

Adaptive Lifting Based Image Compression Scheme Using Artificial Bee Colony Algorithm

M. Mohamed Ismail

Research Scholar,
Karpagam University, Coimbatore

Dr. K. Baskaran

Associate Professor, Deptt. of CSE,
Government college of Technology, Coimbatore -13

Abstract – The increment in the sizes of the images by the technological advances accompanies high demand for large capacities, high performance devices, high bandwidths etc. Therefore, image compression techniques are essential to reduce storage, computational or transmittal costs. Wavelet transform is one of the compression techniques especially used for images and multimedia files. This paper, proposes a framework for constructing adaptive update for lifting scheme. Artificial bee colony algorithm is used to find different update coefficient by local search, at last optimally choose the best update coefficient to get best quality of compressed image. In the update step we modifying the center pixels with the co-efficient in 8 – different direction with a considerable window size by using local search, we obtain a best directional window with a considerable size using artificial bee colony algorithm to obtain the best reconstructed image, which can be considered as an optimization task. Artificial Bee Colony algorithm which is a recent and successful optimization tool is used to determine the directional window size to produce the best compressed image in terms of both compression ratio and quality. The proposed work gives better PSNR when compared to existing methods. So, the transmission cost to transmit the encoded data and memory space to store the encoded data can be reduced with help of adaptive update lifting scheme with artificial bee colony algorithm.

Keywords – Wavelet Transform, Lifting Scheme, Adaptive Lifting Scheme, ABC Algorithm, Image Compression.

I. INTRODUCTION

In the last decade, there has been a lot of technological transformation in the way we communicate. This transformation includes the ever present, ever growing internet, the explosive development in mobile communication and ever increasing importance of video communication.

Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available technologies. In a distributed environment large image files remain a major bottleneck within systems.

Image Compression is an important component of the solutions available for creating image file sizes of manageable and transmittable dimensions. Platform portability and performance are important in the selection of the compression/decompression technique to be employed.

The discrete wavelet transform (DWT) refers to wavelet transforms for which the wavelets are discretely sampled. A transform which localizes a function both in space and

scaling and has some desirable properties compared to the Fourier transform. The transform is based on a wavelet matrix, which can be computed more quickly than the analogous Fourier matrix.

A wavelet transform is realized using filter banks which split the image information into frequency sub bands. Due to their inherent property of producing floating point output, classical filter banks cannot in general be used in lossless compression schemes, since the coding cost for the coding of the floating-point wavelet coefficients would be prohibitively large. The lifting scheme has recently attracted much interest. It is away to implement critically sampled filter banks which have integer output. In section II A general lifting scheme is discussed and compared with adaptive lifting scheme where the update step is modified with ABC algorithm section III discusses about the proposed work and section IV explains the ABC algorithm section V explains the proposed algorithm .

II. LIFTING SCHEME

The lifting scheme has recently attracted much interest. It is away to implement critically sampled filter banks which have integer output. An algorithm for decomposing wavelet transforms into lifting steps was described in [11]. The lifting scheme can custom design the filters, needed in the transform algorithms, to the situation at hand. It is processed in space domain, independent of translating and dilating, needless of frequency analysis. In this sense it provides an answer to the algebraic stage of a wavelet construction, also leads to a fast in-place calculation of the wavelet transform, i.e. it does not require auxiliary memory. For different wavelet has different image compress effect, the compressed image quality and the compress rate is not only relational to the length of the filter, but also concerns with the orthogonality, biorthogonality, vanishing moment, regularity and local frequency. In this proposed work, we implement adaptive lifting scheme based wavelet decomposition instead of wavelet decomposition. Then with the help of artificial bee colony algorithm, we find the best directional window size to get better compression ratio with considerable quality.

