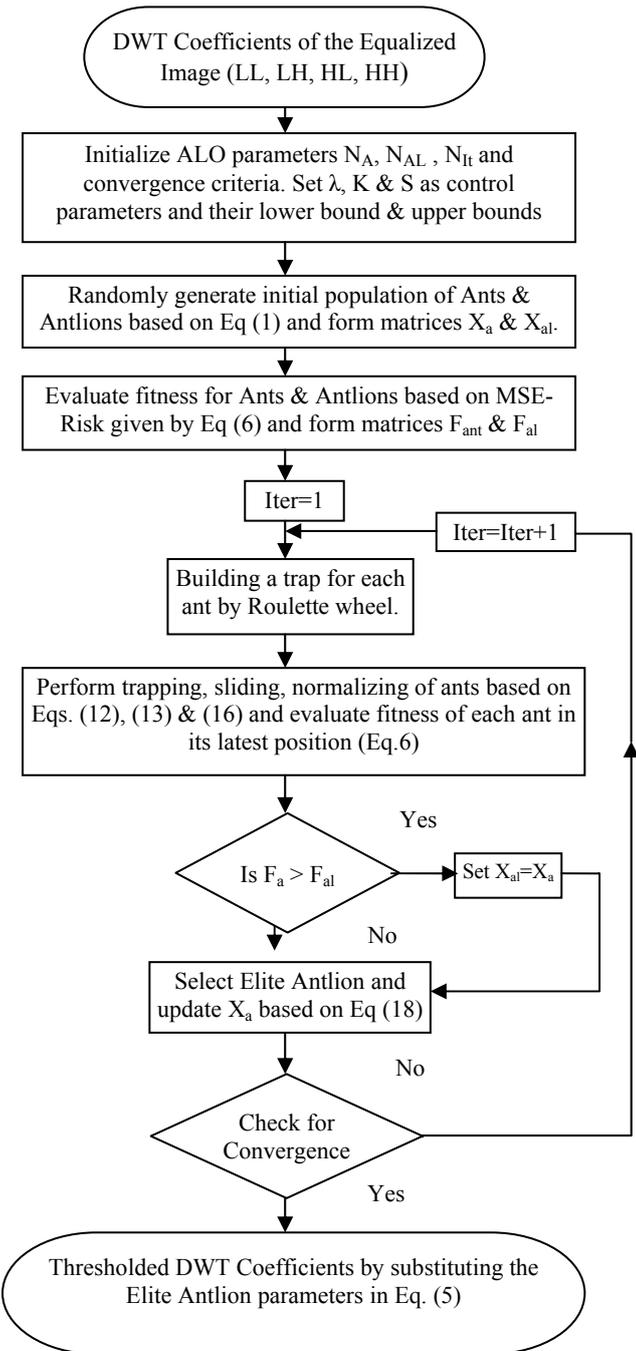


Fig.1: ALO implementation for Optimal Estimation of Thresholded DWT Coefficients for suppressing noise component

A. Initialization

Ants and antlions represent the possible set of solutions in the hyper dimension at search space which is termed as search agents. Set number of ants N_A , number of antlions N_{AL} , number of random steps allowed for each ant N_{It} which is same as number of iterations, number of variables to be optimized N_V and their lower bound (A_i) and upper bound (B_i). Random initial positions of each search agent is

$$X_i^0 = A_i + rand * (B_i - A_i) \quad (7)$$

Where X_i^0 is the initial position of each search agent for a particular dimension. The position of each search agent is initialized in all the dimensions of the problem. i.e for all variables. *rand* is a randomly generated number in the interval $[0, 1]$.

