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# Improved wavelet based compression with adaptive lifting scheme using Artificial Bee Colony algorithm

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*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 the computational or transmittal costs. Wavelet transform is one of the compression techniques especially used for images and multimedia files. In wavelet transform, approximation and detail coefficients are extracted from the signal by filtering. Both approximation and detail coefficients are re-decomposed up to some level to increase frequency resolution.***

***In this paper, we propose a framework for constructing adaptive wavelet decompositions using the lifting scheme. A major requirement is that perfect reconstruction is possible with better quality. Once coefficients are generated, the best directional window sizes are determined 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. Then we compare the performance of proposed method*** **with the existing method in term of both PSNR and compression ratio.**

***Index Terms****—Image Compression, Wavelet Packet Decomposition, wavelet transform, adaptive lifting scheme, Multi-level Decomposition, Artificial Bee Colony Algorithm.*

## I. INTRODUCTION

Wavelet decomposition has established itself as one of the state of the art techniques for image coding problems because of its capability for allowing the generation of lossy versions of an original image at multiple resolutions and bitrates. Many applications such as the transmission of depth maps for the construction of 3-D views of a scene or the efficient storage and communications of medical images require lossless coding. 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. 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.

## II.WAVELET TRANSFORM

A standard compression procedure contains the decomposition, lifting scheme for decomposed coefficient andreconstruction steps. In the compression step, data is splitted into its frequency components or into components in another domain. In adaptive lifting step, we want to choose a best directional window size for better compression. In the reconstruction step, in contrary to the decomposition step, parts that are not eliminated are formed to construct the reduced data.

*A.Wavelettransform*

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

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

where$\psi_{a,b}$is defined as follows:

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

Where$\Psi(t)$ is the mother wavelet and $\Psi_{a,,b}(t)$are scaled and Shifted versions of this wavelet. The signal or image is decomposed into four different frequencies: approximation, horizontal detail, vertical detail and diagonal detail.

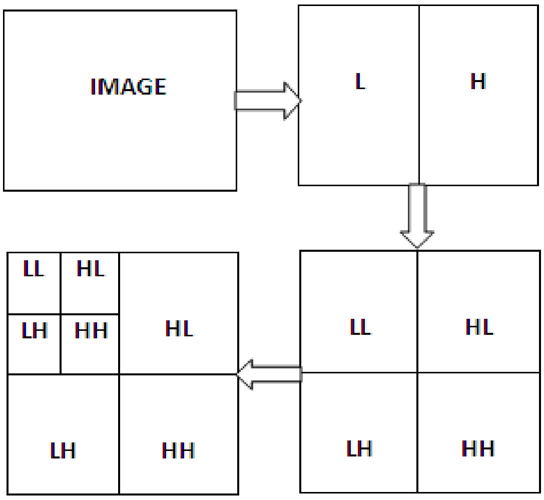



Fig.1: 2-level Wavelet decomposition

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 [9].

## III.ADAPTIVEBASING SCHEME BASED DECOMPOSITION

The lifting scheme is a very general and highly flexible tool for building new wavelet decompositions from existing ones. It can be applied with various goals in mind. A first objective might be to "improve" a given wavelet decomposition, e.g., by increasing the number of vanishing moments it possesses. However, from a completely different point of view, the lifting scheme can be exploited as a tool for building wavelets on irregular grids, e.g., a triangulation of some odd-shaped geometrical surface. Furthermore, it offers the possibility of replacing linear filters by nonlinear ones, such as rank-order filters or morphological operators [13].

The input signal of the lifting scheme is split into two disjoint sets with even and odd samples, respectively. If the signal has a local correlation, then these two sets are highlyCorrelated. n the predict stage, a filter-predictor uses the even samples to predict the odd ones. The error of prediction represents the detail, high-pass coefficients. In the update stage, the error of prediction is used to update the current phase and improve the "smoothness" of the even samples, producing the low-pass coefficients. In the reconstruction stage, prediction and update are done in reverse order, and finally, the two disjoint sets merge into one to achieve the perfect reconstructed signal.