The economy of the wavelet transform stems from the fact that the DWT tends to compress real-world signals into just a few coefficients of large magnitude. Compression follows from the "vanishing moments" property of wavelets, which guarantees that the wavelet coefficients of low-order polynomial signals are zero [3]. Thus, if a signal is exactly polynomial, it can be completely described using scaling coefficients alone. In more realistic situations, the signal will not be polynomial,

but may be well-approximated by a *piecewise* polynomial function. Because wavelet functions also have localized support, most of the wavelet coefficients of such a signal will be zero except those corresponding to wavelets having support near the breakpoints of the polynomial segments. It is fruitful to view the DWT as prediction-error decomposition. The scaling coefficients at a given scale (m) are "predictors" for the data at the next higher resolution or scale ($m - 1$).

The wavelet coefficients are simply the "prediction errors" Between the scaling coefficients and the higher resolution data that they are attempting predict. This interpretation has led to a new framework for DWT design known as the *lifting scheme*. Our analysis builds on this interpretation.

A. The Lifting Concept

Lifting is a spatial (or time) domain construction of biorthogonal wavelets developed by Sweden. We present here an overview of our interpretation of the lifting concept. Lifting consists of iteration of the following three basic operations (Figure 1)

Split:

Divide the original data into two disjoint subsets. Although any disjoint split is possible, in the standard lifting scheme we split the original data set $x[n]$ into $x_e[n] = x[2n]$, the even indexed points, and $x_o[n] = x[2n + 1]$, the odd indexed points.

Predict:

Generate the wavelet coefficients $d[n]$ as the error in predicting $x_o[n]$ from $x_e[n]$ using prediction operator P :

$$d[n] = x_o[n] - P(x_e[n]) . \quad (1)$$

Update:

Combine $x_e[n]$ and $d[n]$ to obtain scaling coefficients $c[n]$ that represent a coarse approximation to the original signal $x[n]$. This is accomplished by applying an update operator U to the wavelet coefficients and adding to $x_e[n]$.

$$c[n] = x_e[n] + U(d[n]) . \quad (2)$$

These three steps form a *lifting stage*. Iteration of the lifting stage on the output $c[n]$ creates the complete set of DWT scaling and wavelet coefficients $C_j[n]$ and $d_j[n]$.

At each scale, we weight the $C_j[n]$ and $d_j[n]$ with k_e and k_o respectively, as shown in Figure2. This normalizes the energy of the underlying scaling and wavelet functions. The lifting steps are easily inverted, even if P and U are nonlinear, space-varying, or non-invertible. Rearranging (1) and (2), we have

$$\begin{aligned} x_e[n] &= c[n] - U(d[n]), \\ x_o[n] &= d[n] + P(x_e[n]). \end{aligned}$$

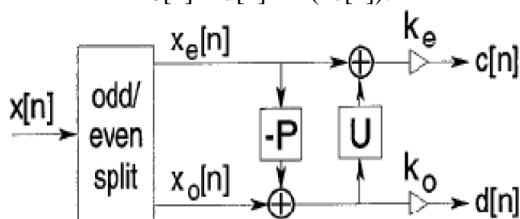


Fig.1. Lifting stage: Split, Predict, Update. k_e and k_o normalize the energy of the underlying scaling and wavelet functions.

As long as the same P and U are chosen for the forward and inverse transforms, the original signal will be perfectly reconstructed. The inverse lifting stage is shown in Fig.2.

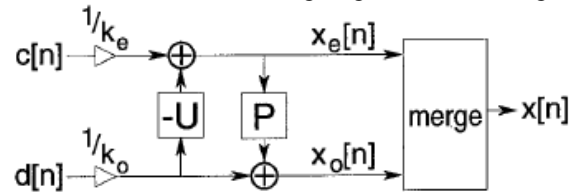


Fig.2. Typical inverse lifting steps: undo the Update, undo the Predict, and Merge the even and odd samples.

