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Optimal Image Compression based on Hybrid Bat Algorithm and Pattern Search

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Abstract

In this paper, multilevel image thresholding for image compression is proposed for the first time using Shannon entropy and Fuzzy entropy, which are maximized by the nature-inspired hybrid Bat algorithm and Pattern Search (hBA-PS).The ordinary thresholding method gives high computational complexity, but while extending for multilevel image thresholding, the optimization techniques are needed in order to reduce the computational time. Particle Swarm Optimization (PSO) and FA (Firefly Algorithm) undergo instability when the particle velocity is maximum. It is evident that Bat Algorithm (BA) is good in exploitation whereas Pattern Search (PS) is good in exploration. We hybridized the BA and PS based on their strengths and weaknesses. The proposed technique (hBA-PS) is compared with Differential Evolution (DE), PSO and BA for which the experimental results are compared in terms of Standard deviation, Computational time, Peak Signal to Noise Ratio (PSNR), Weighted PSNR and Reconstructed image quality. The performance of the proposed algorithm is found to be better with Fuzzy entropy compared to Shannon.

Keywords : Bat algorithm, Pattern Search, Image compression, Thresholding, Shannon entropy, Fuzzy entropy.

I. Introduction

The image compression technique is reducing the number of bits [XII], which are essential to enhance the storage capacity. Several methods were proposed for image compression in Joint Photographic Expert Group (JPEG) and JPEG-2000 [XVIII]. Transformed methods such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Tchebichef Transform [VII] and Non-transformed methods like Vector Quantization and Thresholding are used in Image Compression. Extracting background image is a challenging task in selecting a gray level threshold from image processing. Thresholding techniques are upholding various real-time applications in progressive robustness, accuracy and less time convergence. There are two ways to approach thresholding, parametric and non- parametric. The main disadvantage of a parametric approach is excessive time consumption, whereas thresholding is carried on class variance as in Otsu's technique in non-parametric approaches, which depends on the conditions of entropies [VIII]. Based on the intensity values, the fundamental assumption of thresholding methods is to classify the object and background. These can be classified into bi-level and multi-level thresholding. In case of bi-level thresholding, only one threshold is opted to divide the image into two classes, whereas in multi-level thresholding, more than one threshold must be determined. Detailed research on image thresholding is classified into six categories [XVI], based on Clustering, Entropy, Histogram shape, Object attribute, spatial and local methods. Considering the histograms of the gray level images, the images based on calculating threshold are classified [IV]. The image is divided by evaluating the variance of pixel intensities according to the Otsu's method [X]. An inbuilt mat lab function was used [XVII] for the compression i.e. Birge Massart thresholding and the outcomes are compared with unimodal thresholding. Its drawback is the exponential rise of CPU time and to overcome this problem, evolutionary and swarm-based calculation techniques are opted.

The moment preserving principle [II] is for effective and efficient color image thresholding. A particular approach is followed [V] to select the wavelet packets with low computational cost which optimizes the operational rate-distortion (R-D), thresholds and quantizers in order to develop JTQ-WP. Compression of ECG signals along with 2-D DWT was proposed [XIX]. Type-II fuzzy thresholding was performed on Bandlet transform in image compression to identify unequal edges of the image instead of smooth regions [XIV]. A non-uniform procedure was proposed [XI] on the effects of thresholding in the reconstructed image. Tucker tensor decomposition [XIII] based on coefficient thresholding and zigzag traversal was proposed, and followed by logarithmic quantization on both the transformed tensor core and its factor matrices. Particle Swarm Optimization (PSO) is developed for usual image compression [VI] based on 2-D DWT image thresholding with the support of swarm evolutionary and optimization method.

In this paper, we applied Hybrid Bat algorithm and Pattern Search based on image thresholding for image compression by optimizing the Shannon and Fuzzy entropy and the obtained results were compared with other optimization algorithms such as PSO, DE and BA as shown in Fig.1. The compressed image is further compressed by encoding

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techniques such as run length and arithmetic coding. The coded bits are transmitted over a communication channel to the receiver, which are decoded and re-arranged to get back the original reconstructed image. For the better performance estimation of proposed algorithm, we considered objective function value, standard deviation, PSNR, WPSNR, Compression ratio (CR), Bits per pixel (BPP), and Computational complexity.

For the rest of the paper, the architectural structure is as follows; Section II provides a brief review of the framework of formulating the optimum thresholding methods, Overview of the proposed algorithm (hBA-PS) and its enhancement is discussed in Section III, whereas Section IV presents the results and the conclusions in Section V.

