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Performance Analysis of Control Parameters of Artificial Bee colony Algorithm for JPEG Images

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Abstract**: *The technological advancement and innovations needs more bandwidth, large capacities and high performance devices. Compression on digital images plays an important role in data compression as a typical multimedia technique. Wavelet Packet Decomposition is one of the image compression technique in which both approximation and detail coefficients of an image are extracted repeatedly up to a filtering level. Deciding the best topology of the wavelet packets can be considered as a structural optimization problem. Swarm intelligence has been popularly used for solving the optimization problems: Artificial Bee Colony (ABC) is the most recently proposed algorithm based on the systematic foraging behavior of honey bees. In this paper Wavelets Packet Decomposition is applied to JPEG images using various Wavelet families. Once coefficients are generated, the optimum threshold values are determined using Artificial Bee Colony (ABC) algorithm to obtain the best reconstructed image. The results are compared on the basis of some control parameters. It is observed that Wavelet Packet optimization using Daubechies filter is better that the other filters.***

Index Terms**: *Artificial Bee Colony Algorithm (ABC), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Wavelet Packet Decomposition (WPD).***

I. INTRODUCTION

Image is one of the most important media of information contributing to multimedia. Digital images are large and consume very important resources of the system. Large memory and high bandwidth are required for efficient storage and transmission of the images. Image compression removes the redundancy in an image resulting in more compact representation. Recently, for image compression Discrete Wavelet Transform and wavelet packet has emerged as popular techniques [1]. This paper compares compression performance of different wavelets for digital images [2]. Based on the rests, it is proposed that proper selection of wavelet improves the quality as well as compression ratio [3]. The prime objective is to select the proper wavelet during the transform phase to compress the image [4]. In Wavelet Packet Decomposition more filtering is conducted since both approximation and detail coefficients are reanalyzed. After generating the coefficients determining the optimum threshold values to obtain the best reconstructed image can be considered as an optimization task. Karaboga has described an Artificial Bee Colony (ABC) algorithm based on the behaviour of honey bees for numerical optimization problems [5].

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Karaboga and Basturk have compared the performance of the ABC algorithm with the performance of other well-known modern heuristic algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) on unconstrained and constrained problems [6]. It has been shown that the ABC algorithm can be efficiently used for solving unconstrained and constrained optimization problems [7, 9].
The rest of the paper is organized as follows: Section II describes Wavelet Packet Decomposition in detail. Section III explains Artificial Bee Colony algorithm along with quality measures. Section IV shows experimental results and discussion considering gray scale images which are of JPEG format. Section V discusses the conclusions.

II. WAVELET PACKET DECOMPOSITION

Unlike in Wavelet Transform, each detail coefficient is also decomposed in Wavelet Packet Decomposition. Therefore, Wavelet Packet Decomposition more filtering is conducted since both approximation and detail coefficients are reanalyzed. Wavelet Packet Decomposition (WPD) is a Wavelet Transform where the signal is passed through more filters than the Discrete Wavelet Transform (DWT). In the DWT, each level is calculated by passing only the previous approximation coefficients through low and high pass quadrature mirror filters. However in the WPD, both the detail and approximation coefficients are decomposed to create the full binary tree as shown in figure 1. For n levels of decomposition the WPD produces 2^n different sets of coefficients. Due to the down sampling process the overall number of coefficients is still the same and there is no redundancy. From the point of view of compression, the result may not be good with the standard wavelet transform, as it is limited to wavelet bases that increase by a power of two towards the low frequencies. A better result may be possible by using another combination of bases to produce a more desirable representation for a particular signal. A novel family of wavelet bases introduced by Daubechies are characterized by three essential properties: they are orthonormal (respectively biorthogonal), compactly supported and the scaling functions have the ability to reproduce a predefined set of exponential polynomials.

