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Optimized Wavelet-Based Satellite Image De-Noising With Multi-Population Differential Evolution-Assisted Harris Hawks Optimization Algorithm

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ABSTRACT In this research, we propose to utilize the newly introduced Multi-population differential evolution-assisted Harris Hawks Optimization Algorithm (CMDHHO) in the optimization process for satellite image denoising in the wavelet domain. This optimization algorithm is the improved version of the previous HHO algorithm which consists of chaos, multi-population, and differential evolution strategies. In this study, we applied several optimization algorithms in the optimization procedure and we compared the de-noising results with CMDHHO based noise suppression as well as with the Thresholding Neural Network (TNN) approaches. It is observed that applying the CMDHHO algorithm provides us with better qualitative and quantitative results comparing with other optimized and TNN based noise removal techniques. In addition to the quality and quantity improvement, this method is computationally efficient and improves the processing time. Based on the experimental analysis, optimized based noise suppression performs better than TNN based image de-noising. Peak Signal to Noise Ratio (PSNR) and Mean Structural Similarity Index (MSSIM) are used to evaluate and measure the performance of different de-noising methods. Experimental results indicate the superiority of the proposed CMDHHO based satellite image de-noising over other available approaches in the literature.

INDEX TERMS CMDHHO, optimization algorithm, satellite image de-noising, TNN, wavelet domain

I. INTRODUCTION

An image may be distorted from the original when it has contaminated by noise. A wide range of unwanted noises may influence the visibility of images. Such noises can affect the images during acquisition and transmission procedures. Unfortunately, these artifacts can corrupt the image resolution, quality, and accuracy. Noise removal is among the significant tasks in image and signal processing. Discarding the noisy portions and keeping the substantial characteristics became the principal objective in de-noising approaches. Many methods have been proposed for reducing the possible noises from the images and enhancing their quality. Wavelet-based trivariate shrinkage filter and spatial based joint bilateral filter have been presented by Yu *et al.*, in [1]. Noise suppression with multiresolution bilateral filtering was introduced by Zhang and Gunturk [2]. Support vector regression has been utilized as an image de-noising approach in [3], [4]. The Bayesian approach has been utilized in joint inter- and interscale statistical model [5], and also in wavelet

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thresholding for image de-noising [6]. In de-noising in the wavelet domain, choosing a suitable model for the distribution of wavelet constituents is of the critical tasks. Thus, Laplace distributions [7] have been used for wavelet-based noise removal. D. T. Kuan *et al.* proposed an adaptive noise smoothing filter for images [8]. This filter is adaptable to the nonstationary local image statistics when there exist various kinds of noises that are signal-dependent. Fast wavelet techniques for near-optimal image processing is introduced in [9]. Chambolle in [10] presented nonlinear wavelet image processing and noise removal in the wavelet domain. In this research, an association between image processing algorithms and variational problems has been inspected and surveyed in the wavelet domain. Wavelet threshold estimators for data with correlated noise were presented by Johnstone and Silverman [11] which they have applied soft threshold function to the wavelet components. Moreover, Lossy compression has been utilized for image de-noising based on wavelet transform in [12], [13]. Vidakovic introduced the nonlinear wavelet shrinkage using coherent Bayesian inference for wavelet-based noise reduction [14].

Ideal spatial adaptation by wavelet shrinkage [15] was introduced by Donoho and Johnstone in 1994. In this study, standard hard and standard soft threshold functions have been introduced. Noise reduction with nonnegative garrotte has been proposed in [16]. In these methods, the threshold functions set the non-important components to zero.

Applying suitable threshold function and obtaining the optimum threshold value are of the important and challenging tasks in wavelet based noise reduction. In this regard, universal thresholding is presented in [15]. Hidden Markov model-based signal processing has been conducted in a study proposed by M. S. Crouse *et al.*, [17]. Adaptive wavelet thresholding is introduced in [18]. In this study, noise suppression using a data-driven and sub-band adaptive thresholding is proposed in the wavelet domain. M.K. Mihcak *et al.* proposed a statistical model of wavelet components for low-complexity noise reduction [19]. This model is spatially adaptive and it is applicable to image de-noising. Adapting to unknown smoothness via wavelet shrinkage has been proposed by Donoho and Johnstone in 1995 [20] to discard the noise from an image using adaptive wavelet thresholding. Hankel low-rank approximation for seismic noise attenuation and SAR image denoising via sparse representation in shearlet domain have been proposed in [40] and [41] respectively. Speckle suppression based on weighted nuclear norm minimization is introduced in [42]. Recently de-noising in the wavelet domain combined with nonlinear threshold function became very popular among researchers in image processing. Nasri and Nezamabadi-pour in [21] proposed a new adaptive thresholding function for image de-noising in the wavelet domain. In their study, they proposed a new type of TNN for enhancing the results of Zhang's TNN approach in [22]. Noise removal using TNN with a new improved threshold function has been introduced in 2017 [23]. Image de-noising using a thresholding neural network combined with smooth sigmoid based shrinkage (SSBS) function has been proposed in [24]. L. Sendur and I. W. Selesnick in [25] proposed bivariate shrinkage functions for wavelet-based denoising exploiting interscale dependency. Coifman and Donoho proposed translation-invariant de-noising [26]. Image de-noising using an un-decimated wavelet transform (UWT) with a soft thresholding technique has been presented by Golilarz and Demirel [27]. J. Portilla *et al.*, in 2003 proposed image de-noising using scale mixtures of Gaussians in the wavelet domain [28]. Golilarz *et al.*, in 2017 introduced three-dimensional wavelet transform utilizing smooth nonlinear soft thresholding function for Hyper-spectral remote sensing image de-noising [29].