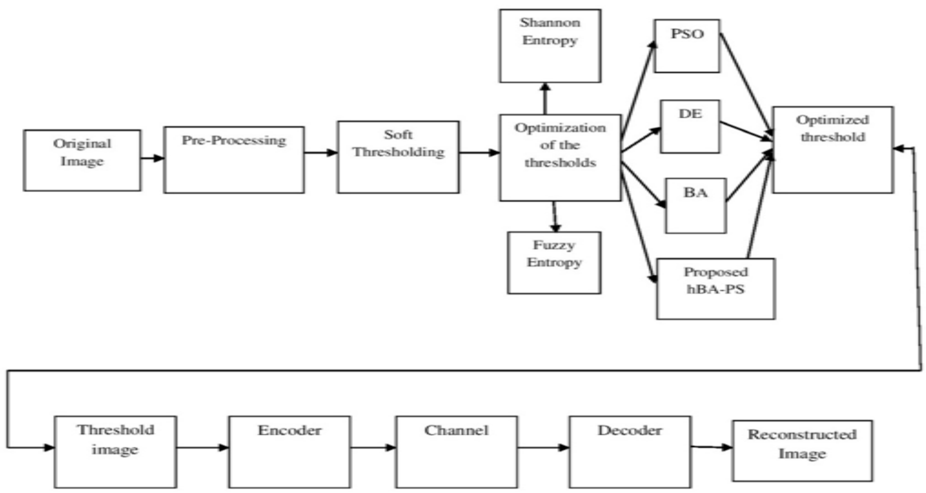

Fig.1 Proposed block diagram of image compression approach

II. Formulating the optimum thresholding methods

Thresholding methods are computationally expensive whether they are local or global. In the process to optimize the objective function outcomes in the lessening procedure of computational time, there is a need of optimization techniques. The optimal thresholds are found by the optimization techniques by maximizing the objective function such that the background and foreground of the image are clearly distinguished by reconstructed image. In this, Shannon and Fuzzy entropies are chosen as the objective functions. Assuming an image containing L gray levels and the range of gray levels are {0, 1, 2,.., (L - 1)}. Then probability P_k = h(k)/N (0 <k< (L - 1)), where N denotes total number of pixels in the image which is equal to $\sum_{k=0}^{L-1} h(k)$ and h(k) implies to number of pixels for the corresponding gray level L.

Concept of Shannon Entropy

The number of messages to transmit are $N = 2^n$ (if N = 8) then the number of bits required is n (n = 3), for each of N messages $\log_2^N$ number of bits are needed. If observed the repetition of same message from a collection of N messages, and if the messages can be assigned on a non-uniform probability distribution, then it is possible to use fewer than logN bits per message and it is called Shannon entropy. Let Y be the random variable (discrete) with elements $\{Y_1, Y_2 \ldots, Y_n\}$ then probability mass function P(Y) is given as per Eq.(1).

$$\mathrm{H(Y)} = \mathrm{E[I(Y)]} = \mathrm{E}\left[-\ln\left(\mathrm{P(Y)}\right)\right] \tag{1}$$

Where I shows the content of information, E denotes the expected value operator and considers random variable I(Y). So the Shannon entropy is re-written as per Eq.(2) and is considered as the objective function which is to be optimized based on optimization techniques.

$$\mathrm{H(Y)} = \sum_{i=1}^{n} \mathrm{P}(y_i)\mathrm{I}(y_i) = -\sum_{i=1}^{n} \mathrm{P}(y_i)\log_b \mathrm{P}(y_i) \tag{2}$$

Where b is generally the base of the algorithm and it is equal to 2. If P (yi) = 0 for some values of i, then the multiplier $0\log_b 0$ is assumed as zero which is consistent with the limit

$$\lim_{p\to 0+} p\log(p) = 0 \tag{3}$$

The Eq.s (1),(2) and (3) are for discrete values of Y.

Concept of Fuzzy Entropy

Let D={(i, j): i=0,1,2,…..,M-1; j=0,1,2,…….N-1} and G={0,1,2,……,L-1}, Where M, N and L are the width, height and number of gray levels in the image respectively. I(x, y) is the intensity of image at position (x, y) and D_k = {(x, y): I(x, y) = k, (x, y) = D}, k=0, 1, 2,…., L-1. Let us assume two thresholds T_1, T_2, which divides the domain D of the original image into three regions E_d, E_m and E_b. E_d region covers the pixels when the intensity values are less than T_1, E_m covers the pixels when the intensity are between T_1, T_2 and E_b covers the pixels when the intensity values are greater than T_2. $\Pi_3=\{E_d, E_m, E_b\}$ is an unknown probabilistic partition of D, its distribution is given as [XX] $P_d = P(E_d)$, $P_m = P(E_m)$, $P_b = P(E_b)$. μ_d, μ_m and μ_b are the membership functions (μ) of E_d, E_m and E_b respectively and require six parameters [a_1, b_1, c_1, a_2, b_2, c_2]. Based on the membership functions the threshold values (T_1, T_2) are variable. For each k= 1, 2, 3,… 255, let

$$\mathrm{D_d} = \{(x,y): \mathrm{I}(x,y) \le \mathrm{T}_1, (x,y) \in \mathrm{D_k}\} \tag{4}$$

$$\mathrm{D_m} = \{(x,y): \mathrm{T}_1 < I(x,y) \le \mathrm{T}_2, (x,y) \in \mathrm{D_k}\} \tag{5}$$

$$\mathrm{D_b} = \{(x,y): \mathrm{I}(x,y) > \mathrm{T}_2, (x,y) \in \mathrm{D_k}\} \tag{6}$$