A.Types Of Wavelet Transform

1. Biorthogonal Wavelet Transform

On the bases of orthogonality condition the Wavelets can be classified as Semi-orthogonal, Biorthogonal or Non-orthogonal. Biorthogonal Wavelets are families of compactly supported symmetric Wavelets. The symmetry is desirable as it results in linear phase of the transfer function. In the Biorthogonal case, there

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are two scaling functions and Wavelet functions. The dual scaling and Wavelet functions have the following properties:

1. They are zero outside of a segment.
2. The calculation algorithms are maintained, and thus very simple.
3. The associated filters are symmetrical.
4. The functions used in the calculations are easier to build numerically than those used in the Daubechies wavelets.

2. Daubechies Wavelet Transform

The Daubechies wavelet transforms are defined by computing running averages and differences via scalar products with scaling signals and wavelets. Moreover for the Daubechies wavelet transforms, they produce averages and differences using just a few more values from the signal. They provide us with a set of powerful tools for performing basic signal processing tasks such as compression and noise removal for audio signals and for images, and include image enhancement and signal recognition. The Daubechies wavelet transform conserves the energy of signals and redistributes this energy into a more compact form.

3. Coiflets Wavelet Transform

Coiflets are Discrete Wavelets designed by Ingrid Daubechies. The aim was to have scaling functions with vanishing moments. The wavelet function has N/3 vanishing moments and scaling functions N/3-1, and has been used in many applications. Both the scaling function (low-pass filter) and the wavelet function (High-Pass Filter) must be normalized by a factor $1/\sqrt{2}$. The Wavelet coefficients are derived by reversing the order of the scaling function coefficients and then reversing the sign of every second one.

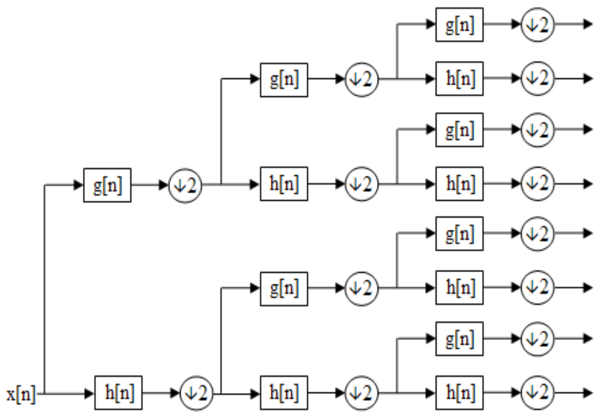

Figure 1: Discrete Wavelet Transform Filter banks

Wavelet Transform defined by Eq. (1) decomposes a signal into constituent parts in the time-frequency domain on a basis function localized in both time and frequency domains.

$$(W\psi f(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \qquad (1)$$

Where $\psi_{a,b}$ is defined as

$$\psi_{a,b(t)} = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), a \neq 0, b \in \mathcal{R} \qquad (2)$$

Where main Wavelet can be Haar Wavelet, Daubechies Wavelet, Biorthogonal and Coiflets etc. in order to compress the image. The signal or image is decomposed into four different frequencies: approximation, horizontal detail, vertical detail and diagonal detail. The decompositions are repeated on the approximation coefficients up to a level. Since details are not decomposed at the high levels and can be described by the small scale wavelet coefficients, wavelet transform is not suitable for images having rapid variations. To address this issue, wavelet packets were introduced by Coifman and Wickerhauser. Basic wavelet packets are defined by Eqs. 3 and 4.

$$\psi^{2n}(x) = \sqrt{2}\sum_{k} h_k \psi^n(2x-k) \qquad (3)$$

$$\psi^{2n+1}(x) = \sqrt{2}\sum_{k} g_k \psi^n(2x-k) \qquad (4)$$

Wavelet packets decomposition is recursively applied to both approximation and detail coefficients and it builds a binary tree.