One of the problems of using TNN based noise removal is that it is a time-consuming process. In TNN, gradient-based learning is utilized to find an optimum threshold value which is time-consuming [30]. Then to overcome this drawback, optimized adaptive thresholding based noise removal is proposed in [31]. Bhandari *et al.*, in [31] utilized JADE optimization algorithm instead of the steepest descent gradient-based LMS method to expedite the process of obtaining the optimum threshold value and other parameters. To improve the efficiency of de-noising based on JADE algorithm, Golilarz *et al.*, in [30] utilized the Harris Hawks optimization (HHO) algorithm [32] to enhance the quality of optimized based image de-noising approach, and lessen the computational time as well. In this paper, we propose to utilized the improved differential evolution-driven multi-population algorithm (CMDHHO) introduced by Chen *et al.*, in [38] which is the improved version of Harris Hawks Optimizer (HHO). This optimization algorithm is utilized to improve the performance of HHO based satellite image de-noising. Results show the superiority of this method over HHO and other optimization algorithms available in the literature for satellite image noise suppression in terms of PSNR and MSE.

II. IMAGE DE-NOISING PROCEDURE

In the wavelet-based noise removal approach, by applying wavelet transform we will get wavelet coefficients. These coefficients which we got from the first step, should be tuned using a suitable threshold value to preserve the crucial features and attribute of the image and discard the non-important components. These tuned components are called as thresholded wavelet coefficients. Then, it is time to apply the inverse wavelet transform (IWT) on these tuned thresholded wavelet coefficients providing us with the noise free image [30], [34]. Many thresholding functions have been proposed for wavelet threshold based image de-noising. Among them, the adaptive non-linear functions could improve the effectiveness of thresholding. Nasri and Nezamabadi-pour proposed a new adaptive nonlinear threshold function with three shape tuning parameters to be used in TNN based noise removal [21].

$$f(u,t,x,y,z) = \begin{cases} u - 0.5\dfrac{t^x \times z}{\omega^{x-1}} + (z-1)t, & u > t \\ 0.5\dfrac{z \times |u|^y}{t^{y-1}}\mathrm{sgn}(u), & u \leq t \\ u + 0.5\dfrac{(-t)^x \times z}{\omega^{x-1}} - (z-1)t, & u < -t \end{cases} \tag{1}$$

where, u is the wavelet coefficient, x and y are the shape tuning parameters, z calculate the asymptote of the function.

Admittedly, the above function performs well in the optimized based satellite image de-noising promisingly.

III. OPTIMIZED BASED IMAGE DE-NOISING

Recently applying the optimizations algorithms on various subjects in image and signal processing has become very popular among researchers. To improve the effectiveness of TNN based noise removal, nature-inspired optimization algorithm can be applied on the wavelet noisy coefficients to obtain the optimized thresholded wavelet components.

A. SALP SWARM ALGORITHM (SSA)

This optimization algorithm is proposed in [37] to solve the single and multi-objective optimization problems. This algorithm is inspired by moving and teaming up manner of salps to navigate in the ocean. Salps are from the Salpidae family and have tissues similar to jellyfishes. Salp chain or salps swarming manner is one of their interesting manners in deep ocean. Finding the global optimum is the greatest objective of the single-objective salp swarm optimization algorithm. In this optimization model, the leader targets the food source and it is followed by all the salps until the food source can be replaced by global optimum so that the swarm can target it afterward. During the optimization process, the source of food may be updated due to the fact that a better solution can be found using salps' exploration and exploitation for space. The SSA has a good convergence rate and it acts well in searching for the optimum solutions of problems [37]. The mathematical model for the salp chain is as follows. The position of the leader can be updated by the following formula [37]:

$$q_y^1 = \begin{cases} F_y + k_1((U_y - L_y)k_2 + L_y), & k_3 \geq 0 \\ F_y - k_1((U_y - L_y)k_2 + L_y), & k_3 < 0 \end{cases} \tag{2}$$

where, q_y^1 is the leader's position, F_y is the food source position, U_y is the upper bound and L_y is the lower band in the *ith* dimension. k_2 and k_3 are random numbers generated in the interval [0, 1].