If the conditional probability of E_d, E_m and E_b is $p_{d|k}$, $p_{m|k}$ and $p_{b|k}$ respectively under the circumstance that the pixel pertains to D_k with $p_{d|k} + p_{m|k} + p_{b|k} = 1$(k=0, 1, 2, 3.., 255) then above equations can be rewritten as

$$p_{kd} = p(D_d) = p_k \times p_{d/k} \quad (7)$$

$$p_{km} = p(D_m) = p_k \times p_{m/k} \quad (8)$$

$$p_{kb} = p(D_b) = p_k \times p_{b/k} \quad (9)$$

Let the grade of pixels with gray level value of k belong to the class dark (E_d), dust (E_m) and bright (E_b) be equivalent to its conditional probability $p_{d|k}$, $p_{m|k}$, $p_{b|k}$ respectively. As per Eqs. (10), (11) and (12),

$$p_d = \sum_{k=0}^{255} p_k * p_{d/k} = \sum_{k=0}^{255} p_k * \mu_d(k) \quad (10)$$

$$p_m = \sum_{k=0}^{255} p_k * p_{m/k} = \sum_{k=0}^{255} p_k * \mu_m(k) \quad (11)$$

$$p_b = \sum_{k=0}^{255} p_k * p_{b/k} = \sum_{k=0}^{255} p_k * \mu_b(k) \quad (12)$$

The fuzzy membership functions [XX] are shown in Fig. 2. Class dark $\mu_d(k)$, dust $\mu_m(k)$ and bright $\mu_b(k)$ are assigned with the membership functions Z(k, a_1, b_1, c_1, a_2, b_2, c_2), U(k, a_1, b_1, c_1, a_2, b_2, c_2) and S(k, a_1, b_1, c_1, a_2, b_2, c_2) respectively.

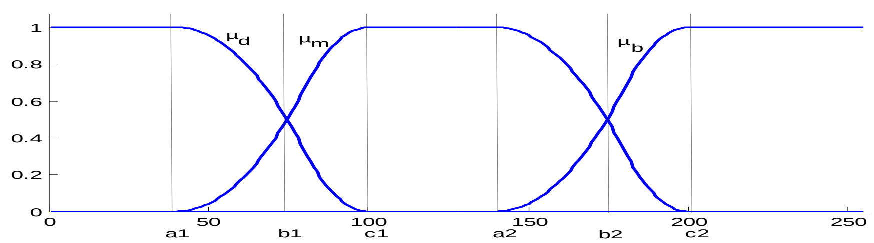

Fig.2 Membership function graph with a_1=40; b_1=80; c_1=100; a_2=140; b_2=180; c_2=200.

Hence the fuzzy entropy function of each class could be given as per Eqs. (13), (14), (15).

$$H_d = -\sum_{k=0}^{255} \frac{p_k * \mu_d(k)}{p_d} * \ln\left(\frac{p_k * \mu_d(k)}{p_d}\right) \quad (13)$$

$$H_m = -\sum_{k=0}^{255} \frac{p_k * \mu_m(k)}{p_m} * \ln\left(\frac{p_k * \mu_m(k)}{p_m}\right) \quad (14)$$

$$H_b = -\sum_{k=0}^{255} \frac{p_k * \mu_b(k)}{p_b} * \ln\left(\frac{p_k * \mu_b(k)}{p_b}\right) \quad (15)$$

By summarizing the fuzzy entropy of each class, the entire fuzzy entropy is calculated as per Eq.(16).

$$H(a_1, b_1, c_1, a_2, b_2, c_2) = H_d + H_m + H_b \quad (16)$$

The objective function mentioned in Eq.(16) optimize or maximize H(a_1, b_1, c_1, a_2, b_2, c_2) function by varying the values (a_1, b_1, c_1, a_2, b_2, c_2) using optimization techniques. The optimized values are then used to calculate the threshold values as per Eq. (17)

$$\mu_d(T_1) = \mu_m(T_1) = 0.5 \text{ and } \mu_m(T_2) = \mu_b(T_2) = 0.5 \quad (17)$$

T_1 and T_2 are the points of interaction of $\mu_d(k)$, $\mu_m(k)$ and $\mu_b(k)$ curve as shown in Fig.2. The values of T_1 and T_2 are calculated which are given as per Eqs. (18) and (19).

$$T_1 = \begin{cases} a_1 + \sqrt{(c_1 - a_1) * (b_1 - a_1) / 2} & (a_1 + c_1)/2 \le b_1 \le c_1 \\ c_1 - \sqrt{(c_1 - a_1) * (c_1 - b_1) / 2} & a_1 \le b_1 \le (a_1 + c_1)/2 \end{cases} \quad (18)$$

$$T_2 = \begin{cases} a_2 + \sqrt{(c_2 - a_2) * (b_2 - a_2) / 2} & (a_2 + c_2)/2 \le b_2 \le c_2 \\ c_2 - \sqrt{(c_2 - a_2) * (c_2 - b_2) / 2} & a_2 \le b_2 \le (a_2 + c_2)/2 \end{cases} \quad (19)$$

