



Effect of Meta-Heuristics Swarm Based Algorithm on DCT and DWT for Best Image Compression

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ABSTRACT

The objective of image compression is to reduce irrelevance and redundancy of the image data in order to store or transmit data in efficient form. DCT and DWT are used as the compression techniques. In discrete wavelet transform, each level is calculated by passing only approximation coefficients through low and high pass quadrature mirror filters. The discrete cosine transform (DCT) helps to separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). In this paper, a meta-heuristic swarm based algorithm (ABC) is used to improve the quality of compressed image. Relative data redundancy and many parameters are also studied.

Keywords

Discrete Cosine Transform, Discrete Wavelet Transform, Wavelet packet decomposition, Artificial Bee Colony Algorithm, Optimization algorithms.

1. INTRODUCTION

By the technological developments, more storage or bandwidth is required to store or transfer the data. Because the costs of the resources are high, the data is stored in fewer bits as compared to the original one, which is called compression [2]. Lossless and lossy compression techniques are two broad categories of compression techniques. In the lossless techniques, the redundant data are eliminated and the original data can be again obtained without any loss. If losing some of the data after compression is moderated, it is possible to apply a lossy compression technique which causes some distortions in the original image. The discrete cosine transform (DCT) [3] help to separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain. In wavelet transform components with high frequency are represented by less data. In wavelet transform [4], basis functions are derived from the main wavelet by shifting in time and scaling. The signal is decomposed by first applying low pass filter to obtain approximation coefficients and second high pass filter to obtain detail coefficients. It produces approximation, horizontal detail, vertical detail and diagonal detail coefficients. Unlike in wavelet transform, each detail coefficient is also decomposed in wavelet packet decomposition [12]. Therefore, in wavelet packet decomposition more filtering is conducted since both approximation and detail coefficients are reanalyzed. Artificial Bee Colony (ABC) [1] algorithm is an optimization algorithm which simulates the foraging behavior of honey bees. In this paper, ABC algorithm is used to solve the

compression problem which can be considered as multi-objective since there is a trade-off between high compression rate and high quality. ABC is new population based optimization technique that has been used to find an optimal solution in numeric optimization problem [6]. The Bee Colony Optimization is used for Travelling Salesman problem with its basic mechanism of bees foraging behavior and its efficiency in solving shortest path among various routes [5]. This swarm based [10] algorithm is compared with other existing algorithm like GA, PSO [9], differential evolution algorithm (DE), GABCS on many functions [6, 7, 8]. Moore introduced an approach based on genetic algorithm (GA) [14]. In [13] Modified artificial bee colony algorithm is used for constrained problems optimization. In [15] [16] and Karaboga et al. applied ABC algorithm to neural network training. In 2011, Zhang et al. employed the ABC for optimal multi-level thresholding [17] MR brain image classification. In this paper, Section 2 describes optimization algorithms, Section 3 describes proposed work, Section 4 gives the experimental results.

2. OPTIMIZATION ALGORITHMS

Population-based optimization algorithms find near-optimal solutions to the difficult optimization problems by motivation from nature. A common feature of all population-based algorithms is that the population consisting of possible solutions to the problem is modified by applying some operators on the solutions depending on the information of their fitness. Hence, the population is moved towards better solution areas of the search space. Evolutionary algorithm and swarm intelligence-based algorithms are two important classes of population-based optimization algorithms. Although Genetic Algorithm (GA), Genetic Programming (GP), Evolution Strategy (ES) and Evolutionary Programming (EP) are popular evolutionary algorithms. GA is based on genetic science and natural selection and it attempts to simulate the phenomenon of natural evolution at genotype level while ES and EP simulate the phenomenon of natural evolution at phenotype level. One of the evolutionary algorithms which have been introduced recently is Differential Evolution (DE) algorithm. DE has been particularly proposed for numerical optimization problems. A popular swarm-intelligence-based algorithm is the Particle Swarm Optimization (PSO) algorithm which was introduced by Eberhart and Kennedy in 1995. PSO is also a population-based stochastic optimization technique and is well adapted to the optimization of nonlinear functions in multidimensional space. The classical example of a swarm is bees' swarming around their hive but it can be extended to other systems with a similar architecture. For optimizing multi-variable and multi-modal numerical functions, Karaboga described an Artificial Bee Colony (ABC) [1] algorithm in 2005. Basturk



and Karaboga compared the performance of ABC algorithm with those of GA, PSO and PS-EA; and DE, PSO and EA on a limited number of test problems. Particleswarm optimization. In PSO, a population of particles starts to move in search space by following the current optimum particles and changing the positions in order to find out the optima.