Note that k_1 can be obtained as follows:

$$k_1 = 2e^{-(\frac{4m}{M})^2} \tag{3}$$

where, m and M are the current and maximum iteration, respectively.

The follower's position can be updated by

$$q_y^x = 0.5AT^2 + V_0 T \tag{4}$$

where, $x \geq 2$, q_y^x is the position of *xth* follower in *yth* dimension, V_0 is the beginning speed, T is the time, $A = \frac{V_{final}}{V_0}$ and $V = \frac{q - q_0}{T}$ Considering that the difference between iterations is one and $V_0 = 0$, equation (4) can be written as:

$$q_y^x = 0.5(q_y^x + q_y^{x-1}) \tag{5}$$

where, $x \geq 2$, q_y^x is the position of *xth* follower in *yth* dimension [37].

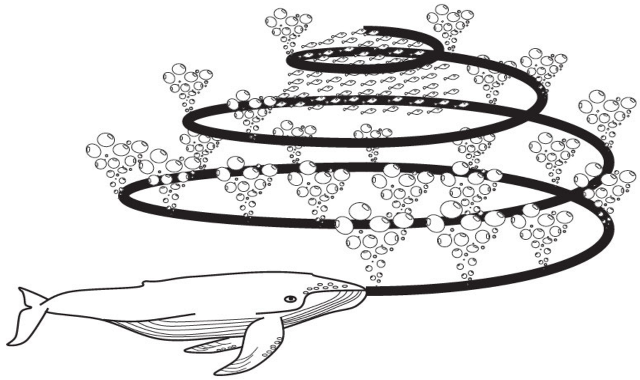

FIGURE 1. Bubble-net feeding manner of humpback whales [35].

B. WHALE AND CHAOTIC WHALE OPTIMIZATION ALGORITHM

Whale optimization algorithm (WOA) [35] is a nature-inspired meta-heuristic algorithm that mimics the hunting strategy of humpback whales and this strategy is also known as the bubble-net foraging approach which can be done by producing different bubbles when the whales are going to surround and enclose the hunt. Figure 1 shows bubble-net foraging behavior of humpback whales [35]. These whales can dive up to 15m down and create bubbles and then go to the surface. So, there are three main steps prior to reaching the prey in WOA, namely: surrounding the prey, producing bubble-net foraging and searching for the prey. The slow convergence rate is the most important drawback of WOA. Chaotic Whale Optimization Algorithm (CWOA) is proposed in 2018 [36] to improve the performance analysis of WOA. Additionally, it could improve the convergence speed and efficiency. To do so, a wide variety of chaotic maps (associate the chaos unpredictable manner) are taken into account in the optimization algorithm to control the exploration and exploitation. Thus, CWOA performs well in searching the global optima comparing with WOA.

C. BRIEF EXPLANATION OF HHO OPTIMIZER

The HHO optimization algorithm is a nature-inspired algorithm proposed by Ali asghar Heidari *et al.*, [32]. This algorithm is inspired by the cooperative manner of Harris Hawks in surprising and attacking the prey. There are three phases in the HHO algorithm, namely: exploration, the transition from exploration to exploitation, and exploitation. Based on the prey's escaping manner and Harris Hawks chasing strategy, there are four attacking strategies in the exploitation phase as can be seen in the figure below. The solid mathematical modeling is fully explained in [32], [30] and [46].