The two level thresholding can not only be contracted to single level, but also further extended to three or more. Initially, there are six parameters to be optimized for two thresholds but when the levels of thresholds are increased the no. of parameters are also increased. So fuzzy entropy takes much time for convergence. Hence the image compression for two level image thresholding with the Shannon and Fuzzy entropies proved effective and efficient, but for multilevel thresholding both entropy techniques consume much time convergence and increase exponential level of thresholds. For improving the performance of these methods we applied optimization techniques such as DE, PSO, BA and proposed algorithm for the compression of images. These techniques are used to maximize the Shannon and Fuzzy entropies as mentioned in Eq. (2) and (16).

III. Overview of hybrid bat algorithm and pattern search (hBA-PS)

Bat algorithm

PSO and Quantum PSO generated an efficient threshold. In case of high practical velocity, it undergoes instability in convergence [XV]. To generate nearby global thresholds, the Firefly algorithm (FA) was developed, even it encountered a problem when no such brighter fireflies were identified in the search space [I]. To avoid such problems, a Bat algorithm (BA) was developed by Yang [XXI] with two tuning parameters which give global thresholds with less iteration. It is based on three assumptions: The first is, to sense the distance, recognize the food/prey and background barriers; the second is, they fly randomly with velocity (V_i) at position (Y_i) with a fixed frequency (Q_{min}), varying wavelength (λ) and loudness (A_0) in search of prey. The third is, vary in different ways of loudness (A_0) from larger value (A_{max}) to (A_{min}). Intensification and diversification of algorithms are obtained through pulse rate and loudness parameter respectively. It mainly works on the distance, object, position, and frequency of a bat. Let the number of thresholds is (C) and bats are {B_1, B_2,.., B_k,…., B_n}. The frequency of sound (Q_k) of a bat (B_k) can be attained as per Eq. (20).

$$Q_k = R_1 \sum_{i=1}^{m} (C_{ki})/m \quad (20)$$

Where R1 = pulse rate

The object Distance (S) from a bat (B_k) is the product of (C_k), (Q_k) and a random weight value of each object as per Eq.(21).

$$S_{object} = Q_k \times C_k \times w \quad (21)$$

w = step size of the random walk. Generally, bats start flying from the zero position and as they reach nearer to the object/prey, the position varies. As bat outreaches closer to the prey the error (E_k), position (Y_k) can be calculated as per Eq.(22), Eq. (23) respectively.

$$E_k = S_{object} - 1 \quad (22)$$

$$Y_k = Y_k + E_k \quad (23)$$

The frequency (Q) is updated in step size (w) after the variation in the pose of a bat. The frequency (Q_k) of a bat (B_k) is controlled by the pulse rate (R_1) and automatically adjusted in every iteration as per Eq. (24).

$$R_1 = Q_k + (R_2 \times E_{k2} \times Y_k) \quad (24)$$

R_2 is a bat learning parameter (constant).

$$w = w + (2 \times \beta \times E_k) \quad (25)$$

Where β is the random number

Pattern Search Algorithm

Hooke and T.A Jeeves [III] developed this algorithm for reaching a real time numerical and engineering problems. It optimizes the fitness/ objective function, which consists of exploratory and pattern moves. In this paper, the outcome of the Bat algorithm is the initial solution $Y^{(0)}$. Initially, iteration perturbation vectors start at the positions [0.5 -0.5], [0.5 0.5], [-0.5 -0.5] and [-0.5 0.5] with acceleration factor, which is equal to one. The perturbation vectors generated for next solution $Y^{(1)}$, then it is added to $Y^{(0)}$ as per Fig. 3. If the fitness of $Y^{(1)}$ are better values than $Y^{(0)}$, then the successful perturbation vectors are considered, algorithm replaces $Y^{(0)}$ with $Y^{(1)}$. Whenever these vectors occur, the algorithm shifts to pattern move where the acceleration factor (a) is multiplied by factor 2, which is called an expansion factor. In this process, it is repeated for the maximum iterations until we get the best solution, whereas the algorithm acceleration factor is divided by a factor 2 and then it is known as contraction factor.

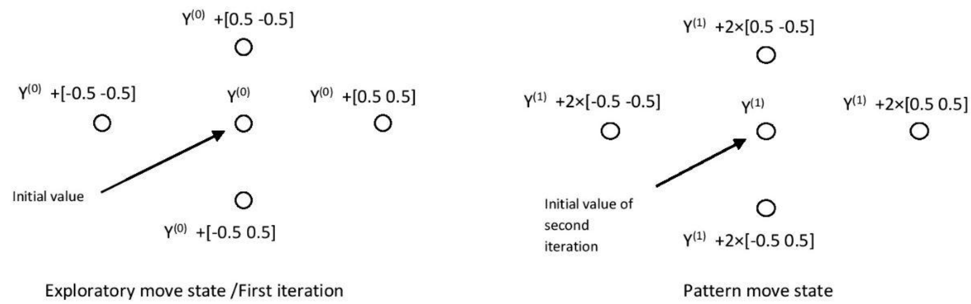

Fig.3 Exploratory move state and Pattern move state of Pattern search

Proposed hBA-PS Based Fuzzy/ Shannon Entropy

Input: Initialize the population (N), Maximum number of iterations, level of thresholding (Th) and its corresponding values (a_1, b_1, c_1, a_2, b_2, c_2). Output: The optimized values (a_1, b_1, c_1, a_2, b_2, c_2) are its corresponding thresholding values and reconstructed image.