III. ARTIFICIAL BEE COLONY ALGORITHM

The Artificial Bee Colony (ABC) algorithm is a recently introduced optimization algorithm for real-parameter optimization, which simulates the foraging behaviour of a bee colony [5].The ABC algorithm consists of three kinds of bees: employed bees, onlooker bees and scout bees. Employed bees are responsible for exploiting the nectar sources explored before and giving information to the waiting bees (onlooker bees) in the hive about the quality of the food source sites which they are exploiting. The Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. Scouts either randomly search the environment in order to find a new food source depending on an internal motivation or based on possible external clues [6]. The entire algorithm can be summarized as follows:

1. At the initial phase of the foraging process, the bees start to explore the environment randomly in order to find a food sources.

2. After finding a food source, the bee becomes an employed forager and starts to exploit the discovered source. The employed bee returns to the hive with the nectar and unloads the nectar. After unloading the nectar, she can go back to her discovered source site directly or she can share information about her source site by performing a dance on the dance area. If her source is exhausted, she becomes a scout and starts to randomly search for a new source.

3. Onlooker bees waiting in the hive watch the dances advertising the profitable sources and choose a source site depending on the frequency of a dance proportional to the quality of the source. The employed bee whose food source has been abandoned becomes a scout.

The steps of the basic ABC algorithm proposed by Karaboga [8] can be explained as follows:

A) Initialization of food source sites:

Within the range of the boundaries of the parameters initial food sources are produced randomly. The algorithm starts with randomly producing food source sites which correspond to the solutions in the search space.

$$x_{ij} = x_j^{min} + rand(0,1)\left(x_j^{max} - x_j^{min}\right) \qquad (1)$$

Where i = 1. . .SN, j = 1. . .D.

SN is the number of food

sources and D is the number of optimization parameters. In addition, counters which store the numbers of trials of solutions are reset to 0 in this phase. After initialization, the population of the food sources (solutions) is subjected to repeat cycles of the search processes of the employed bees, the onlooker bees and the scout bees. For Termination of the ABC algorithm, the criteria may be, reaching a maximum cycle number (MCN).

B) Allocation of employed bees to the food source sites:

The number of food source sites is equal to the number of employed bees because each employed bee is allocated to one food source site. Depending on local information (visual information) an employed bee produces a modification on the position of the food source (solution) in her memory in order to find a neighbouring food source and evaluates its quality which is defined by equation (2).

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \qquad (2)$$

Where x_i is the neighbourhood of every food source site, and a food source v_i is determined by changing one parameter of x_i. In Eq. (2), j is a random integer in the range [1, D] and K $\in$ {1, 2,.......SN} is a randomly chosen index that has to be different from i. $\emptyset_{ij}$ is a uniformly distributed real random number in the range [-1, 1].
The parameter can be set to an acceptable value if a parameter value produced by this operation exceeds its predetermined boundaries.

$$If\ \ x_i > x_i^{max}\ then\ x_i = x_i^{max}$$
$$If\ \ x_i < x_i^{min}\ then\ x_i = x_i^{min}$$

A fitness value for minimization problem can be assigned to the solution v_i after producing v_i within the boundaries which is given by equation (3)

$$fitness_i = \begin{Bmatrix} 1/(1+f_i) & if\ f_i \geq 0 \\ 1+abs(f_i) & if\ f_i < 0 \end{Bmatrix} \qquad (3)$$

Where f_i is the cost value of the solution v_i. The cost function can be directly used as a fitness function for maximization problems; a greedy selection is applied between x_i and v_i. Depending on fitness values representing the nectar amount of the food sources at x_i and v_i the better one is selected. The employed bee memorizes the new position and forgets the old one if the source at v_i is superior to that of x_i in terms of profitability, Otherwise the previous position is kept in memory. If x_i cannot be improved, its counter which holds the number of trials is incremented by 1; else the counter is reset to 0.

C) Calculation of probability values involved in probabilistic selection:

After Employee bees complete their searches they share their information related to the nectar amounts and the positions of their sources with the onlooker bees on the area which is the multiple interaction features of the artificial bees of ABC algorithm. After that onlooker bee calculates the nectar information which is taken from all employed bees and chooses a food source site with a probability related to its nectar amount. This probabilistic selection depends on the fitness values of the solutions in the population. There are many types of selection scheme such as ranking based, roulette wheel, stochastic universal sampling, tournament selection or another selection scheme. The formula for calculating the probabilities is given by equation (4).