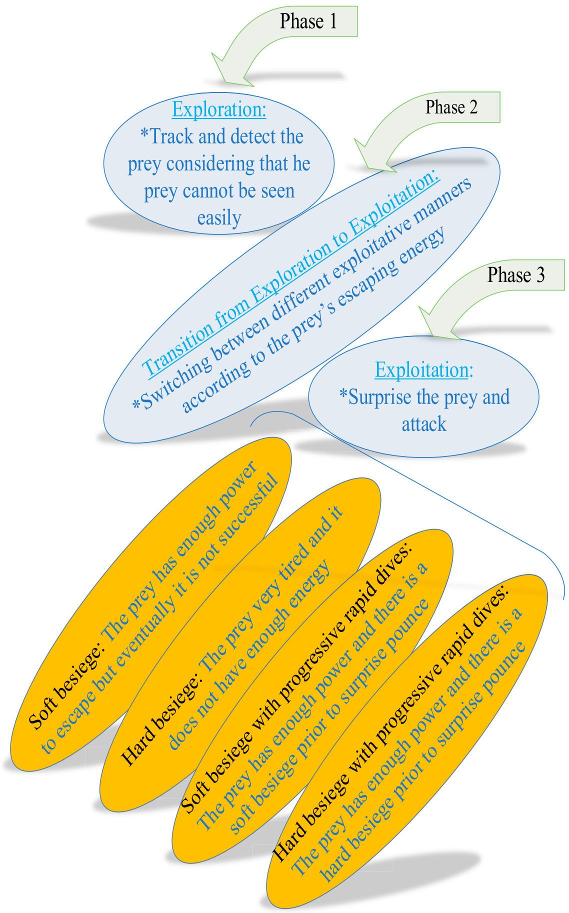

FIGURE 2. Three phases and four attacking strategies in HHO.

D. QRHHO

A quasi-reflected Harris hawks algorithm (QRHHO) has been proposed in [33] to enhance the efficiency of HHO. The improved algorithm consists of a quasi-reflection-based learning mechanism (QRBL) and HHO algorithm together. QRHHO algorithm contains two main stages [33]. In the first stage, in order to enhance the efficiency and diversity of the population, the QRBL mechanism will be applied to the population's initialization. Next, in order to enhance the convergence rate, the QRBL strategy will be added to each population location update to improve the convergence rate. In the beginning, the QRHHO produces a random population as follows.

$$RP_0 = \left\{ Y_{u,v} \right\}, \quad u = 1, 2, \ldots, N; \; v = 1, 2, \ldots, D \tag{6}$$

where, RP_0 is the random population, N is the population size and D is the dimension. Next, to compute the quasi-reflective of each solution, QRBL can be utilized and as a result we can acquire the quasi-reflective population as below.

$$RP_0^{QR} = \left\{ Y_{u,v}^{QR} \right\}, \quad u = 1, 2, \ldots, N; \; v = 1, 2, \ldots, D \tag{7}$$

Next, obtain and compare the fitness values of two populations, then choose the best N individuals as the initial population. Hawks positions can be updated utilizing the standard HHO algorithm, then a new population will be acquired. Thereafter, a quasi-reflected population will be obtained using QRBL. Based on the best fitness values of these populations, the best N individuals will be chosen by QRHHO for the next initial population. We continue these steps until we reach the maximum iteration number.

E. CMDHHO

HHO is a swarm-based stochastic algorithm in which there may exist some drawbacks in the convergence and local optima [38]. To address these issues, CMDHHO which is an improved differential evolution-driven multi-population algorithm containing three major strategies, namely: chaos, multi-population, and differential evolution strategy has been proposed in [38]. These strategies are described below. To enhance the exploitation tendency of HHO, chaos mechanism is presented. For improving the global search ability, the multi-population strategy has been introduced. Then, to improve the quality of the solution, differential evolution has been proposed.

Strategy 1 (Chaos): Chaos theory is applied on the random search procedure to improve the impact of the random search. In the proposed algorithm, the chaotic sequence can be produced utilizing the logistic mapping in chaos theory as follows.

$$c_{j+1} = \rho c_{j+1} \times (1 - c_j), \quad j = 1, 2, \ldots, k - 1 \tag{8}$$

where, ρ is the control parameter and k denotes the number of Harris Hawks.

Then a new population pc is produced as below based on combining the solutions of population p with chaotic sequence c.

$$pc = c_j \times p, \quad j = 1, 2, \ldots, k \tag{9}$$

By combining pc and p, new fitness value will be evaluated. Then a new population will be emerged by choosing the solutions of the fitness values. These steps need to be continued *(K-1)* times.

Strategy 2 (Multi-population topological structure): This structure plays an influential role in making balance between the exploration and exploitation phases. In the first step of this strategy, various sub-populations are detached from the whole population. The population size of all these sub-populations is the same. This characteristic of the sub-populations provides us with a brief and concise population structure and also it is possible to make the overall procedure more simple. By continuing the iterative procedure, whenever the sub-population experienced the augment in the population size and decline in the amount, the dynamic