The detailed algorithm is explained as follows:

Step 1: Initialize parameters such as Thresholds (N),Velocity (V), Loudness (A), Pulse rate (R), frequency minimum (Q_{min}) and maximum (Q_{max}). Thresholds are initialized randomly Y_i, (i = 1,2, 3, -----, N).

Step 2: Figure out the Best fitness thresholds (Y_{best}), which were calculated as per Eq. (2) for Shannon entropy and Eq. (16) for Fuzzy entropy.

Step 3: Update the thresholds towards (Y_{best}) as per Eq. (28), by adjusting the frequency, distance as per Eqs. (26), (27) respectively.

Frequency-update: $$Q_i(t+1) = Q_{max}(t) + (Q_{min}(t) - Q_{max}(t)) \times R \quad (26)$$

Distance- update: $$V_i(t+1) = V_i(t) + (Y_i - Y_{best}) \times Q_i(t+1) \quad (27)$$

Position –update: $$Y_i(t+1) = Y_i(t) + V_i(t+1) \quad (28)$$

Step 4: During the selection of the step size of random walks; if the generated random number is greater than the pulse rate ‘R' move the thresholds around the best thresholds as per Eq. (29).

$$Y_i(t+1) = Y_{best}(t) + w \times R \quad (29)$$

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Here w = step size of a random walk within 0 to 1.

Step 5: Generate an updated threshold by random flight: If the generated random number is less than loudness, then accept the new threshold if its fitness is better than the old one.

Step 6: Rank the bats/thresholds and find the current best (Y_{best}).

Step 7: Continue step (2) to (6) so far to reach maximum iterations.

Pattern search Algorithm:
Step 8: Bat algorithm is allocated to solutions (K) and mesh contraction /expansion factor (P) to get optimal solutions.
Step 9: Verify all likely solutions (Y_i) where i = 1, 2, 3 … K.
Step 10: Compute the objective function $f(Y_k)$, and then calculate the step of search S_k by using Exploratory move.
Step 11: If the newly obtained objective function $f(Y_k+S_k)$ is less than $f(Y_k)$, then the new solution is $Y_{k+1}= (Y_k+S_k)$ or else $Y_{k+1}= Y_k$.
Step 12: The updated optimal solution is processed for the selected thresholds.

IV. Results and discussion

The proposed algorithm is evaluated by considering the standard benchmark images like Lena, Gold hill, Lake, and Cameraman with size of 225×225. In general, the possibilities of selecting a good threshold are increased if the histogram peaks are tall, narrow, and symmetric and separated by deep valleys. In Fig.4 the corresponding histograms of all test images are observed. Cameraman and Gold hill image histograms peaks are tall, narrow and symmetric, whereas for Lena are not tall and narrow. Hence it is hard to compress with other methods. Therefore hBA-PS is proposed and the obtained results are compared with other optimization algorithms.

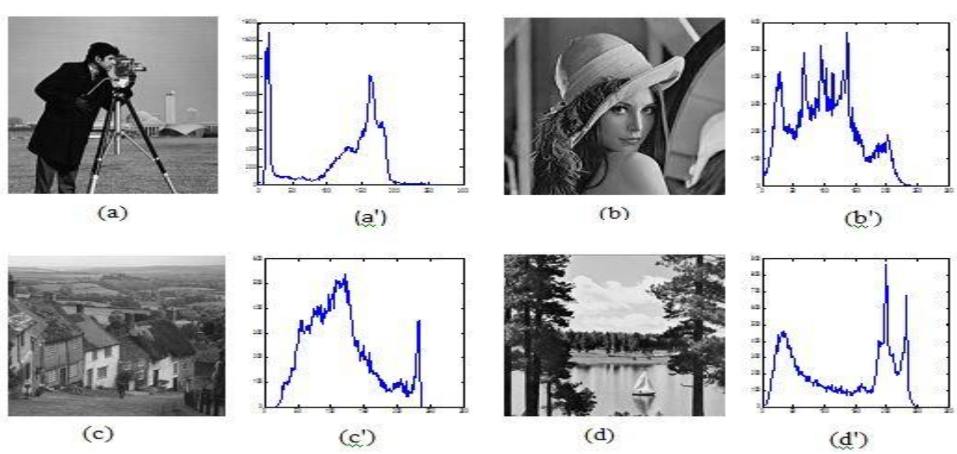

Fig.4. Test images and corresponding histograms a) Cameraman b) Lena c) Gold hill d) Lake

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Selection of DE, PSO, BA and PS parameters

The maximum number of iterations (N) are 30 and population/solutions are 10 times of threshold value (i.e. if threshold =2 then population = 10×2) are employed to all optimization techniques. The DE gives the best results when weighting factor (F) value is 0.5 and the crossover probability (CR) is 0.9. The PSO algorithm depends on two tuning parameters such as acceleration constants (C_1 and C_2) and inertia weight factor (W). Generally, PSO has given the best fitness values when C_1 and C_2 are set at 2.