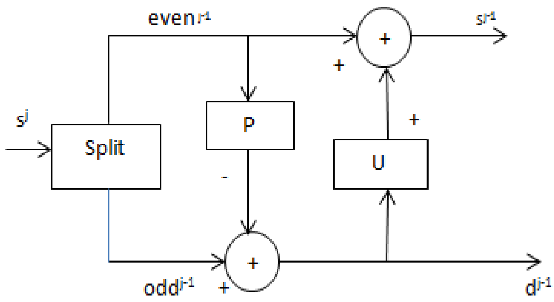



Fig.2: a) Forward transform

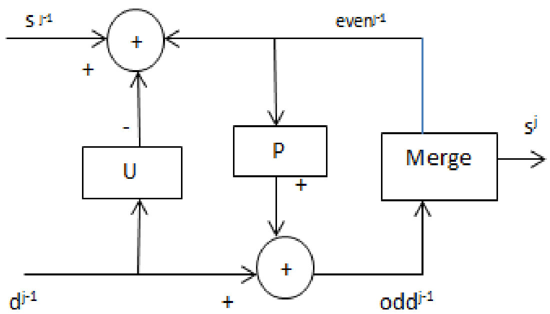



Fig.2: b) Inversetransform.

The prediction step is given as;

$d_{j-1} = odd_{j-1} - p(even_{j-1})$(3)

The Update step is given as;

$S_{j-1} = even_{j-1} + u(\ d_{j-1})$ (4)

Whereas, 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.

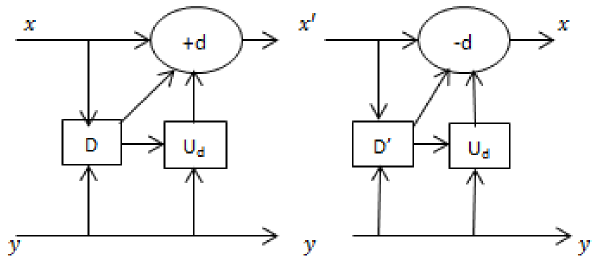



Fig.3. Adaptive update lifting scheme

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 $x$ :

$$x' = U(x, y_h, y_v, y_d) \qquad (5)$$

Here, $U$ is update operator, in which coefficients are chosen by decidable factor $D$ .
*Prediction*: Using the updated low-frequency coefficient$x'$ to predict $y_h, y_v, y_d$:

$$y_h' = y_h - p_h(x', y_v, y_d) \text{(6a)}$$

$$y_v' = y_v - p_v(x' - y_d) \text{(6b)}$$
$$y_d' = y_d - p_d(x') \qquad \text{(6c)}$$

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 $x$, $yh$, $yv$, and $yd$. This update and prediction scheme ensures perfect reconstruction without recording any overhead information [10][12] .

In update, wecan modifiedthe co-efficient in 8 – different direction with a considerable window size and by using local search algorithm ,we obtain a best directional window with an considerable size.

Choosing a global directional window size will not give better compression and quality; to achieve this we must optimally choose direction and window size using Artificial Bee Colony Algorithm.

## IV. ARTIFICIAL BEE COLONY ALGORITHM

Artificial Bee Colony (ABC) optimization algorithm introduced by Karaboga[1] [3] [5] uses the recruitment and abandonment modes of the foraging process. Employed bees, onlooker bees and scout bees are the phases of the algorithm. In the employed bees' phase, a local search is conducted in the neighbourhood of each solution by turn and the better one is kept. In the onlooker bees' phase, a local search is conducted in the neighbourhood of the solutions chosen depending on the probability values calculated based on the fitness values. In the scout bees' phase, exhausted sources are determined and a random new solution is inserted in the population instead of the exhausted source. 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.[6].

### *A. Phase*

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

### *B. Employed Bees' Phase*

In the employed bees' phase, a local search in the neighbourhood of each directional window, represented by *xi*, is conducted, which is defined by using Eq. (7):

$$v_{ij} = \begin{Bmatrix} x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}), if R_{ij} < MR \\ x_{ij} \qquad\qquad , \ otherwise \end{Bmatrix} (7)$$

where$k$ *is* $\{1, 2, . . . SN\}$ is a randomly chosen index that has to be different from *i*. $\varphi ij$is a uniformly distributed real random number in the range [-1,1]. *MR* is the modification rate which takes value between 0 and 1. A lower value of *MR* may cause solutions to improve slowly while a higher one may cause too much diversity in a solution and hence in the population. After generating a new neighbour solution ($vi$) 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.

