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A New Image Compression Scheme with Wavelet Transform and SPIHT Algorithm using PSO

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ABSTRACT

The necessity in image compression continuously grows during the last decade. A number of image compression techniques have been developed in the past different kind of application. But, majority of the image compression approaches available in the literature have poor visual quality and low PSNR (Peak Signal to Noise Ratio) value. In recent years, discrete time wavelet transform (DWT) is observed to be very efficient for image compression techniques. The existing work implemented with SPIHT (Set Partitioning in Hierarchical Tress) compression scheme. This paper introduce a proposed method of implementation wavelet family which is combine with SPIHT compression scheme using PSO (Particle Swarm Optimization) which gives significant improvement in image visual quality such as PSNR value than existing work.

Keywords - Discrete time Wavelet Transform (DWT), Image Compression, PSNR, PSO, SPIHT

I. INTRODUCTION

When we speak of image compression, basically there are two types : lossless and lossy. With lossless compression, the original image is recovered exactly after decompression. Much higher compression ratios can be obtained if some error, which is usually difficult to perceive, is allowed between the decompressed image and the original image. This is lossy compression.we shall concentrate on wavelet based lossy compression of grey level images. In this paper we shall concentrate on lossy compression method like SPIHT algorithm and optimization technique like PSO. Particle Swarm Optimization (PSO) is computational method that optimize a problem by iteratively trying to improve performance with regard to given measure of quality. we have implemented SPIHT algorithm with various wavelet family (haar wavelet, daubechies wavelet, symlet wavelet, coiflets wavelet, biorthogonal wavelet, discrete approximation of meyer wavelet). The output image of the SPIHT algorithm is fed to the PSO as input and obtain final output image.The output image of PSO is significant better in terms of visual quality than output image of the SPIHT algorithm.

II. WAVELET TRANSFORMATION IMAGES

Wavelets [1] are mathematical function that decomposed data into different frequency component, and then study each component with a resolution matched to its scale. Wavelet has advantages over traditional Fourier methods [2] in analyzing physical situation where the signal contains discontinuities and sharp spikes.

The wavelet transformation [2] is a mathematical tool for decomposition. The wavelet transform is identical to hierarchical sub band filtering system. The basic idea of the DWT for two dimensional image is described as follows: An image is first decomposed into four parts based on frequency sub bands, by critically sub sampling horizontal and vertical channels using sub band filters named as: Low-Low(LL), Low-High(LH), High-Low(HL) and High-High(HH)sub bands as shown in Fig. 1. [3]

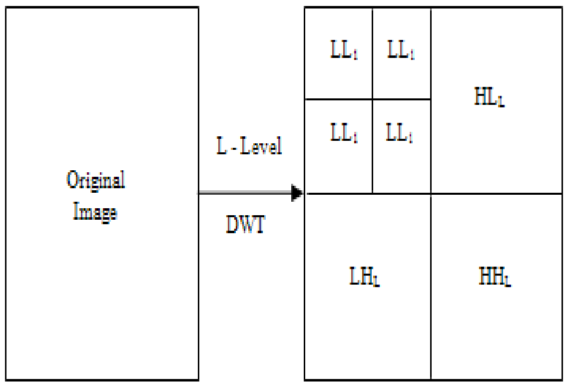

Fig. 1 Wavelet Transform

Wavelet transform efficiently work on low frequency sub band so, the sub band LL is further decomposed and critically sub sampled. This process is repeated at several times, which is based on application. Each level has various bands information such as LL, LH, HL, HH frequency bands. From these discrete wavelet transform (DWT) coefficients, the original image can be reconstructed. This reconstruction process is called the inverse discrete wavelet transform (IDWT).