Table 1: Results over 50 independent runs of tuning BA Parameters

Parameter	Max.	Mean	Std.dev.	Others
A=0.1	13.978990	13.883929	0.000939	
A=0.2	13.988383	13.978383	0.019949	
A=0.3	13.989494	13.984844	0.094949	
A=0.4	13.999889	13.988484	0.094838	R=0.4
A=0.5	13.985843	13.939393	0.084844	D=Th=2
A=0.6	**13.994383**	**13.909484**	**0.094949**	K=30
A=0.7	13.984848	13.920394	0.094844	
A=0.8	13.980292	13.983939	0.094949	
A=0.9	13.980393	13.969303	0.029382	
A=1	13.989303	13.983933	0.083222	
R=0.1	13.984949	13.978484	0.004049	
R=0.2	13.980939	13.971234	0.093844	
R=0.3	13.989382	13.980938	0.007383	
R=0.4	13.980292	13.989033	0.009393	
R=0.5	13.980943	13.979393	0.019933	A=0.6
R=0.6	13.984939	13.980005	0.014883	D=Th=2
R=0.7	**13.990008**	**13.990001**	**0.029393**	K=30
R=0.8	13.989484	13.979494	0.011234	
R=0.9	13.990040	13.983393	0.005467	
R=1	13.980838	13.979494	0.010494	
K=20	13.988485	13.983938	0.029493	A=0.6
K=30	13.989735	13.975584	0.023946	R=0.7
K=50	13.984847	13.894946	0.007685	D=Th=2
K=100	**13.991029**	**13.999382**	**0.019493**	

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The common parameters such as number of solutions (K), maximum number of iterations (N), dimensions (D), Loudness (A) and Pulse rate (R) influence the performance of BA and PS. The variation of objective function maximum value, mean, standard deviation with respect to the control parameters for standard test image like Gold hill with th=2 are shown in Table 1 where 50 independent experiments are conducted for fixing of BA parameter for validation of the algorithm. From Table 1, it is observed that the objective value is maximum at Loudness (A) = 0.6 and Pulse rate (R) = 0.7 and N =100 and carried for all other images. The value of objective function beyond N =100 is slightly improved, where the computational time also increased. The PS parameters: mesh size = 1, mesh expansion factor = 2, mesh contraction factor = 0.5.

Table 2: Comparison of Objective Value & Standard deviation for different algorithms

Images	Opt Tech	Objective value		Standard deviation	
		Shannon	Fuzzy	Shannon	Fuzzy
Cameraman	DE	21.0129	23.6330	0.02235	0.056
	PSO	21.0559	23.0776	0.19668	0.1946
	BA	21.2378	23.2842	0.25852	0.1927
	hBA-PS	21.2380	23.6667	0.14566	0.1888
Lena	DE	21.4863	24.0294	0.0062	**0.033**
	PSO	21.4878	24.3009	0.12514	**0.196**
	BA	21.3736	24.3738	**0.2003**	0.2314
	hBA-PS	21.3862	24.5877	0.2888	0.1987
Goldhill	DE	21.2202	23.4269	0.00453	0.0386
	PSO	21.2128	24.0563	0.29592	0.2259
	BA	21.1616	24.2146	0.06719	**0.2626**
	hBA-PS	21.2099	24.3768	0.28987	0.1987
Lake	DE	21.6607	24.3738	0.00621	0.0343
	PSO	21.736	24.5610	0.20724	0.2344
	BA	21.7581	24.7666	0.05222	0.1253
	hBA-PS	21.7593	24.8019	0.29097	0.1909

Algorithms DE, PSO and BA and hBA-PS are applied on Shannon entropy and Fuzzy entropy objective functions and the proposed algorithm results are compared to the earlier ones which are shown in Table 2. Hence, it is observed that objective function value of Fuzzy entropy is higher than Shannon entropy in all cases and algorithms with the cost of high computational complexity. It is also noticed that standard deviation of fuzzy entropy is lower than Shannon except in few cases which are highlighted in the Table.2. Hence, when compared to other techniques, hBA is stable.

It is observed that Fuzzy entropy gives improved reconstructed image quality and higher PSNR values than Shannon. The WPSNR [IX] is precise and incorporate the human visual system into account while measuring the resemblance between the input and processed images. The better PSNR, WPSNR values and less mean square error with hBA-PS when compared to other algorithms are shown in Table 3.