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \qquad (4)$$

The number of onlookers visiting food sources increases as the nectar amount of food sources (the fitness of solutions) increases in the probabilistic selection scheme which is called as the positive feedback feature of ABC algorithm.

D) Food source site selection by onlookers based on the information provided by employed bees:

In the ABC algorithm, a random real number within the range [0, 1] is generated for each source. If the probability value associated with that source is greater than this random number then the onlooker bee produces a modification on the position of this food source site by using Eq. (2) as in the case of the employed bee. After the source is evaluated, greedy selection is applied and the onlooker bee either memorizes the new position by forgetting the old one or keeps the old one. If solution x_i cannot be improved, its counter holding trials is incremented by 1; else, the counter is reset to 0. This process is repeated until all onlookers are distributed onto food source sites.

E) Abandonment criteria: Limit and scout production

In a cycle, after all employed bees and onlooker bees complete their searches, the algorithm checks to see if there is any exhausted source to be abandoned. For deciding, whether a source is to be abandoned, the counters which have been updated during search are used. If the value of the counter is greater than the control parameter of the ABC algorithm, known as the ‘‘limit”, then the source associated with this counter is assumed to be exhausted and is abandoned. The food source abandoned by its bee is replaced with a new food source discovered by the scout, which represents the negative feedback mechanism and fluctuation property in the self-organization of ABC. This is simulated by producing a site position randomly and replacing it with the abandoned one. Let the abandoned source be x_i, then the scout randomly discovers a new food source to be replaced with xi. This operation can be defined as in (1). In basic ABC, it is assumed that only one source can be exhausted in each cycle, and only one employed bee can be a scout. If more than one counter exceeds the ‘‘limit” value, one of the maximum values may be chosen. All these units and interactions between them are shown as a flowchart on Figure 2.

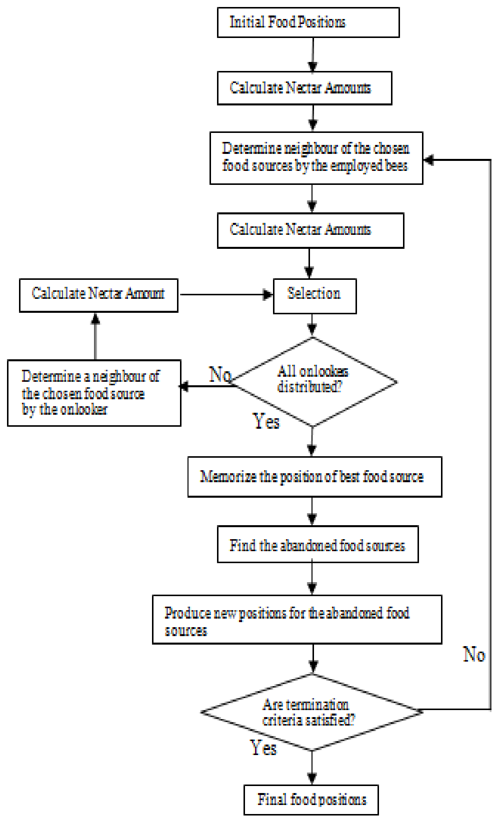

Figure2: Flowchart of Artificial Bee Colony Algorithm

B. Quality Measures

1) Structural similarity index (SSIM): SSIM evaluates the visual quality between original image and the compressed image.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

2) Compression Ratio (CR): Compression ratio is defined as ratio of the size of original data set to the size of the compressed data set.

$$Compression\ Ratio(CR) = \frac{100}{100 - perf0}$$

3) Peak Signal-to-Noise Ratio (PSNR): PSNR provides a measurement of the amount of distortion in a signal, with a higher value indicating less distortion. For n-bits per pixel image, PSNR is defined as:

$$PSNR = 20\log_{10}\left(\frac{255}{\sqrt{MSE}}\right)$$

Where, MSE is the Mean Square Error between two original and the reconstructed image..