The location of ants are stored in the matrix and used during searching process

$$X_{ant} = \begin{bmatrix} ant_{1,1} & ant_{1,2} & \dots & ant_{1,N_V} \\ ant_{2,1} & ant_{2,2} & \dots & ant_{2,N_V} \\ \vdots & \vdots & \ddots & \vdots \\ ant_{N_A,1} & ant_{N_A,2} & \dots & ant_{N_A,N_V} \end{bmatrix} \quad (8)$$

Fitness of each ant is calculated based on the objective considered and stored in the following matrix

$$F_{ant} = \begin{bmatrix} F_t([ant_{1,1} & ant_{1,2} & \dots & ant_{1,N_V}]) \\ F_t([ant_{2,1} & ant_{2,2} & \dots & ant_{2,N_V}]) \\ \vdots \\ F_t([ant_{N_A,1} & ant_{N_A,2} & \dots & ant_{N_A,N_V}]) \end{bmatrix} \quad (9)$$

The location of the ant lions in the same search space are also stored as

$$X_{al} = \begin{bmatrix} antlion_{1,1} & antlion_{1,2} & \dots & antlion_{1,N_V} \\ antlion_{2,1} & antlion_{2,2} & \dots & antlion_{2,N_V} \\ \vdots & \vdots & \ddots & \vdots \\ antlion_{n,1} & antlion_{n,2} & \dots & antlion_{N_A,N_V} \end{bmatrix} \quad (10)$$

Each antlion fitness is calculated based on the objective considered and stored in the following matrix

$$F_{al} = \begin{bmatrix} F_t([antlion_{1,1} & antlion_{1,2} & \dots & antlion_{1,N_V}]) \\ F_t([antlion_{2,1} & antlion_{2,2} & \dots & antlion_{2,N_V}]) \\ \vdots \\ F_t([antlion_{N_A,1} & antlion_{N_A,2} & \dots & antlion_{N_A,N_V}]) \end{bmatrix} \quad (11)$$

B. Updation

During this step, possible solutions represented by antlions are modified in the direction of exploring the searching space to get global solution. It involves the following operations

Building trap

More hunger antlions tend to dig out larger traps during full moon for effective hunting. A roulette wheel is applied to model this aspect based on antlions' fitness during iterations. Each ant is glued to a particular antlion during

this step. Antlion having more fitness can catch more than one ant in this process. They have been evolved and adapted this way to improve their chance of survival. This mechanism shows high chances for catching ants.

Trapping in antlion's pits

Ant lions' traps affect the random walks of ants in the search space. Thereby Antlions direct ants towards unexplored search regions. This can be mirrored by the following equations

$$C_i^t = Antlion_j^t + C^t \tag{12a}$$

$$D_i^t = Antlion_j^t + D^t \tag{12b}$$

where C_i^t is the minimum of i^{th} variable in t^{th} iteration, D_i^t is the maximum of i^{th} variable in t^{th} iteration, C^t is the minimum of all variables in t^{th} iteration and D^t is the maximum of all variables in t^{th} iteration.

Sliding ants towards antlion

During the building and trapping steps, traps are built based on antlions' strength and ants are required to shift their position randomly. When they judge there is an ant in the trap, they throw sand over the pit from the center to make the ant fall inside the pit. Thereby prevent the ant from escape. To model this step, the radius of ant's random circular walk is reduced adaptively depending on the present iteration level. The subsequent equations are introduced in this regard:

$$C^t = \frac{c^t}{I}; D^t = \frac{d^t}{I}; I = f(w, t, It) = 10^{w \frac{t}{It}} \tag{13}$$

where I is a ratio that can be adaptively modified based on the iterative level, t is the present iteration, It is the maximum number of iterations, and w is a constant defined based on the iterative level ($w = 2$ when $t > 0.1 It$, $w = 3$ when $t > 0.5 It$, $w = 4$ when $t > 0.75 It$, $w = 5$ when $t > 0.9 It$, and $w = 6$ when $t > 0.95 It$).