3. PROPOSED WORK

Proposed work is as follows:

1. Input Image
2. Apply Wavelet Transform
3. Apply ABC Algorithm
4. Optimum Thresholds
5. Best Compressed Image

3.1 ABC

The artificial bee colony algorithm (ABC)[1] is an optimization algorithm based on the intelligent foraging behavior of honey bee swarm, proposed by Karaboga in 2005. In the ABC model, the colony consists of three groups of bees: employed bees, onlookers and scouts. The main steps of the algorithm are given below:

1. Initial food sources are produced for all employed bees
2. REPEAT
 - 2.1 Each employed bee goes to a food source in her memory and determines a neighbour source, then evaluates its nectar amount and dances in the hive.
 - 2.2 Each onlooker watches the dance of employed bees and chooses one of their sources depending on the dances, and then goes to that source. After choosing a neighbour around that, she evaluates its nectar amount.
 - 2.3 Abandoned food sources are determined and are replaced with the new food sources discovered by scouts.
 - 2.4 The best food source found so far is registered.
3. UNTIL (requirements are met)

3.2. DCT

The Two Dimensional DCT

The 2-D DCT is direct extension of the 1-D and is given by

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos \frac{\pi(2m+1)p}{2M} \cos \frac{\pi(2n+1)q}{2N}, 0 \leq p \leq M-1, 0 \leq q \leq N-1$$

$$\alpha_p = \begin{cases} 1/\sqrt{M}, & p = 0 \\ \sqrt{2/M}, & 1 \leq p \leq M-1 \end{cases}$$

$$\alpha_q = \begin{cases} 1/\sqrt{N}, & q = 0 \\ \sqrt{2/N}, & 1 \leq q \leq N-1 \end{cases}$$

The values B_{pq} are called the DCT coefficients of A

The DCT is an invertible transform, and its inverse is given by

$$A_{mn} = \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} \alpha_p \alpha_q B_{pq} \cos \frac{\pi(2m+1)p}{2M} \cos \frac{\pi(2n+1)q}{2N}, 0 \leq m \leq M-1, 0 \leq n \leq N-1$$

$$\alpha_p = \begin{cases} 1/\sqrt{M}, & p = 0 \\ \sqrt{2/M}, & 1 \leq p \leq M-1 \end{cases}$$

$$\alpha_q = \begin{cases} 1/\sqrt{N}, & q = 0 \\ \sqrt{2/N}, & 1 \leq q \leq N-1 \end{cases}$$

In this, an image (in colour or grey scales) is first subdivided into blocks of 8x8 pixels. The Discrete Cosine Transform (DCT) is then performed on each block. This generates 64 coefficients which are then quantised to reduce their magnitude. The coefficients are then reordered into a one-dimensional array in a zigzag manner before further entropy encoding. The compression is achieved in two stages; the first is during quantisation and the second during the entropy coding process.

3.3 DWT

Discrete Wavelet Transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. It converts an input series x_0, x_1, \dots, x_m , into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length $n/2$ each) given by:

$$H_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot S_m(z) \quad (1)$$

$$L_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot t_m(z) \quad (2)$$

Where $s_m(z)$ and $t_m(z)$ are called wavelet filters, k is the length of the filter, and $i=0, \dots, [n/2]-1$. In practice, such transformation will be applied recursively on the low-pass series until the desired number of iterations is reached.