4) PerfL2 and Perf0: The performance of the technique is measured in terms of percentage of zeroes (Perf0), percentage of energy retained (PerfL2). In 2-DWT, perf0 and perfL2 are used to describe L2- norm recovery and compression score in percentage. When compressing with Orthogonal Wavelets the energy retained is:

$$\mathrm{PerfL2} = \frac{(\text{Vector} - \text{norm}(\text{coeff of the current decomposition}, 2))^2 * 100}{(\text{Vector} - \text{norm}(\text{original signal}, 2))^2}$$

The number of zeros in percentage is defined by:

$$\mathrm{Perf0} = \frac{(\text{Number of zeros of the current decomposition}) * 100}{(\text{Number of coefficients})}$$

Different values of threshold values are tried with, to change the energy retained and number of zeros values. The threshold is the number below which detail coefficients are set to zero. The higher the threshold value, the greater is the loss in energy as more zeros will be set. Thresholding can be done globally or locally. Control parameters are:

1) **NP (N):** It is number of bees in the colony (employed bees plus onlooker bees).
2) **Limit (L):** It controls the number of trials to improve certain food sources. If a food source could not be improved within defined number of trial, it is abandoned by its employed bee.
3) **Max Cycle (M):** It defines the number of cycles for foraging. This is a stopping criterion.

Problem specific parameters are:

1. D is the number of parameters of the problem to be optimized
2. Runtime defines the number of times to run the algorithm.
3. Lower bound is lower bound of problem parameters.
4. Upper bound is upper bound of problem parameters.
5. Constrained number is the number of constraints

IV. EXPERIMENTAL RESULTS

The input image is taken and different Transforms are applied to it in order to find out the best compressed image. The images chosen are gray scale images. They are Lena, boat and barbara. They are of same format (JPEG). Image compression is done using Wavelet Packet Decomposition considering different types of filters such as Biorthogonal, Daubechies, and Coiflets etc. The results are compared on the basis of PSNR, SSIM, Perf0 and Compression Ratio (CR) parameters and decomposition level is chosen as 3 for all the images. Table 1, 2, 3, and 4 shows the results of comparison made by changing the control parameters such as colony size (N), food sources (L) and maximum cycle (M).

Table 1: Experiment Results based on PSNR, SSIM, PERF0, and CR for N=30, L=50, M=500

Image	Filters					
Lena(131X131)	Parameters	bior 1.1	db2	db10	coifl	haar
N=30, L=50, M=500	PSNR	23.7256	25.212	24.4701	25.4712	23.7256
n=3	SSIM	0.59946	0.58163	0.59076	0.57461	0.5654
	PERF0	43.0298	50.9798	48.4894	51.3079	43.0298
	CR	1.7553	2.04	1.9413	2.0537	1.7553
Boat(131X131)	PSNR	29.0612	28.6531	27.4877	28.5622	29.0612
	SSIM	0.78119	0.78768	0.73507	0.77988	0.78054
n=3	PERF0	43.3533	45.9602	40.6831	47.0336	43.3533
	CR	1.7653	1.8505	1.6859	1.888	1.7653
Babara (131X131)	PSNR	30.8954	31.8461	31.1299	31.5858	30.8954
	SSIM	0.45499	0.43287	0.45418	0.43367	0.46333
n=3	PERF0	42.3889	51.8594	47.4901	51.5557	42.3889
	CR	1.7358	2.0772	1.9044	2.0642	1.7358

Table 2: Experiment Results based on PSNR, SSIM, PERF0, and CR for N=100, L=50, M=500