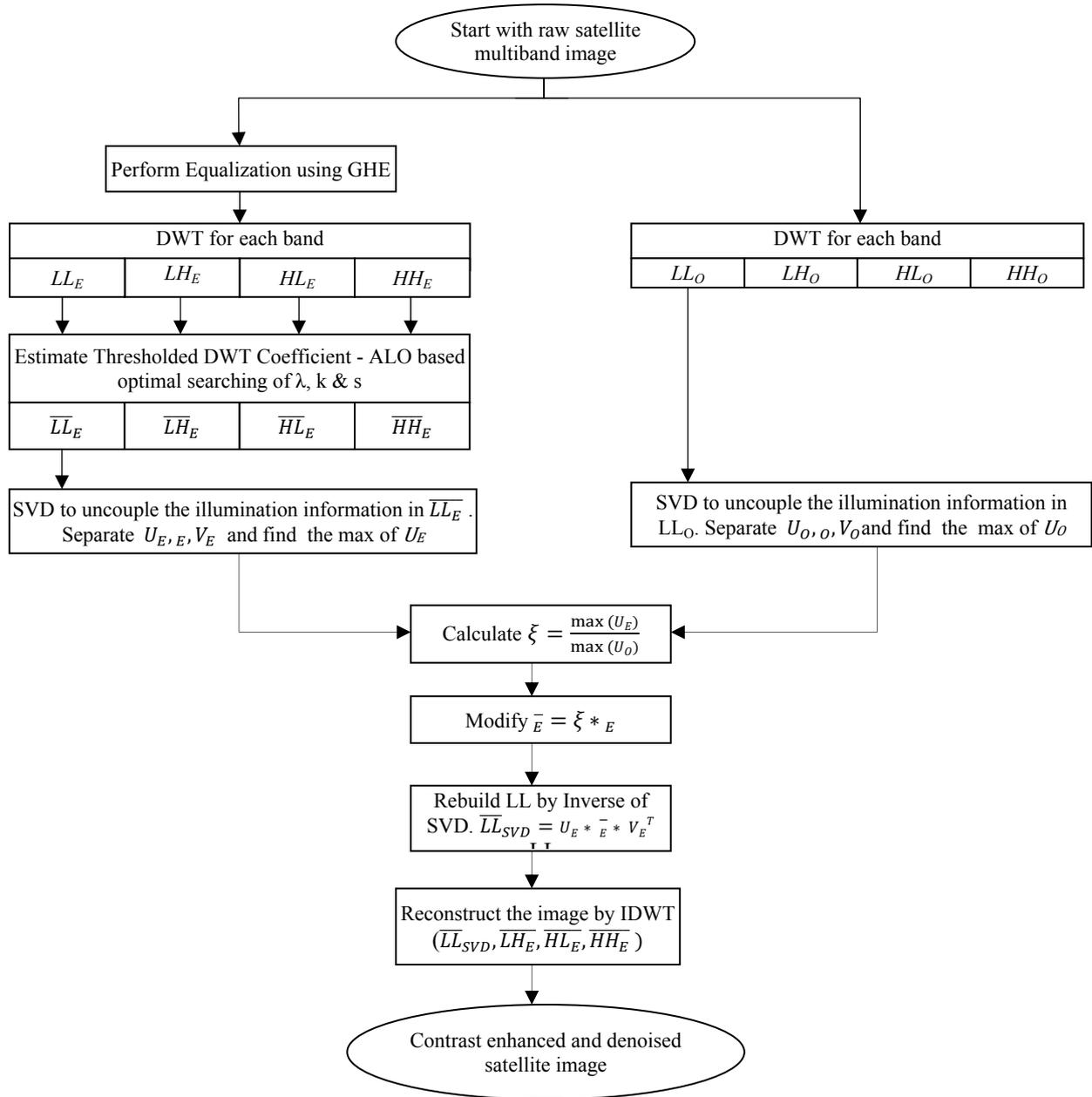


Fig.2 : Block diagram of proposed contrast enhancement methodology

The constant are used for correcting the precision level of exploitation. C^t and D^t equations mimics sliding process of the ant inside the pits by shrinking the radius of ant's positions near to the trap. This guarantees exploitation of search space.