### *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. 8) proportional to its fitness value:

$$p_i = \frac{fitness_{\ i}}{\sum_{i=1}^{SN} fitness_{\ i}} \qquad (8)$$

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.*

*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) isexhausted, it is abandoned and a new random solution is generated.

*E.Proposed Method*

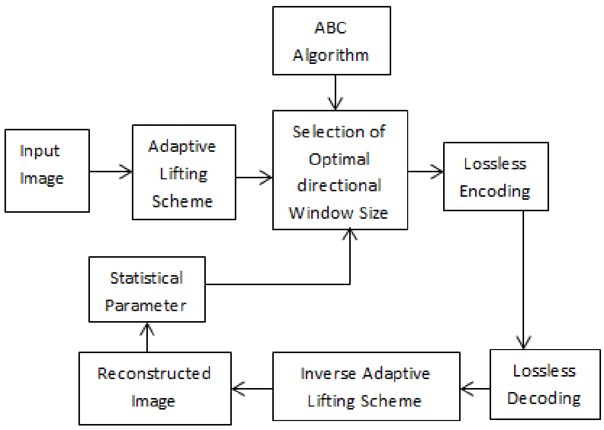



Fig 4.Proposed block diagram

*A. Proposed Algorithm*

**Step 1:** Acquire Input Gray scale Image.

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

**Step 3:** Decompose the image for next prediction step as (odd-even)/2.

**Step 4:** For prediction of co-efficient, fix the maximum coverage size as 'M' and initialized 'K=0'.

**Step 5:** Scan each pixel in the decomposed image.

**Step 6:** Calculate partition area using (i,j)*(M-K).

**Step 7:** Construct a new direction and area operator to update the quality properties of the predicted image.
**Step 8:** Call direction finding algorithm to predict 'a' and 'b' co-efficient of all 8- direction combination.

**Step 9:** Calculate update weight by using Update lifting formula for each direction prediction and find MSE and compression ratio for all combination.

**Step 10:** Memorize the best individual MSE, CR and its direction using ABC local search.

**Step 11:** Iterate K from (0 to M).

**Step 12:** Using ABC local search, memorize the best window size in terms of its MSE and CR for each reference pixel.

**Step 13:** Encode the co-efficient to get a final compressed image.

**Step 14:** Decode the compressed image.

**Step 15:** Get re-constructed image by inverse adaptive decomposition.

## V. EXPERIMENTAL RESULTS

In this study, ABC algorithm is used to optimally choose the best directional window size for good compression. The compression problem has two objectives to achieve: high quality and high compression ratio. This kind of problems is called multi-objective problems. In this study, the multi-objective optimization problem is transformed to a single objective constrained problem by considering thepeak signal-to-noise ratio (PSNR) as the objective function and the compression ratio value as a constraint.
However, there is a trade-off between compression rate and quality since while CR is increased, PSNR is reduced.

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

In this experiment the suitable control parameters like colony size, maximum cycle number, limit and MR values for ABC were selected as recommended in [1].

Fig 5: a) Original image

| CR | PSNR with lifting and ABC | PSNR With WAVELET TRANSFORM | ENCODING TIME | DECODING TIME |
|---|---|---|---|---|
| 45.3294 | 31.0428 | 26.8734 | 0.472680 | 0.163131 |
| 50.8231 | 26.8395 | 21.4673 | 0.454877 | 0.094041 |
| 53.6367 | 22.0544 | 17.4526 | 0.437077 | 0.069492 |
| 55.3426 | 18.5003 | 13.9881 | 0.430185 | 0.058359 |
| 56.1223 | 15.9282 | 10.4637 | 0.433819 | 0.051356 |