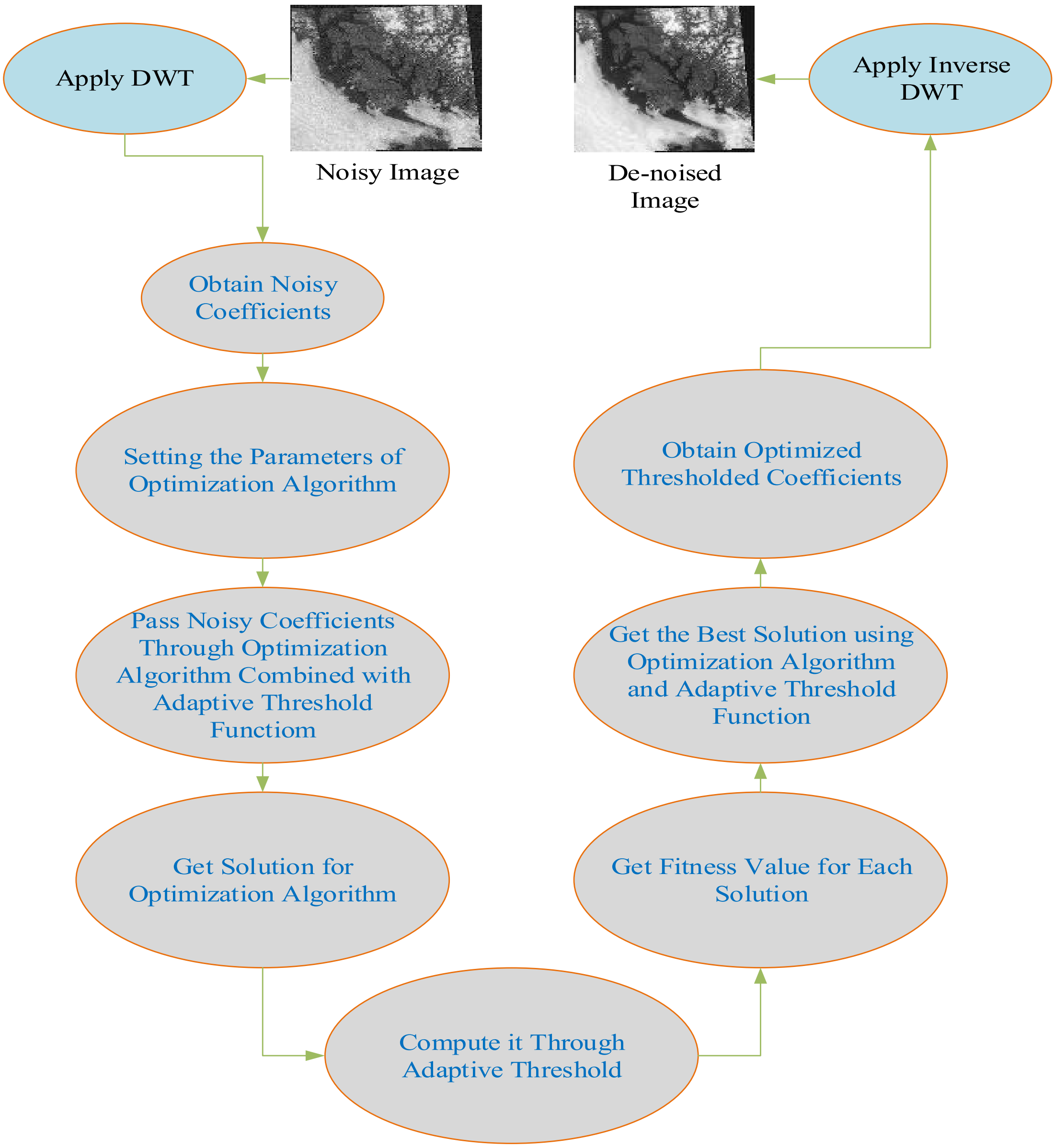

FIGURE 3. The steps of obtaining optimized output de-noised image in detail.

sub-population number strategy (DNS) plays its role with the objective of leading the method to the local search.

Furthermore, for sharing the information between sub-populations, a purposeful detecting strategy (PDS) will be utilized during the searching procedure. Meanwhile, for performing the exploitative drifts, PDS improves the ability of the algorithm as well. Finally, Sub-populations regrouping strategy (SRS) will be applied as the population is captured in the local optimum.

Strategy 3 (Differential evolution (DE)): To enhance the capability of local search of Harris Hawks Optimization algorithm and the quality of the produced solutions, differential evolutionary is utilized in the proposed algorithm. This strategy begins with utilizing a multi-population strategy for treating a population producing a new population through three operations which are described as follows.

Operation 1 (Mutation):

Step 1: Choose three distinctive individuals randomly from the population.

Step 2: Scale the difference between 2 of the individuals.

Step 3: Combine the distinction vector with the 3rd individual to acquire the last variant individually.

This operation is formulated below:

$$U^j(H) = Y^{q1}(H) + L.(Y^{q2}(H) - Y^{q3}(H)),$$
$$j \neq q1 \neq q2 \neq q3, \quad j = 1, 2, 3, .., N \qquad (10)$$

where, H denotes the number of iteration and L is the scale factor.