Normalize the Random walks of ants

Ant's movement is stochastic in nature during the food searching process. This random walk is emulated for next movement as

$$X(t) = [0, \text{cums}(2r(t_1) - 1), \text{cums}(2r(t_2) - 1), \dots, \text{cums}(2r(t_{N_t}) - 1)] \tag{14}$$

where *cums* calculates the cumulative sum and $r(t)$ is defined as follows:

$$r(t) = \begin{cases} 1 & \text{if } rand > 0.5 \\ 0 & \text{if } rand \leq 0.5 \end{cases} \tag{15}$$

To keep the random walks inside the search space, they are normalized using the following equation inheriting (14)

$$X_i^t = \frac{(X_i^t - A_i) \times (D_i^t - C_i^t)}{(B_i - A_i)} + C_i \tag{16}$$

where X_i^t is the position of i^{th} variable in t^{th} iteration of a particular ant.

Catching prey and rebuilding the pit

The fitness of each ant in its present position is evaluated based on the objective function and is stored in the F_{ant} matrix. Update the antlion position to the latest position of the ant if the hunted ant has a better fitness otherwise keep the original antlion position for the next iteration. The latest antlion position is stored in the X_{al} matrix.

$$Antlion_j^t = Ant_i^t \text{ if } f(Ant_i^t) > f(Antlion_j^t) \tag{17}$$

Elitism

It is crucial to keep the best solution obtained at each step of optimization task. The fittest ant lion acquired so far is preserved as the elite. Since the elite is the best antlion, it should be capable to affect the motions of all ants during the random walk thereby updating of ants position is occurred in the search space. Thus, it is mandatory that every ant randomly walks around a chosen antlion by the roulette wheel and the elite simultaneously. It is modeled as

$$Ant_i^t = \frac{Antlion_a^t + Antlion_e^t}{2} \tag{18}$$

C. Convergence

If the convergence criterion is not satisfied then the ants update their position based on step 2 for further exploration of the searching space otherwise the searching procedure is terminated. The position of elite antlion gives the best possible solution to the given optimization problem. The convergence criteria may be either an acceptable solution found or a state with no further improvement in solution has been reached or a predefined number of random walk have been completed

D. Implementation of ALO

The DWT coefficients are modified to eliminate the noise associated with the image. The successful noise elimination depends on the effective searching of optimum

shape tuning parameters for estimating better thresholded DWT coefficients. ALO implementation for optimal searching of threshold parameter λ , asymptotic parameter k and shape tuning parameter s for each sub-band in a direction of estimating the thresholded wavelet coefficients by minimizing the MSE-Risk is presented in Fig.1. Applying inverse DWT on the estimated thresholded DWT coefficients results a denoised image. Before applying IDWT on thresholded DWT coefficients, contrast enhancement step is performed which is detailed in the next section.

IV. PROPOSED ENHANCEMENT METHODOLOGY

Multi-band satellite images have poor contrast due to insufficient enlightenment in the area of the study and noise due to the communication channels of the image acquisition system. The input image is initially equalized on the application of generalized histogram equalization process. The equalized image and the original image are separated into LL, LH, HL and HH sub-bands by DWT. The equalized image DWT coefficients are corrected to suppress the noise component associated with the image. This process is carried out by the proposed ALO based optimal estimation of thresholded coefficients elaborated in section-3.

Let (LL_o, LH_o, HL_o, HH_o) be the sub-bands of original image and (LL_e, LH_e, HL_e, HH_e) be the sub-bands of equalized image. Noise suppressed equalized thresholded wavelet co-efficient be $\overline{LL}_e, \overline{LH}_e, \overline{HL}_e, \overline{HH}_e$.

The illumination information is embedded in the LL sub-band and the edge information is concentrated in other high frequency sub-bands. Correction is required in LL sub-band to enhance the illumination level of the satellite image. Singular Value Decomposition (SVD), a mathematical technique can be viewed as a tool to uncouple a particular vector from a matrix of having correlated vectors.