B. Adaptive lifting scheme:

The adaptive LS is a modification of the classical lifting. Figure 3 shows an example of an adaptive ULS followed by a fixed prediction. At each sample n , an update operator is chosen according to a decision function $D(x[n], y)$. The crucial point is that $D(x[n], y)$ depends on y , as in the classical and space-varying lifting, but it also depends on the sample being updated. For this reason a problem arises because the decoder does not dispose of the sample $x[n]$ used by the coder to take the decision. The decoder only knows $x_o[n]$, which is an updated version of $x[n]$ through an unknown update filter.

In the standard lifting scheme discussed above, the update operator and the addition are fixed, in the adaptive case, the choice of these operations depends on the information locally available within both the approximation signal and the detail signal. In fact, this choice will be triggered by a so-called decision map(9).

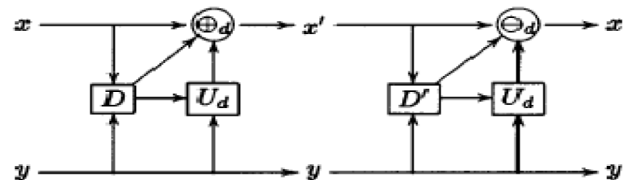


Fig.3. Adaptive update lifting scheme

Adaptive lifting scheme performs update first, and then performs prediction according to its lifting structure. Assume $x = x_0(2m, 2n)$, where x_0 is the input image, which is split into two signal one is average signal x and detail signal y . The detail signal y includes horizontal signal y_h , vertical signal y_v , and diagonal signal y_d .

The 2-D adaptive lifting structure is as follows:

Update: Using coefficient y_h, y_v, y_d , to update x :

$$x = U(x, y_h, y_v, y_d) \quad (3)$$

Here, U is update operator, in which coefficients are chosen by decidable factor D .

Prediction: Using the updated low-frequency

Coefficient x' to predict y_h, y_v, y_d :

$$y'_h = y_h - p_h(x, y_v, y_d) \quad (4)$$

$$y'_v = y_v - p_v(x' - y_d) \quad (5)$$

$$y'_d = y_d - p_d(x) \quad (6)$$

Here p_h, p_v, p_d , are the prediction schemes for different frequency bands. The scheme adaptively chooses update operator U and prediction operator P according to the local feature adjacent to x, y_h, y_v , and y_d . This update and prediction scheme ensures perfect reconstruction without

recording any overhead information In the standard lifting schemes the update operator U and the addition are fixed whereas in the adaptive lifting schemes the choice of these operations depends on the information locally available in the approximation signal x and the detail signal y . In fact, this choice will be triggered by the so called decision map $D: X \times Y \rightarrow D^Z$ where D is the decision set. For every possible decision $d \in D$ of the decision map, we have a different update operator U_d and addition \oplus_d . Thus the analysis step is given by,

$$x(n) = x(n) \oplus_{d_n} U_{d_n}(y)(n) \quad (7)$$

Where $d_n = D(x, y)(n)$ is the decision at location n . Assuming that the reversibility condition on \oplus_d holds for every possible decision $d \in D$ and it is given by

$$x(n) = x(n) \ominus_{d_n} U_{d_n}(y)(n) \quad (8)$$

Where \ominus_{d_n} denotes the subtraction that inverts \oplus_d .

The decision $d_n = D(x, y)(n)$ depends on the original signal x . However, at synthesis, we do not know but "only" its update x' . In general, this prohibits the computation of d_n and in such cases, perfect reconstruction is out of reach. However, as there exist a number of situations in which it is still possible to recover d_n from an a posteriori decision map (10).