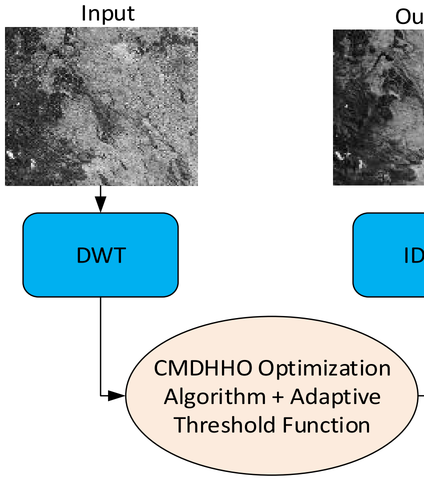

FIGURE 4. Flowchart of the proposed CMDHHO based de-noising algorithm.

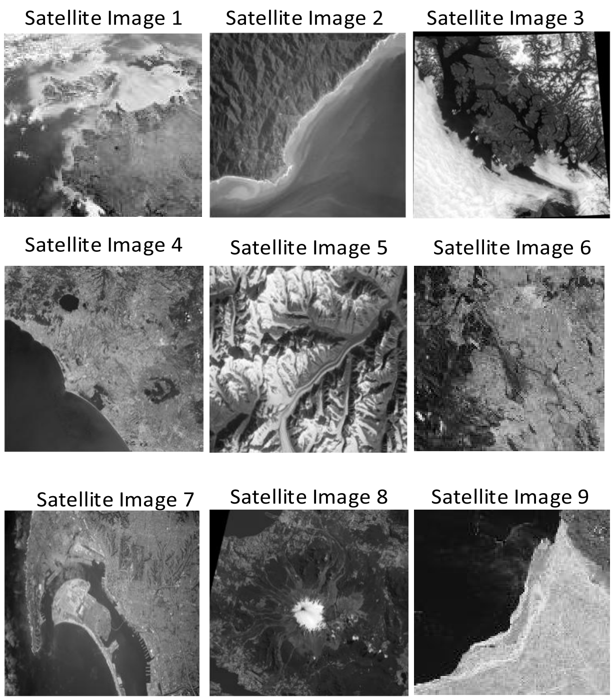

FIGURE 5. Satellite images used in the experimental part.

Operation 2 (Crossover operation): The differential strategy utilizes the crossover operation to enhance the individuals' variety. This function is formulated in the equation (11).

$$A_z^j(H) = \begin{cases} U_z^j(H), & \text{if } rand(0, 1) \leq cr \| z = z_{rand} \\ Y_z^z(H), & \text{otherwise}, \end{cases} \quad z = 1, 2, \ldots, D \tag{11}$$

where, cr is the probability of crossover which $\in [0, 1]$.

Operation 3 (Selection operation): By comparing the individual $A^j(H)$ produced by the crossover operation with the original individual $Y^j(H)$, the individual $Y^j(H+1)$ of the next generation can be concluded as follows.

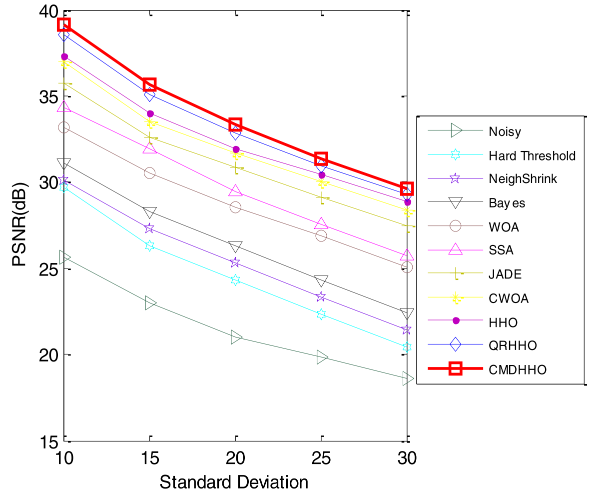

FIGURE 6. Comparison between different image denoising methods in terma of PSNR for Test Image 7.

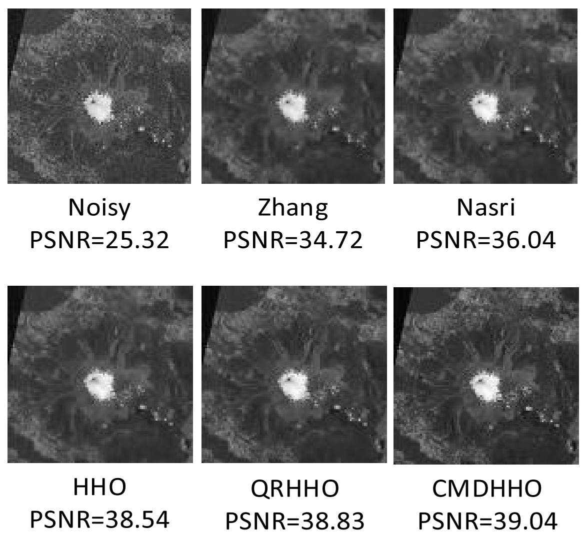

FIGURE 7. Comparisons of Qualitative and quantitative results between different techniques for Image 8 for standard deviation of 10.