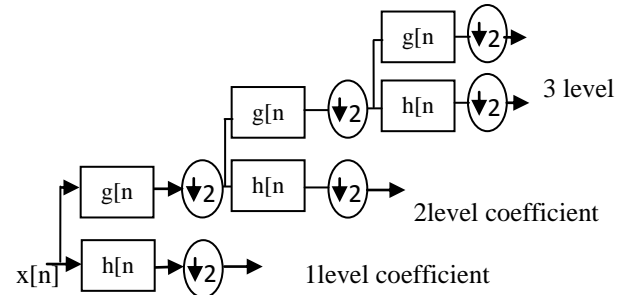


Fig 1:- Discrete Wavelet Transform

This work involves compression of images using DWT and DCT and then applying ABC. We take an image as input and will compress it using discrete wavelet transform and discrete cosine transform. After decomposing we will get different approximation and detail coefficients depending on number of levels we have given for decomposition.

Using PERFO value and PSNR value we will construct a cost function which we will optimize to get the threshold values.



4. EXPERIMENTAL RESULTS

In this work Lenna (Fig. 1(a)), Flower (Fig. 1(b)), Barbara (Fig. 1(c)) these test images are used to be compressed. In order to construct wavelet decomposition tree level 3, 4, 5, 6 are analyzed. PSNR is the peak signal-to-noise ratio. Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the PSNR is

$$PSNR = 20 * \log_{10} (255 / \sqrt{MSE})$$

where $I(x,y)$ is the original image, $I'(x,y)$ is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognise that it is a better one. By the penalty approach constrained problem can be considered as unconstrained optimization problem by adding the constraint violation to the cost function. To find optimal threshold values in each level for selecting wavelet packet coefficients, ABC algorithm tries to minimize the penalized cost function which is based on quality measured by PSNR and compression based on $perf0$.

$Cost = -perf0 + a * (\text{sign}\{PSNR_c - PSNR\} + 1) * (PSNR_c - PSNR)$ In this experiments $PSNR_c$ and a are set to 25 and 100. Values 30, 500, 50, 0.8 are set for colony size, maximum cycle number, limit and MR parameters, respectively.

Vertical, horizontal and diagonal threshold values at each level are determined by ABC algorithm. The number of thresholds (the number of parameter to be optimized, D) is level * 3. Compression ratio, $perf0$, $perf12$, PSNR and structural similarity index (SSIM) of the reconstructed images through the threshold values obtained from ABC algorithm are presented in Table 1. $perf12$ is the compression score in percentage, SSIM given by below equation evaluates the visual quality between original image and the compressed image

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C1)(2\sigma_{xy} + C2)}{(\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C2)}$$

Compression ratio is calculated by,

$$Compression\ ratio = 100 / (100 - perf0)$$

Relative data redundancy can be represented by ,

$$Rd = 1 - (1 / Compression\ ratio)$$

Test images are shown in Fig. 2. Compressed images are shown in Figure 3, 4, 5 and 6 for levels 3, 4 and 5, 6 respectively. The most compressed image is Barbara at level 5 for DWT while the most quality image is Flower at level 4 for DCT. For Lenna image the best compression is obtained at level 6 for DWT+ABC. For flower image, best compression is at level 5 for DWT+ABC. For Barbara image, the best compression is at level 5 for DWT+ABC. Overall, selecting coefficients depending on the threshold values produced by ABC algorithm provides compressed images with acceptable PSNR and SSIM values. The decomposition level has also effect on the performance of compression process. Increment in the decomposition level has positive effect on the compression ratio while it has negative effect on the quality as expected. It can be noted that images with similar PSNR values have different visual quality metric, SSIM, since it combines luminance comparison, contrast comparison and structure comparison and satisfies symmetry. The value of relative data redundancy is low for the image flower for DCT at level 5. For the image Lenna the value of relative data redundancy is high at level 5 for DWT. For the Barbara image the value of relative data redundancy is high at level 5 for DWT.



a)Lenna image b)Flower image c)Barbara image Fig. 2 Test images used in the experiments.