By applying SVD technique in \overline{LL}_e coefficient the illumination information E is separated from other vectors U_E and V_E . The existing illumination information E is scaled or corrected by a factor ξ which is given by

$$\xi = \frac{\max(U_E)}{\max(U_O)} \tag{19}$$

$$\overline{E} = \xi * E \tag{20}$$

where U_O is the matrix resulted from the application of SVD on original LL_o co-efficient. Rebuilding of new low-low sub-band is carried out by taking the inverse SVD on illumination scaled U_E, \overline{E} and V_E as

$$\overline{LL}_{SVD} = U_E * \overline{E} * V_E^T \tag{21}$$

Inverse DWT on $(\overline{LL}_{SVD}, \overline{LH}_e, \overline{HL}_e, \overline{HH}_e)$ reconstructs the contrast enhanced, edge preserved, denoised satellite image. The steps involved in the proposed approach are well documented in the Fig.2.

$$Output_image = IDWT(\overline{LL}_{SVD}, \overline{LH}_e, \overline{HL}_e, \overline{HH}_e) \tag{22}$$

V. PERFORMANCE MEASURES

Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are the error metrics used to examine the effectiveness of proposed method. PSNR index computes the peak signal-to-noise ratio, in decibels between input image and enhanced image which is based on the MSE values computed over every pixel.