Image	Filters					
Lena(131X131)	Parameters	bior 1.1	db2	db10	coifl	haar
N=100, L=50, M=500	PSNR	23.7256	25.212	24.4701	25.4712	23.7256
n=3	SSIM	0.58963	0.58039	0.59113	0.57	0.59397
	PERF0	43.0298	50.9798	48.4894	51.3079	43.0298
	CR	1.7553	2.04	1.9413	2.0537	1.7553
Boat(131X131)	PSNR	29.0612	28.6531	27.4877	28.5622	29.0612
	SSIM	0.78183	0.78774	0.74426	0.77344	0.78173
n=3	PERF0	43.3533	45.9602	40.6831	47.0336	43.3533
	CR	1.7653	1.8505	1.6859	1.888	1.7653
Babara (131X131)	PSNR	30.8954	31.8461	31.1299	31.5858	30.8954
	SSIM	0.45215	0.42936	0.45547	0.43088	0.46242
n=3	PERF0	42.3889	51.8594	47.4901	51.5557	42.3889
	CR	1.7358	2.0772	1.9044	2.0642	1.7358

Table 3: Experiment Results based on PSNR, SSIM, PERF0, and CR for N=100, L=100, M=500

Image	Filters					
Lena(131X131)	Parameters	bior 1.1	db2	db10	coifl	haar
N=100, L=100, M=500	PSNR	23.7256	25.212	24.4701	25.4712	23.7256
n=3	SSIM	0.56581	0.57982	0.59073	0.56929	0.59276
	PERF0	43.0298	50.9798	48.4894	51.3079	43.0298
	CR	1.7553	2.04	1.9413	2.0537	1.7553
Boat(131X131)	PSNR	29.0612	28.6531	27.4877	28.5622	29.0612
	SSIM	0.7818	0.78805	0.73912	0.78358	0.78103
n=3	PERF0	43.3533	45.9602	40.6831	47.0336	43.3533
	CR	1.7358	2.0772	1.9044	2.0642	1.7358
Babara (131X131)	PSNR	30.8954	31.8461	31.1299	31.5858	30.8954
	SSIM	0.4595	0.44492	0.45711	0.43895	0.45679
n=3	PERF0	42.3889	51.8594	47.4901	51.5557	42.3889
	CR	1.7358	2.0772	1.9044	2.0642	1.7358

Table 4: Experiment Results based on PSNR, SSIM, PERF0, and CR for N=100, L=100, M=1000

Image	Filters					
Lena(131X131)	Parameters	bior 1.1	db2	db10	coifl	haar
N=100, L=100, M=1000	PSNR	23.7256	25.212	24.4701	25.4712	23.7256
	SSIM	0.56581	0.5895	0.59164	0.57733	0.59089
n=3	PERF0	43.0298	50.9798	48.4894	51.3079	43.0298
	CR	1.7553	2.04	1.9413	2.0537	1.7553
Boat(131X131)	PSNR	29.0612	28.6531	18.4517	28.5622	29.0612
	SSIM	0.78116	0.78724	0.73215	0.76696	0.7814
n=3	PERF0	43.3533	45.9602	40.6831	47.0336	43.3533
	CR	1.7653	1.8505	1.6859	1.888	1.7653
Babara (131X131)	PSNR	30.8954	31.8461	31.1299	31.5858	30.8954
	SSIM	0.46166	0.4292	0.45492	0.43367	0.46082
n=3	PERF0	42.3889	51.8594	47.4901	51.5557	42.3889
	CR	1.7358	2.0772	1.9044	2.0642	1.7358

V.CONCLUSION

In this paper the performance of the Daubechies filter i.e. db2 is found to be better compared to other filters for gray scale images chosen.The highest PSNR value obtained is 31.8461 for barbara image and highest SSIM value obtained is 0.78805 for Boat image. Also for the parameters Perf0 and CR the highest value obtained are 51.8594 and 2.0772 for barbara image. Also changing the values for control parameters such as colony size (N), food sources (L) and maximum cycle (M) doesn't have any effect on the performance of the filter as shown in Table 1, 2, 3 and 4.

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