Table 1. PSNR,SSIM,perf0,perf12,Comp.rate,Rd values of compressed image

		DWT+ABC	DCT+ABC	DWT+ABC	DCT+ABC	DWT+ABC	DCT+ABC
level		Lenna	Lenna	Flower	Flower	Barbara	Barbara
n=3	PSNR	21.5447	25.3467	28.7682	33.8449	25.6369	30.161
	SSIM	0.6643	0.6758	0.6643	0.6758	0.6854	0.6952
	perf0	73.0377	25.9094	67.0044	11.5952	74.8901	21.051
	perf12	99.993	100	99.9523	99.9999	99.9718	99.9999
	comp.rate	3.7089	1.3407	3.0307	1.1312	3.9825	1.2666
	Rd	0.73038	0.25909	0.67004	0.11595	0.7489	0.21051
n=4	PSNR	21.6066	25.4195	28.7784	33.8569	25.7066	33.8569
	SSIM	0.6643	0.6758	0.6643	0.6758	0.6854	0.6952
	perf0	73.7503	25.9262	67.1097	11.6226	75.1053	21.0938
	perf12	99.9929	100	99.9522	99.9999	99.9712	99.9999
	comp.rate	3.8096	1.35	3.0404	1.1315	4.0169	1.2673
	Rd	0.7375	0.25926	0.6711	0.11623	0.75105	0.21094
n=5	PSNR	21.692	31.2431	28.7793	25.52	25.7649	33.858
	SSIM	0.6643	0.6758	0.6643	0.6758	0.6854	0.6952
	perf0	73.8068	25.9262	67.128	11.6287	75.2258	21.1258
	perf12	99.9928	100	99.9522	99.9999	99.9708	99.9999
	comp.rate	3.8178	1.35	3.0421	1.1316	4.365	1.2678
	Rd	0.73807	0.25926	0.67128	0.11629	0.75226	0.21126
n=6	PSNR	21.7421	25.52	28.778	33.8564	25.9862	30.3117
	SSIM	0.6635	0.6769	0.6635	0.6769	0.6843	0.6948
	perf0	73.8663	25.9262	67.1249	11.6394	75.4532	21.138
	perf12	99.9927	100	99.9522	99.9999	99.969	99.9999
	comp.rate	3.8265	1.35	3.0418	1.1317	4.0738	1.268
	Rd	0.73866	0.25926	0.67125	0.11639	0.75453	0.21138

3 Level decomposition



a)Lenna image using DWT+ABC b)Flower image using DWT+ABC c)Barbara image using DWT+ABC



a) Lenna image using DCT+ABC b) Flower image using DCT +ABC c) Barbara image using DCT+ABC
Fig.3. Compressed image obtained by 3 –level decomposition Using DWT and DCT based on the threshold values produced by ABC algorithm

4 Level decomposition



a) Lenna image using DWT+ABC b) Flower image using DWT +ABC c) Barbara image using DWT +ABC



a) Lenna image using DCT +ABC b) Flower image using DCT+ABC c) Barbara image using DCT+ABC

Fig.4. Compressed image obtained by 4 –level decomposition Using DWT and DCT based on the threshold values produced by ABC algorithm.

5 Level decomposition



a) Lenna image using DWT+ABC b) Flower image using DWT+ABC c) Barbara image using DWT+ABC



a) Lenna image using DCT+ABC b) Flower image using DCT+ABC c) Barbara image using DWT+ABC
 Fig.5. Compressed image obtained by 5 –level decomposition Using DWT and DCT based on the threshold values produced by ABC algorithm.

6 Level decomposition



a) Lenna image using DWT+ABC b) Flower image using DWT+ABC c) Barbara image using DWT+ABC



a) Lenna image using DCT+ABC b) Flower image using DCT+ABC c) Barbara image using DCT+ABC

Fig.6. Compressed image obtained by 6 –level decomposition Using DWT and DCT based on the threshold values produced by ABC algorithm

8. CONCLUSION

In this paper we have discussed an application of ABC algorithm for best compressed image with best quality and compression. ABC algorithm helps to optimize our result produced from DCT and DWT. We have analysed the effect of ABC on DWT and DCT for different parameters. Regarding the parameter PSNR values produced for DCT+ABC are good. And Compression rate is high for DWT+ABC compressed image.

8. REFERENCES

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