TABLE 1. For Rice Image

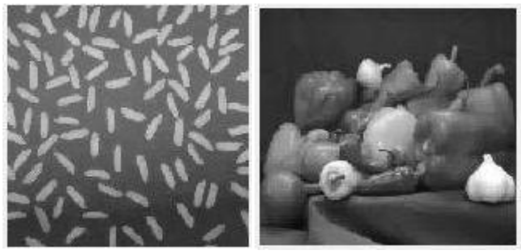


Fig 5: b) With wavelet transform

| CR | PSNR with lifting and ABC | PSNR With WAVELET TRANSFORM | ENCODING TIME | DECODING TIME |
|---|---|---|---|---|
| 43.9998 | 37.7218 | 32.5174 | 0.583446 | 0.255903 |
| 50.3725 | 32.9456 | 27.6927 | 0.498332 | 0.132234 |
| 52.4467 | 28.6053 | 23.3171 | 0.493268 | 0.089798 |
| 54.2783 | 23.6283 | 18.1956 | 0.486027 | 0.066927 |
| 55.8973 | 19.3778 | 14.9800 | 0.482788 | 0.059175 |

TABLE 2. For Pepper Image

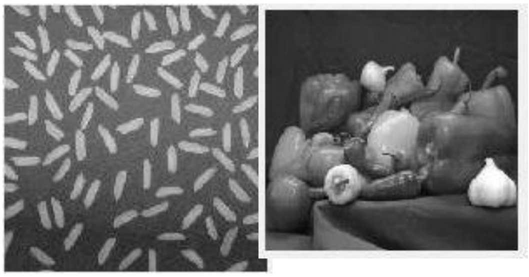
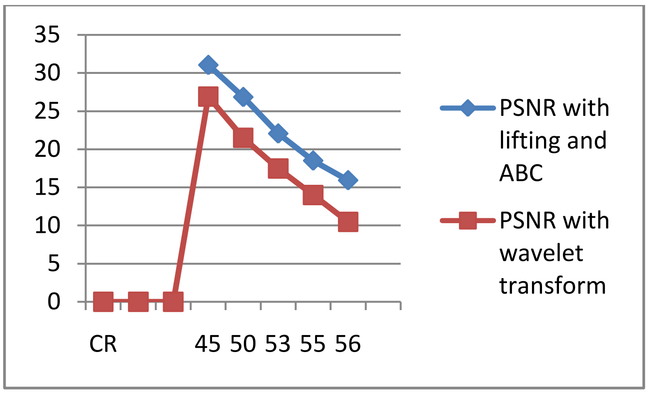


Fig 5: c) With lifting and ABC Algorithm




**Comparison Graph for Rice Image**

## VI. CONCLUSION AND FUTURE WORK

In this paper ABC algorithm can be applied to find the optimal window size to obtain satisfactory compression and quality in a multi-objective manner. In future work, we can find the optimum threshold value by using ABC Algorithm for this same paper to get considerable improvement in 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 InformationTheory 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 Communication1 (2010), no. 1, 179–184.
[5] D. Karaboga, An idea based on honey bee swarm for numericaloptimization, Tech. Report TR06, Erciyes University, EngineeringFaculty, Computer Engineering Department, 2005.
[6] D. Karaboga and B. Akay, A survey: Algorithms simulatingbee swarm intelligence, Artificial Intelligence Review 31 (2009),no. 1, 68–55.
[7] A modified artificial bee colony (abc) algorithm forconstrained optimization problems, Applied Soft Computing (InPress)(2010).
[8] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, Imagequality assessment: From error measurement to structural similarity,IEEETransactios on Image Processing 13 (2004), no. 1,600
[9] Z. Ye and Ye Y. Mohamadian, H., Digital image waveletcompression enhancement via particle swarm optimization, 2009IEEE Int. Conf. on Control and Automation (Chrisrchurch, NewZeland), 2009, pp. 2287–2292
.[10]W. Trappe and K. J. R. Liu, "Adaptivity in the liftingscheme," in 33th Conference on Information Sciences andSystems, 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.
[12]G. Piella and H. J. A. M. Heijmans, "Adaptive liftingschemes with perfect reconstruction," Research Report PNARO104,CWI, Amsterdam, February 2001.E. Le Pennec and S. Mallat, "Image compression
[13] F.W. Moore, A genetic algorithm for optimized reconstruction of quantized signals, Evolutionary Computation, 2005. The 2005 IEEE Congress on, vol. 1, 2005, pp. 105 –111 Vol.1.