Table 3: Comparison of PSNR, WPSNR & MSE values with different algorithms

Images	Opt Tech	PSNR		WPSNR		MSE	
		Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy
Cameraman	DE	31.268	30.991	16.516	16.735	69.55	50.226
	PSO	31.458	31.122	17.492	18.176	66.549	50.208
	BA	31.585	31.532	18.676	18.202	61.274	45.701
	hBA-PS	31.745	31.876	20.987	21.064	51.394	38.347
Lena	DE	31.28	29.885	16.897	17.852	45.73	63.272
	PSO	31.425	30.119	16.906	19.373	46.84	66.768
	BA	31.529	30.277	17.069	19.75	43.707	61.006
	hBA-PS	31.799	31.789	19.986	21.897	42.902	50.923
Goldhill	DE	30.575	30.641	16.909	17.803	56.961	56.099
	PSO	30.681	30.73	17.722	17.994	55.584	54.962
	BA	30.794	30.996	17.819	18.021	54.159	51.694
	hBA-PS	31.793	31.567	19.654	19.874	44.876	45.875
Lake	DE	30.607	30.634	17.254	17.318	56.549	56.19
	PSO	31.468	30.855	17.392	18.146	46.375	53.409
	BA	31.536	31.567	18.058	18.785	45.658	44.159
	hBA-PS	31.902	31.909	19.097	19.098	43.856	41.875

Qualitative Results

Here we focused on threshold value (Th =5) on visual quality based on images reconstructed by using Shannon/Fuzzy entropy with DE, PSO, BA and hBA-PS algorithms are shown in Fig.5 to 12. At a higher level of threshold (Th = 5), it is observed that constructed image visual quality is much improved than Th=2,3 and 4.From Cameraman and Lena images at level 5 thresholds as in Fig. 5h and 6h, visual quality for Fuzzy entropy of hBA-PS is better than BA. It is observed that, with the increase in number of thresholds, the background is clearly recognized (Fig.8h). Similarly, with the visual quality of all other images, hBA-PS is better compared to DE, PSO, BA.

The variations in BPP and CR are tabulated in Table 4.

Table 4: Comparison of Compression Ratio & BPP values for different algorithms

Images	Opt Tech	CR		Bits per Pixel (BPP)	
		Shannon	Fuzzy	Shannon	Fuzzy
Cameraman	DE	10.62	12.442	0.7533	0.643
	PSO	10.203	13.389	0.7841	0.5975
	BA	9.0171	9.2012	0.8872	0.8695
	hBA-PS	8.901	8.993	0.5987	0.8787
Lena	DE	7.8855	8.2802	1.0145	0.9662
	PSO	7.8733	7.8355	1.0161	1.021
	BA	7.8929	9.8015	1.0136	0.8162
	hBA-PS	7.1848	8.2474	0.9888	0.9022
Goldhill	DE	6.3776	6.642	1.2775	1.2045
	PSO	6.2124	5.7119	1.2877	1.4006
	BA	5.5274	6.2086	1.4473	1.2885
	hBA-PS	5.4982	5.3102	1.2939	1.2848
Lake	DE	6.2546	6.0731	1.2791	1.3173
	PSO	6.4996	6.6594	1.2309	1.2013
	BA	5.984	6.6343	1.3369	1.3443
	hBA-PS	5.3773	5.9838	1.2999	1.2984

Reconstructed images and thresholds on histogram of tested images with various thresholds achieved by BA and hBA-PS with Shannon entropy is shown in Fig. 5.to Fig. 8 and Fuzzy entropy are shown in Fig.9 to 12. (a) - (d) shows 2-5 level reconstructed images obtained with BA respectively. (a') - (d') shows 2-5 level thresholds on histogram obtained with BA respectively. (e) - (h) shows 2-5 level reconstructed images obtained with hBA-PS respectively. (e') - (h') shows 2-5 level thresholds on histogram obtained with hBA-PS respectively