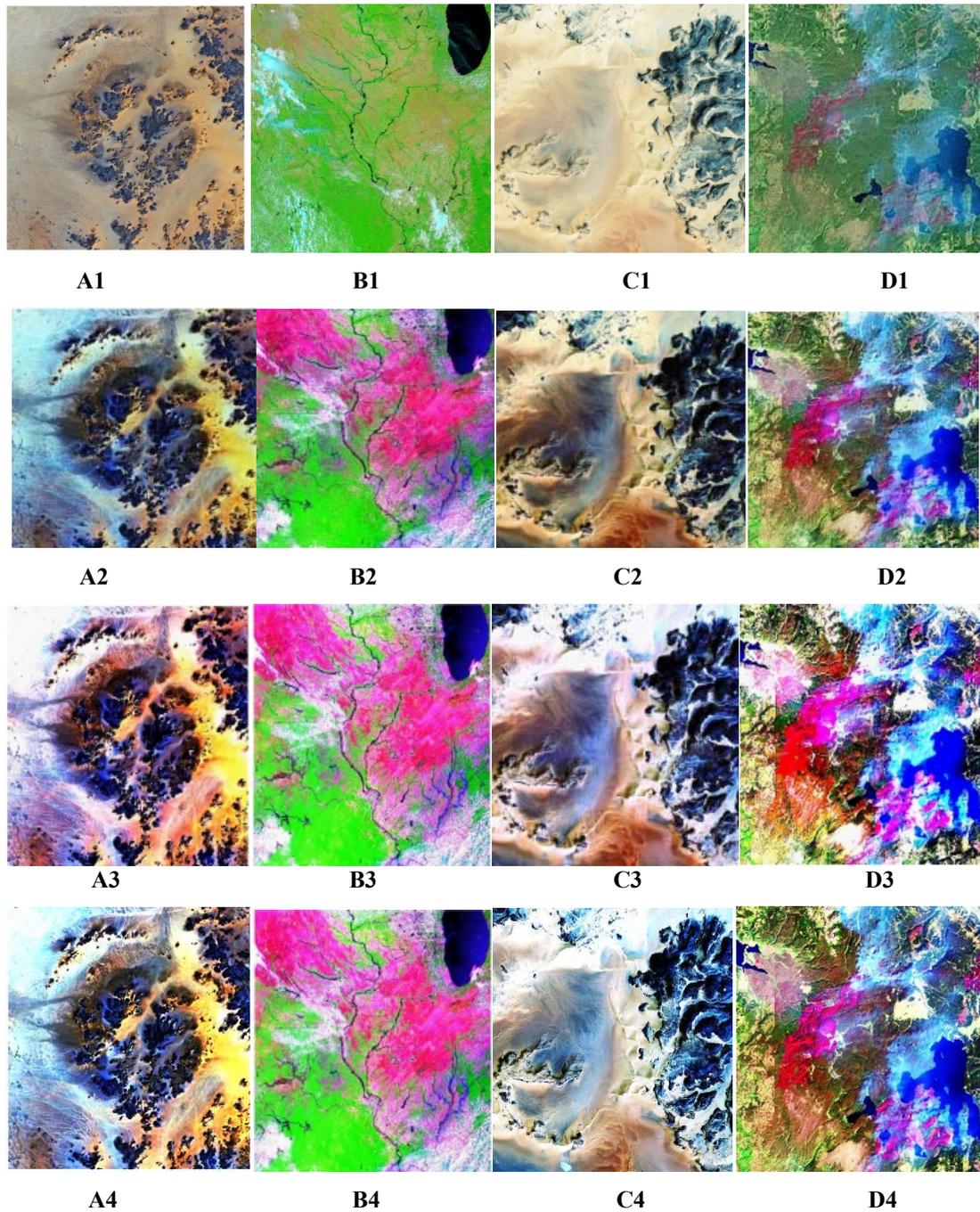


Fig.3. A1–D1: Input satellite images [28-31], A2–D2: Enhancement based on DWT-SVD [20], A3–D3: Enhancement based on DWT-SVD-Cuckoo algorithm [20] and A4–D4: Enhancement based on proposed ALO algorithm.

Table I: Quantitative Performance Comparison for Images A-D

| Test Image | DWT-SVD [20] | | DWT-SVD-CUCKOO [20] | | Proposed ALO | |
|------------|--------------|-----------|---------------------|-----------|--------------|-----------|
| | MSE | PSNR (db) | MSE | PSNR (db) | MSE | PSNR (db) |
| A | 5.9260 | 40.4032 | 1.4269 | 46.5870 | 0.9973 | 51.4651 |
| B | 0.7286 | 49.5058 | 0.3994 | 52.5163 | 0.3621 | 53.8439 |
| C | 6.0490 | 40.3139 | 1.1173 | 47.8914 | 0.8232 | 50.9498 |
| D | 1.7506 | 45.6989 | 0.9219 | 48.8721 | 0.9814 | 51.8112 |