III. PROPOSED BLOCK DIAGRAM

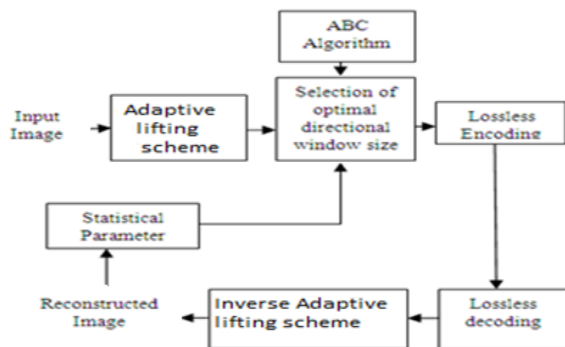


Fig.4. Proposed Block diagram

In existing method using wavelet transform is not giving the better quality for more detail texture image, so it gives a way for adaptive lifting scheme based decomposition. ABC algorithm Artificial Bee Colony algorithm which is a recent and successful optimization tool is used to determine the best directional window size to produce the better by local searching process. Then lossless encoding technique is used to get a perfect compressed image. After the encoding process, it is digital form so one can store or transmit the data to long distance.

Finally the image is reconstructed by applying decoding process for compressed data followed by Inverse adaptive lifting scheme.

A. Need for artificial bee colony algorithm

Choosing a global update coefficient does not give better compression ratio and quality, but artificial bee colony algorithm is used to find different update coefficient by local search at last optimally choose the best update coefficient to get best quality of compressed image.

In update, modifying the center pixels with the co-efficient in 8 – different direction with a considerable window size and by using local search algorithm, to obtain a best directional window with an considerable size artificial bee colony algorithm (3).

IV. ARTIFICIAL BEE COLONY ALGORITHM

Artificial Bee Colony (ABC) is one of the most recently defined algorithms by Dervis Karaboga in 2005, motivated by the intelligent behavior of honey bees. It is as simple as Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms, and uses only common control parameters such as colony size and maximum cycle number. ABC as an optimization tool, provides a population-based search procedure in which individuals called foods positions are modified by the artificial bees with time and the bee's aim is to discover the places of food sources with high nectar amount and finally the one with the highest nectar(2).

In ABC system, artificial bees fly around in a multidimensional search space and some (employed and onlooker bees) choose food sources depending on the experience of themselves and their nest mates, and adjust their positions. Some (scouts) fly and choose the food sources randomly without using experience. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus, ABC system combines local search methods, carried out by employed and onlooker bees, with global search methods, managed by onlookers and scouts, attempting to balance exploration and exploitation process [1].

To decide whether a solution is exhausted or not, a counter is used to store the number of times that it was exploited. In other words the counter holds the number of the local searches in the neighbourhood of that solution. After a new solution is inserted in the population in a phase, the counter is reset to 0[6]

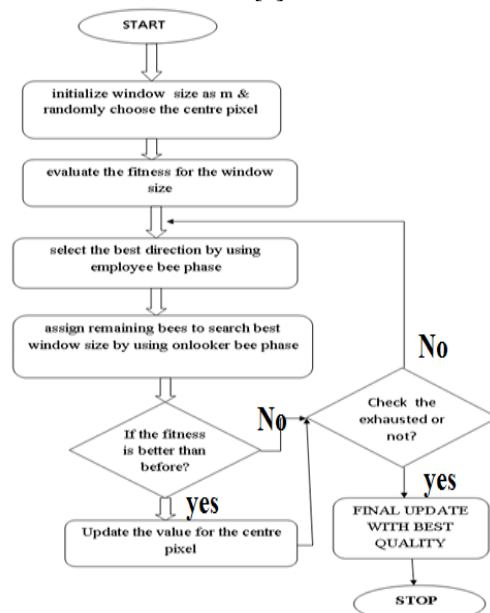


Fig.5. Flow chart for ABC Algorithm

A. Initialization Phase

In the initialization phase of the algorithm, an window size is chosen within the maximum boundaries of each pixels.

```
area=1+floor(maxarea*rand(1));
row=5+floor(r*rand(1));
col=5+floor(c*rand(1));
```

B. Employed bees' phase

In the employed bees' phase, a local search in the neighbourhood of each directional window, represented by x_i , is conducted, which is defined by using :

```
a1=img(row-area,col-area);
b1=img(row,col-area);
c1=img(row+area,col-area);
d1=img(row+area,col+area);
```

If we get better fitness than before ,then memorize the current one.

```
if(localPSNR>prevPSNR)
prevPSNR=localPSNR;
bestimg=reconstimg;
```

After generating a new neighbour solution (i) by local search, the fitness (quality) of new solution is evaluated and the better one is kept in the population. Here the counter is incremented for each local search up to 8 level(4).