$$Y^j(H+1) = \begin{cases} A^j(H), & \text{if } f(A^j(H)) \leq f(Y^j(H)) \\ Y^j(H), & \text{otherwise}, \end{cases} \quad j = 1, 2, \ldots, N \tag{12}$$

For optimized based image de-noising, the optimization algorithm can be applied to wavelet noisy coefficients. These coefficients can be passed through an optimization algorithm consisting of the adaptive threshold to obtain the optimized thresholded components. In this study, we utilized the adaptive nonlinear function with three shape tuning parameters [21] combined with CMDHHO [38] as the proposed method. Therefore, by applying inverse DWT on these constituents, we attain the de-noised image. The steps of acquiring the optimized based image de-noising [31] and its

TABLE 1. PSNR comparison between different de-noising methods.

Image	σ	Hard Threshold	NeighShrink	Bayes	WOA	SSA	JADE	CWOA	HHO	QRHHO	CMDHHO
image 1	10	31.65	33.12	33.48	34.36	35.21	36.13	37.59	37.81	38.22	**38.53**
	20	30.27	32.09	32.29	33.14	34.01	34.82	35.97	36.42	36.84	**37.03**
	30	27.76	29.21	29.87	30.74	31.57	32.12	33.57	33.73	34.07	**34.29**
image 2	10	31.86	33.33	33.53	34.38	35.21	36.06	37.43	37.62	38.02	**38.21**
	20	28.61	30.16	30.45	31.43	32.34	33.09	34.41	34.58	34.95	**35.21**
	30	26.83	28.22	28.75	29.63	30.46	31.11	32.63	32.91	33.31	**33.60**
image 3	10	32.41	34.27	34.76	35.81	36.72	37.42	38.84	38.98	39.44	**39.63**
	20	31.18	32.85	33.24	34.18	35.04	35.88	36.99	37.18	37.52	**37.75**
	30	29.63	31.37	31.76	32.64	33.52	34.13	35.61	35.80	36.13	**36.40**
image 4	10	32.46	33.63	33.98	34.79	35.68	36.21	37.75	37.94	38.39	**38.62**
	20	31.14	32.37	32.69	33.58	34.41	35.21	36.79	36.86	37.24	**37.47**
	30	28.43	29.84	30.32	31.28	32.31	33.04	34.64	34.82	35.26	**35.49**
image 5	10	30.64	31.97	32.28	33.21	34.16	34.91	36.39	36.61	37.06	**37.27**
	20	29.46	30.87	31.21	32.11	32.97	33.73	34.98	35.31	35.72	**35.93**
	30	28.01	29.48	29.81	30.65	31.36	32.24	33.56	33.79	34.12	**34.35**
image 6	10	30.45	32.01	32.12	33.01	33.82	34.64	36.03	36.21	36.59	**36.78**
	20	27.20	28.75	29.02	29.99	30.90	31.70	32.98	33.16	33.52	**33.81**
	30	25.41	26.83	27.35	28.22	29.01	29.69	31.20	31.49	31.94	**32.21**

algorithm is illustrated in detail in the Figure 3. The general flowchart of the proposed CMDHHO based satellite image de-noising is depicted in Figure 4.

IV. EXPERIMENTAL ANALYSIS AND RESULTS

In this section, several experiments have been performed to evaluate the efficiency of the proposed method for de-noising satellite images contaminated by additive white Gaussian noise with zero mean and different standard deviations (σ values).

The universal threshold value can be obtained in VisuShrink method as below formula [15]:

$$T = \sigma\sqrt{2\ln(m)} \tag{13}$$

where, m is the sample size and σ is the robust median estimator [15] as below:

$$\sigma = Median(|W_{i,j}|)/0.6745 \tag{14}$$

where, $W_{i,j}$ is the wavelet components in the HH_1 sub-band [15].

In these experiments, we used 'sym4' wavelet with one decomposition level. Note that Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) have been used as below to measure the performance of various noise removal approaches quantitatively.

$$PSNR(dB) = 10\log_{10}(\frac{255^2}{MSE}) \tag{15}$$

where, MSE is the mean square error which can be obtained as:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - \hat{I}(i,j)]^2 \tag{16}$$

where, I is the original image, $\hat{I}$ is the de-noised image and M, N are the image size [31].

Figure 5 depicts nine satellite images used in these experiments. The dataset is available in [30]. All the experiments and analysis have been performed by Matlab programming on a computer with Intel Core i7 and 16 GB Ram. Note that the parameters of all optimization algorithms are the same with those of the original work.