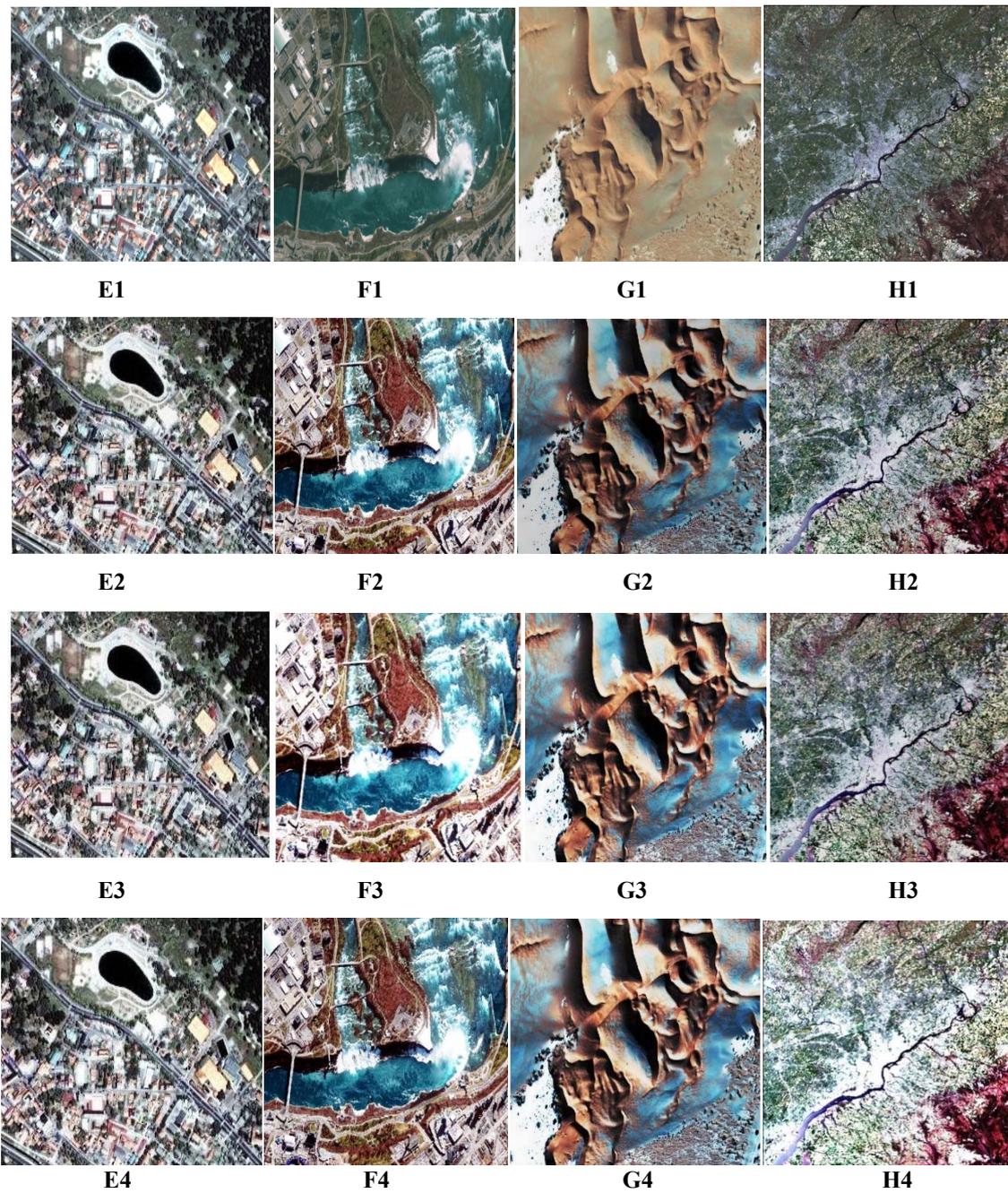


Fig.4. E1–H1: Input satellite images [28, 32-34], E2–H2: Enhancement based on DWT-SVD, E3–H3: Enhancement based on Cuckoo algorithm and E4–H4: Enhancement based proposed ALO algorithm.

Table-2: Quantitative performance comparison for images E-H

| Test Image | DWT-SVD | | | DWT-SVD-CUCKOO | | | Proposed ALO | | |
|------------|---------|-----------|--------|----------------|-----------|--------|--------------|-----------|--------|
| | MSE | PSNR (db) | SSIM | MSE | PSNR (db) | SSIM | MSE | PSNR (db) | SSIM |
| E | 1.2874 | 43.7623 | 0.7893 | 0.7475 | 55.0356 | 0.9162 | 0.5203 | 55.9861 | 0.9542 |
| F | 3.5021 | 41.3178 | 0.6925 | 0.9479 | 47.4428 | 0.7327 | 0.8136 | 49.5466 | 0.7782 |
| G | 3.8734 | 40.5497 | 0.6739 | 0.9790 | 48.2439 | 0.7251 | 0.8659 | 49.2759 | 0.7447 |
| H | 2.1148 | 42.6878 | 0.7471 | 0.7891 | 52.6537 | 0.7964 | 0.6368 | 54.6077 | 0.8199 |

Structural content degradation can be inferred from SSIM index. The SSIM is used to compare the structures of original and thresholded image. The SSIM can take values in [-1, 1] range, and a higher value of SSIM shows better performance.

MSE is evaluated based on

$$MSE(\alpha) = \frac{\sum_{x,y} [I_o(i,j) - I_e(i,j)]^2}{xy} \quad (23)$$

where $I_o(i, j)$ is the intensity at coordinates (i, j) of the original image and $I_e(i, j)$ is the intensity of coordinates (i, j) of the enhanced image. Here, x and y are the number of rows and columns in the image.