Fig. 5: Cameraman

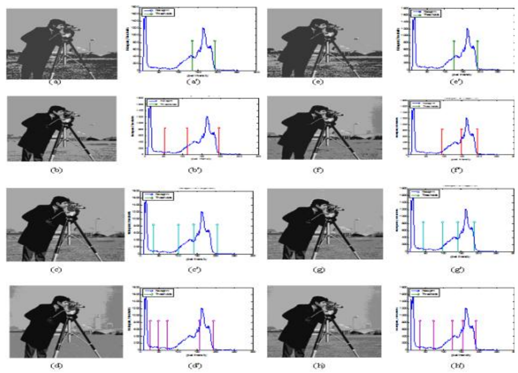


Fig. 6: Lena

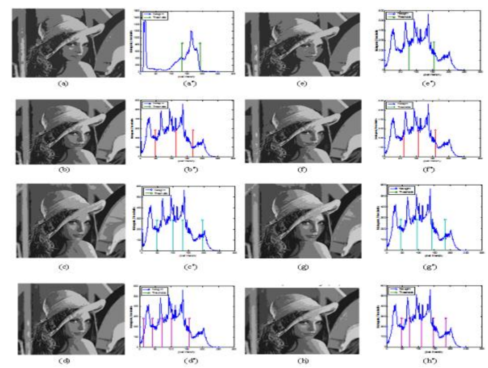


Fig. 7: Gold hill

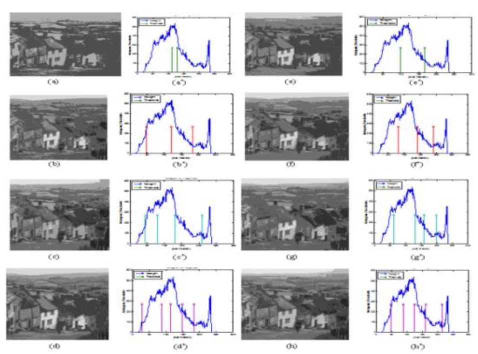


Fig. 8: Lake

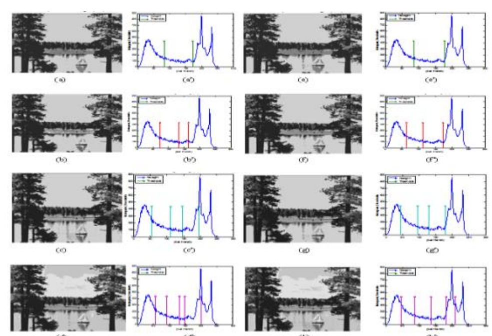


Fig. 9: Cameraman

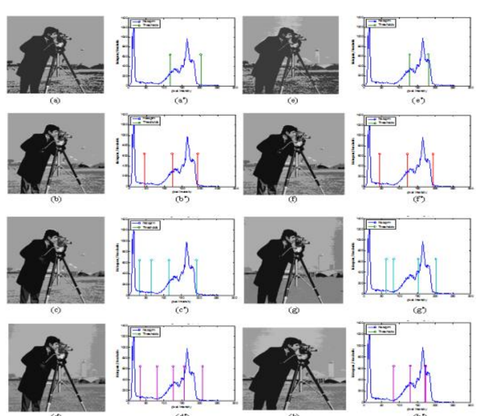


Fig. 10: Leena

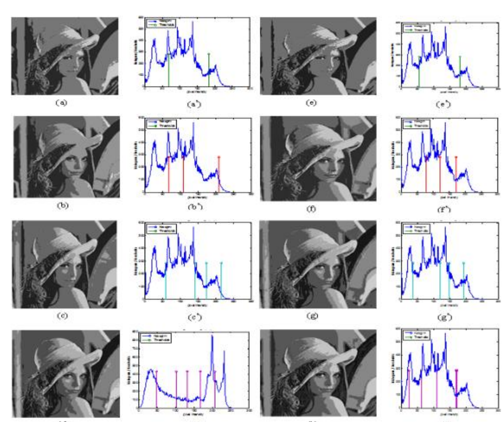


Fig. 11: Gold hill

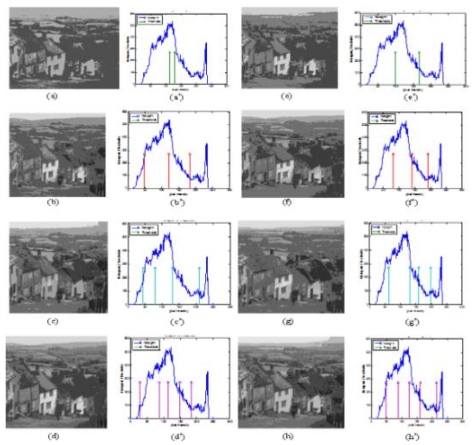
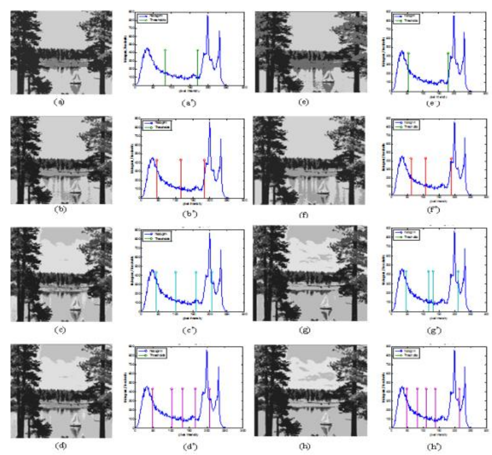


Fig. 12: Lake



V. Conclusion

In this paper, Hybrid Bat Algorithm and Pattern Search (hBA-PS) using multilevel image thresholding for image compression has been proposed. It maximizes the Shannon and Fuzzy entropies for effective and efficient image thresholding. The proposed algorithm is successfully examined on standard test images to show the performance of the algorithm. The procured result of the hBA-PS is compared with other optimization algorithms such as DE, PSO and BA with Shannon and Fuzzy entropies. With these comparisons, it is observed that hBA- PS has a maximum fitness value, higher PSNR, SNR and WPSNR values than other algorithms. It is concluded that the proposed algorithm outperforms DE, PSO and BA in all parameters.

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