C. Onlooker bees' phase

In the onlooker bees' phase, a roulette wheel selection scheme is employed to get a best directional window for various size from 1 to M in terms of it fitness value. In roulette wheel selection, each solution is assigned a probability value (Eq. 6.1) proportional to its fitness value:

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \quad (9)$$

After the source is evaluated, a greedy selection is used and the onlooker bee either memorizes the new position by forgetting the old one or keeps the old one. Here the counter is incremented for each local search up to maximum window size M(5).

D. Scout bees' phase

A counter storing the number of non-progressive local searches exceeds the predetermined number (called "limit"), the solution associated with this counter is assumed to be exhausted. When a source (solution) is exhausted, it is abandoned and a new random solution is generated(7).

V. PROPOSED ALGORITHM

In existing method , decomposing the image using wavelet transform, whereas in proposed method, decomposing the image using wavelet lifting scheme and then apply the artificial bee colony algorithm in the update process to get a considerable quality.

A. Algorithm steps:

Step 1: Acquire Input Gray scale Image.

```
img=imread('cameraman.tif');
```

Step2: Split the image into odd and even pixel regions.

```
odd=img(1:2:end,1:2:end);
even=img(2:2:end,2:2:end);
```

Step 3: Decompose the image for next prediction step as (odd-even).

Step 4: For prediction of co-efficient, fix the maximum coverage size as 'M' and initialized 'K=0'.Where M is maximum window size ,upto which it will do local search for each center pixels. In our program we take maximum window size as

```
maxarea=5;
```

Step 5: Scan each pixel in the decomposed image and calculate its present fitness value and compression ratio.

Step 6: Call direction finding algorithm to predict 'a' and 'b' co-efficient of all 8- direction combination.

```
a1=img(row-area,col-area);
b1=img(row,col-area);
c1=img(row+area,col-area);
d1=img(row+area,col+area);
```

| | | | | | |
|----|----|----|----|----|----|
| | D1 | | V1 | D2 | |
| | | D1 | V1 | | |
| H1 | H1 | H1 | X | H2 | H2 |
| | D3 | D3 | V2 | D4 | |
| D3 | | | V3 | | D4 |

Fig.6. Directional coefficient for center pixel 'x'

```
a2=img(row-area,col+area);
```

```
b2=img(row,col+area);
```

```
c2=img(row+area,col+area);
```

```
d2=img(row-area,col+area);
```

Where x is an center pixel to be update

H1 is predicted coefficient in horizontal left direction

H2 is predicted coefficient in horizontal right direction

V1 is predicted coefficient in vertically top direction

V2 is predicted coefficient in vertically down direction

D1 is predicted coefficient in diagonally top left direction

D2 is predicted coefficient in diagonally top right direction

D4 is predicted coefficient in diagonally bottom left direction

D5 is predicted coefficient in diagonally bottom right direction

Step 7: Calculate update weight by using Update lifting formula for each direction prediction and find MSE and compression ratio for all combination.

For example:

Find the MSE for all directional combinational prediction for center pixel and update it for the center pixel which having better MSE value by using artificial bee colony algorithm.

Two measures are commonly used to evaluate the perceptual quality:

- The Mean Square Error (MSE). It represents the mean squared error between the compressed and the original image and is given by:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} |X(i, j) - X_c(i, j)|^2$$

The lower the value of MSE, the lower the error.