In the first experiment, we compared the proposed CMDHHO based noise reduction with QRHHO [33], HHO based satellite image de-noising [30], CWOA [35], JADE [31], SSA, WOA [35], Bayes [18], NeighShrink [39], and Hard threshold in Table 1 based on the PSNR. As the results in Table 1 show, the proposed technique outperforms other methods in terms of PSNR values.

In the second experiment, we used Figure 6 to show the superiority of the proposed technique. In this experiment we utilized Test Image 7. As it is clear, optimized based noise reduction performs better than TNN based image de-noising methods. TNN based noise removal makes images more blur but the resolution of the images de-noised by the optimization algorithms is much better. In the third experiment, as can be seen from Figure 7, we compared the proposed method with QRHHO [33], HHO based noise reduction [30], Nasri [21], and Zhang [22] visually for Test Image 8 to show that the optimized based noise suppression methods outperform TNN based image de-noising.

Also, in this part, we compared the computation time of optimized based and TNN based noise removal approaches in Table 2. Note that, the processing times given in Table 2 are the average of 10 runs. It is obvious that CMDHHO is the fastest technique comparing with other methods.

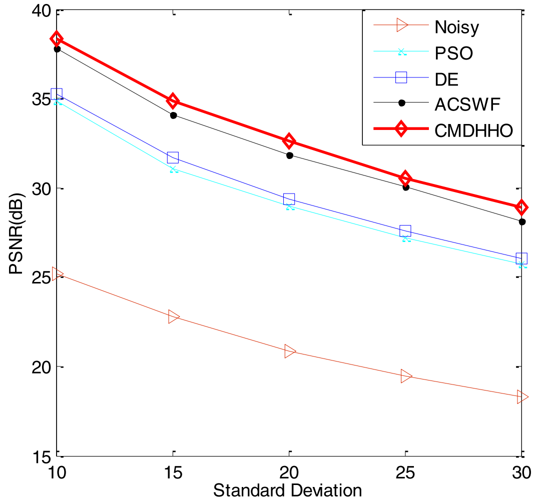

FIGURE 8. Performance analysis comparison between different noise removal methods in terma of PSNR for Test Image 9.

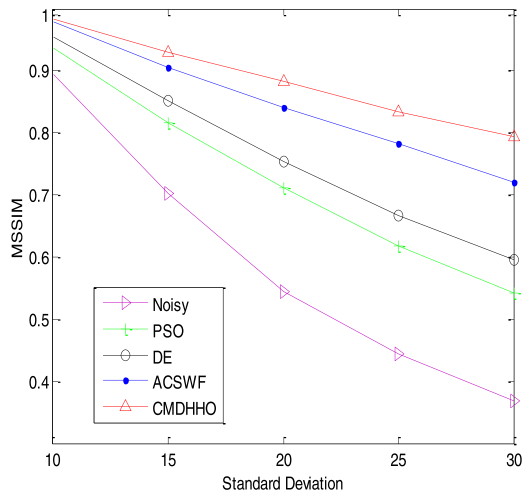

FIGURE 9. Performance analysis comparison between different noise removal methods in terma of MSSIM for Test Image 9.

TABLE 2. Comparison of processing time of different noise reduction methods.

Methods	Zhang	Nasri	HHO	QRHHO	CMDHHO
Time (sec)	7.3	6.1	3.9	3.3	2.9

In the fourth experiment as can be seen from Figure 8 and Figure 9, we used PSNR and MSSIM to evaluate the performance of CMDHHO compared with ACSWF [45], PSO [44] and DE [43] methods for Test Image 9. We ustilized MSSIM in the same way it has been used in [31]. The results show the superiority of the proposed method over other de-noising approaches.

V. CONCLUSION

In this study, we utilized the newly proposed Multi-population differential evolution-assisted Harris Hawks Optimization Algorithm (CMDHHO) in the optimized wavelet-based satellite noise removal approach. CMDHHO is the enhanced form of Harris Hawks Optimization algorithm containing three main strategies, namely: chaos, multi-population, and differential evolution. In this paper, some well-known optimizers like SSA, WOA, CWOA, DE, PSO, QRHHO, HHO, JADE have been utilized and compared with de-noising results of the proposed CMDHHO. De-noising using CMDHHO gives better results quantitatively and qualitatively compared with other optimization-based image de-noising methods. Also, this technique enhances the time of processing. We have used Peak Signal to Noise Ratio (PSNR) and MSSIM for evaluating the analysis of de-noising techniques. Results show that CMDHHO performs well compared with some other optimized based methods in the literature. For the future work, removing different kind of noises such as speckle noise using different de-noising algorithms will be analyzed. Also we will deal with the statistical results based on the statistical tests.

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