PSNR in db is computed using the following expression:

$$PSNR(\beta) = 10 \log_{10} \left(\frac{(L_{max}-1)^2}{MSE} \right) \quad (24)$$

where L_{max} is the maximum possible pixel value of the image.

The SSIM index is determined as:

$$SSIM(x, y) = \frac{(\mu_o \mu_e + C_1)(2\sigma_{oe} + C_2)}{(\mu_o^2 + \mu_e^2 + C_1)(\sigma_o^2 + \sigma_e^2 + C_2)} \quad (25)$$

where, μ_o and μ_e stands for mean intensity of original image and enhanced image respectively, σ_o and σ_e indicates the standard deviations of original and enhanced respectively, σ_{oe} is the covariance between original and enhanced image. C_1 and C_2 are the constants, and are included to avoid instability when μ_o^2 and μ_e^2 are very close to zero.

VI. SIMULATION AND DISCUSSION

The reason behind the need for an efficient and optimized enhancement process is to interpret the captured image by eliminating the noise and improving the contrast between various attributes. This section demonstrates the effectiveness of ALO based methodology over DWT-SVD [11] and DWT-SVD-Cuckoo Search [20] by processing the remotely sensed sample images [28-34].

The ALO parameters employed should be chosen carefully for the efficient performance of the algorithm. Optimal thresholding and shape turning parameters are searched with number of ants is 30 and number of antlions is 20 (i.e number of search agents= 50) and maximum number of random walk N_{it} is 500. Convergence is obtained when there is no change in the fitness value for 50 consecutive generations or when maximum number of generations reached, whichever occur first. The bounds of the problem parameters λ , K & S are [1,150], [0.1, 1] and [1, 4].

Fig. 3 and Fig. 4 shows the sample images (A1-H1), DWT-SVD based processed images (A2-H2), output of existing cuckoo search based methodology (A3-H3) and the enhanced images of the proposed ALO based methodology (A4-H4). The numerical comparison of the performance measures are summarized in Table 1 and Table 2.

Contrast enhancement aims to project the minute details in the image more distinguishable for human understanding. Visual inspection of the enhanced images indicates that the proposed ALO based methodology is able to differentiate the minor details in the input image by achieving optimum contrast enhancement with reducing noise than the existing state of art methods. It is inferred from Table 1, ALO based enhanced image-A has a low MSE of 0.9973 than the output

of DWT-SVD- Cuckoo which results 1.4269. The improved MSE leads to higher PSNR value of the ALO based enhanced image due to its ability to suppress the noise effectively in the input satellite image. Qualitative and numerical measures of the output images also vindicate the effectiveness of the ALO algorithm for searching the optimal value of thresholding and shape tuning parameter which is essential for denoising of the image.

Degradation of structural information such as SSIM is an important criterion for analyzing the performance of the image enhancement techniques. In order to compare the adoptability of the proposed method for enhancement in terms of SSIM index proposed ALO, DWT-SVD and DWT-SVD-Cuckoo approaches are applied to four test images E, F, G & H. Their qualitative and numerical performances are presented in Fig-4 and Table-2 respectively. It is found from Table-2, SSIM index of the enhanced images based on the proposed approach is more than the existing approaches and their values are nearer to one. It implies that the structure of the original image is preserved in the proposed enhancement process. Visual and index measures proved the suitability of the proposed DWT-SVD-ALO based methodology for contrast enhancement of satellite images.

VII. CONCLUSION

In this paper, DWT-SVD based contrast enhancement of noisy satellite images with optimized adaptive thresholding function using ALO algorithm has been presented. The noise reduction of the wavelet coefficient is carried out by ALO based optimal searching of shape tuning parameters guided in the direction of minimizing the MSE risk of the DWT coefficients for better estimation of the thresholded wavelet coefficients. The illumination information in the thresholded coefficient is modified using SVD for improving the contrast of the image without compromising the natural structure. Qualitative and quantitative measures of test images demonstrate the suitability of the proposed DWT-SVD-ALO based methodology for contrast enhancement of satellite images than the existing methodologies.

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