- The Peak Signal to Noise Ratio (PSNR). It represents a measure of the peak error and is expressed in decibels. It is defined by:

$$PSNR = 10 \cdot \log_{10} \left(\frac{255^2}{MSE} \right)$$

Step 8: Memorize the best individual MSE, CR and its direction using ABC local search (11).

Step 9: Iterate K from (0 to M).here we going to predict and update the best value for different range of window size.

For example: For a maximum window size of 5.

We want to find best directional update for center pixel using abc algorithm for

- i) Window size 5
- ii) Window size 4
- iii) Window size 3
- vi) Window size 2
- v) Window size 1

atlast by, using abc algorithm doing comparisinal search with all possible window size and update best directional window size value for the center pixels

Step 10: Using ABC local search, memorize the best window size in terms of its MSE and CR for each reference pixel.

VI. EXPERIMENTAL RESULTS

The proposed algorithm is tested on many standard images of size (256×256).The pepper image has high PSNR when compare to other images.

The Reconstructed images are shown in figure 7 and figure 8. The results are tabulated for various images in Table (1), (2) and Fig.9 Shows the performance graph.

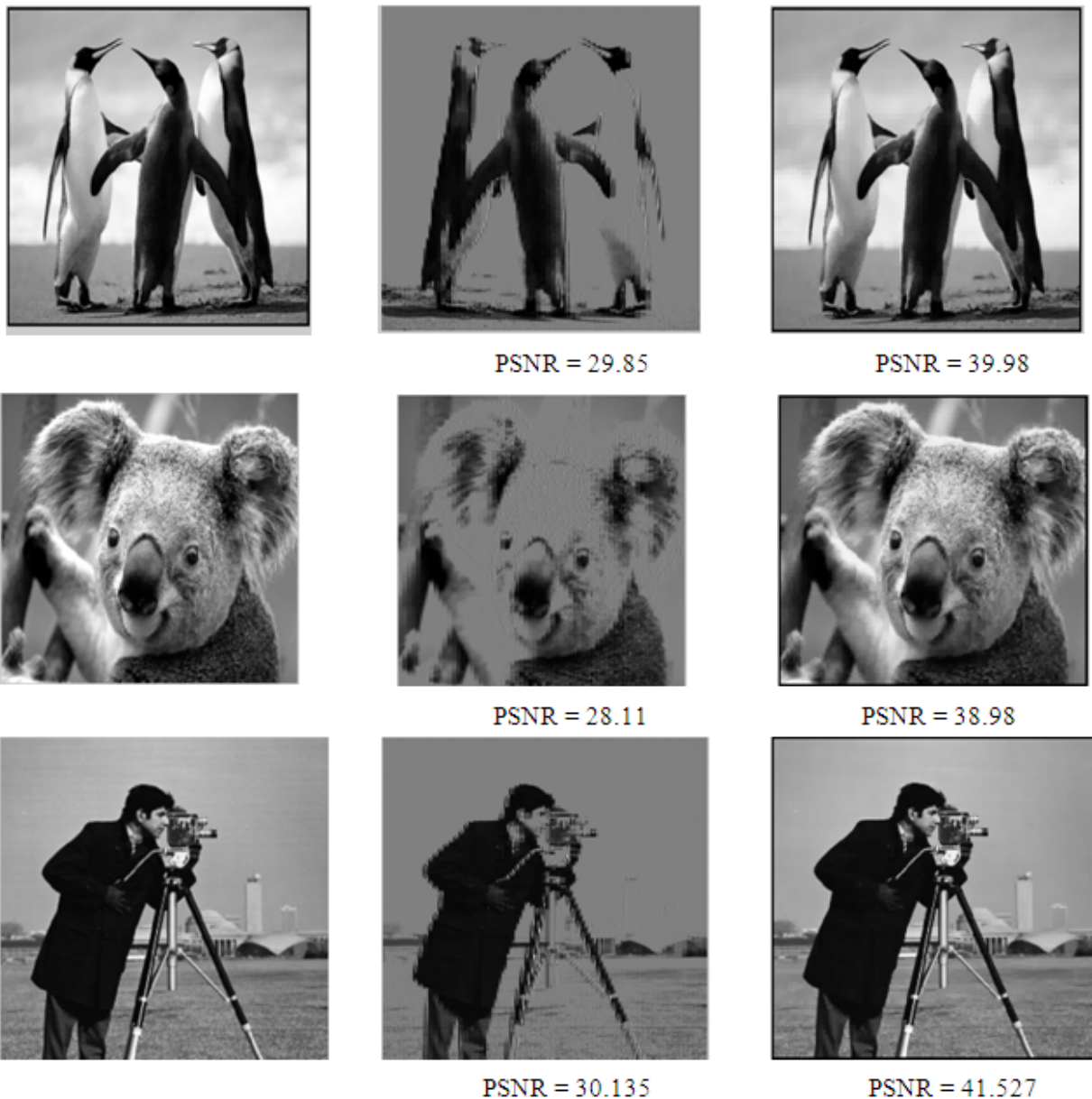


Fig.7. Reconstructed Images with wavelet transform and lifting with ABC
 (a) Original Image (b) Output of Wavelet Transform (c) Output of Lifting Scheme with ABC



Fig.8. Reconstructed Images with wavelet transform and lifting with ABC
 (a) Original Image (b) Output of Wavelet Transform (c) Output of Lifting Scheme with ABC

Table 1: Comparison Table for Cameraman Image

| Compression Ratio | With Wavelet Transform | With Lifting Scheme using ABC | | |
|-------------------|------------------------|-------------------------------|--------------------|--------------------|
| | PSNR in dB | PSNR in dB | Encoding Time secs | Decoding Time secs |
| 30 | 33.135 | 40.52 | 4.550 | 1.732 |
| 40 | 29.635 | 38.11 | 4.451 | 1.727 |
| 50 | 27.135 | 36.03 | 4.372 | 1.717 |
| 60 | 25.635 | 35.86 | 4.265 | 1.702 |
| 70 | 23.135 | 32.31 | 4.211 | 1.687 |

Table 2. Comparison Table for Peppers Image

| Compression Ratio | With Wavelet Transform | With Lifting Scheme using ABC | | |
|-------------------|------------------------|-------------------------------|--------------------|--------------------|
| | PSNR in dB | PSNR in dB | Encoding Time secs | Decoding Time secs |
| 30 | 27.556 | 38.90 | 4.487 | 1.865 |
| 40 | 25.056 | 37.78 | 4.456 | 1.800 |
| 50 | 23.556 | 35.97 | 4.011 | 1.782 |
| 60 | 20.956 | 34.42 | 3.966 | 1.722 |
| 70 | 20.516 | 32.98 | 3.568 | 1.684 |

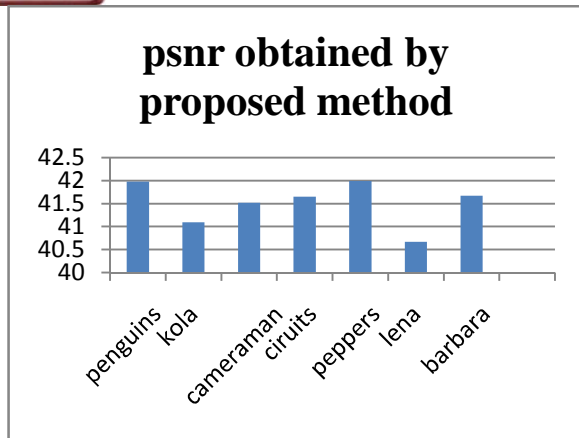


Fig.9. comparison graph of PSNR obtained from proposed method

VII. CONCLUSION AND FUTURE ENHANCEMENTS

In this paper ABC algorithm is applied to adaptive lifting scheme based decomposition to find the optimal directional window size to obtain satisfactory compression and quality. ABC algorithm is implemented in update process of lifting scheme to give better PSNR. From the experimental result, it is concluded that proposed method give improved quality compare to existing method. It gives the way for reduces in data to represent the image and decrease in transmission bandwidth. so, the transmission cost and memory cost is reduced with help of proposed method.

In future work, Artificial bee colony algorithm can be implement in the thresholding process to reduces the number of coefficient representing the image by optimally choosing the thresholding value to get more better compression and quality.

REFERENCES

- [1] B. Akay and D. Karaboga, Parameter tuning for the artificial bee colony algorithm, ICCCI 2009 (R. Kowalczyk N.T. Nguyen and S.-M. Chen, eds.), LNAI, vol. 5796, 2009, pp. 608–619.
- [2] J. Chen, M. Yang, Y. Zhang, and X. Shi, Ecg compression by optimized quantization of wavelet coefficients, ICIC 2006, LNCIS, vol. 345, Springer-Verlag Berlin Heidelberg, 2006, p. 809814.
- [3] R.R. Coifman and M.V. Wickerhauser, Entropy-based algorithms for best basis selection, IEEE Transactions on Information Theory 38 (1992), no. 2, 713–718.
- [4] V. U Kale and N. N. Khalsa, Performance evaluation of various wavelets for image compression of natural and artificial images, International Journal of Computer Science and Communication 1 (2010), no. 1, 179–184.
- [5] D. Karaboga, An idea based on honey bee swarm for numerical optimization, Tech. Report TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005.
- [6] D. Karaboga and B. Akay, A survey: Algorithms simulating bee swarm intelligence, Artificial Intelligence Review 31 (2009), no. 1, 68–55.
- [7] A modified artificial bee colony (abc) algorithm for constrained optimization problems, Applied Soft Computing (In Press).

- [8] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, Imagequality assessment: From error measurement to structural similarity, IEEE Transactions on Image Processing 13 (2004), no. 1, 600[9] Z. Ye and Ye Y. Mohamadian, H., Digital image wavelet compression enhancement via particle swarm optimization, 2009 IEEE Int. Conf. on Control and Automation (Christchurch, NewZeland), 2009, pp. 2287–2292
- [10] W. Trappe and K. J. R. Liu, “Adaptivity in the lifting scheme,” in 33th Conference on Information Sciences and Systems, Baltimore, March 1999, pp. 950-
- [11] R. Claypoole, G. Davis, W. Sweldens, and R. Baraniuk, “Nonlinear wavelet transforms for image coding via lifting,” submitted to IEEE Transactions on Image Processing 1999.

AUTHOR’S PROFILE



Prof. M. Mohamed Ismail

was born on 03.05.1965 now residing at 9/10, First Street, Anbu Nagar, Sathuvachari, Vellore-632009, Tamilnadu, India. He is Working as Associate Prof, Deptt. of Computer Science at Mazharul Uloom College, Ambur -635 802, from 4.10.1989 till date .He completed his M.Sc. physics in 1987 with first class from Bharathidasan University, Trichy , PGDCA in 1988 with first class from Bharathidasan University, Trichy, M.Sc. (info Technology) in 2000 with first class from Alagappa University, Karaikudi and M. Phil. (Computer Science) in 2001 with first class from Alagappa University, Karaikudi. At present doing part - time Ph.D. in computer Science at Karpagam University. He has attended one orientation and 4 Refresher courses for Computer lecturer at various universities in Tamilnadu and have Research papers published in international journals and also have passed module I of certified Mutual fund Advisor from National stock Exchange, Chennai.

Dr. K. Baskaran

was born on 30.4.1965 now residing at Coimbatore. He is working as Associate Prof. at Government college of Technology Coimbatore. He completed his B.E degree from Annamalai University and M.E degree from Bharathiar University, Coimbatore and Ph. D. from Anna University Chennai in the year 2006 and have published many papers in national and international journals and guiding many Ph. D. scholars at present.