III. SPIHT ALGORITHM

In the SPIHT algorithm [4], the image is first decomposed into a number of sub-bands by means of hierarchical wavelet decomposition. For example, the sub-bands obtained for two-level decomposition are shown in Fig. 2 The sub-band coefficients are then grouped into sets known as spatial-orientation trees, which efficiently exploit the correlation between the frequency bands. The coefficients in each spatial orientation tree are then progressively coded from the most significant bit-planes (MSB) to the least significant bit-planes (LSB), starting with the coefficients with the highest magnitude and at the lowest pyramid levels.

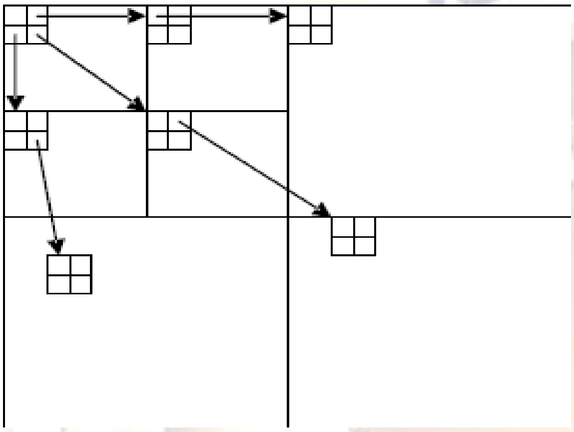

Fig. 2 Two-level wavelet decomposition and spatial orientation tree [6]

The SPIHT multistage encoding process employs three lists and sets [4-6]:

1) The list of insignificant pixels (LIP) contains individual coefficients that have magnitudes smaller than the threshold.
2) The list of insignificant sets (LIS) contains sets of wavelet coefficients that are defined by tree structures and are found to have magnitudes smaller than the threshold (insignificant). The sets exclude the coefficients corresponding to the tree and all sub tree roots and they have at least four elements.
3) The list of significant pixels (LSP) is a list of pixels found to have magnitudes larger than the threshold (significant).
4) The set of offspring (direct descendants) of a tree node, O (i , j), in the tree structures is defined by pixel location (i, j). The set of descendants, D (i, j), of a node is defined by pixel location (i, j). L (i, j) is defined as L (i, j) = D (i, j) – O (i, j).

The threshold, T, for the first bit-plane is equal to 2^n, and
n = log2 (max (i, j) {|c (i, j)|}

Where c (i, j) represents the (i, j)th wavelet coefficient. All the wavelet coefficients are searched in order to obtain the maximum c (i, j) after executing the discrete wavelet transform. For operations in the subsequent bit-planes of threshold T, n is reduced by 1.

For each pixel in the LIP, one bit is used to describe its significance. If it is not significant, the pixel remains in the LIP and no more bits are generated; otherwise, a sign bit is produced and the pixel is moved to the LSP. Similarly, each set in the LIS requires one bit for the significance information. The insignificant sets remain in the LIS; the significant sets are partitioned into subsets, which are processed in the same manner and at the same resolution until each significant subset has exactly one coefficient. Finally, each pixel in the LSP is refined with one bit.
The above mentioned procedure is then repeated for the subsequent resolution.

Step1: Initialization: output $n = \lfloor \log_2 (\max_{(i,j)} \{|c_{i,j}|\}) \rfloor$; set the LSP as an empty list, and add the coordinates $(i, j)\varepsilon H$ to the LIP,and only those with descendants also to the LIS, as type A entries.

Step2: Sorting Pass:
2.1) for each entry (i, j) in the LIP do:
  2.1.1) output $S_n(i, j)$;
  2.1.2) if $S_n(i, j) = 1$ then move (i, j) to the LSP and output the sign of $c_{i,j}$;
2.2) for each entry (i, j) in the LIS do:
  2.2.1) if the entry is of type A then
- output $S_n(D(i, j))$;
- if $S_n(D(i, j)) = 1$ then
  for each $(k, l) \in O(i, j)$ do:
  - output $S_n(k, l)$;
  - if $S_n(k, l) = 1$ then add (k, l) to the LSP and output the sign of $c_{k,l}$;
  - if $S_n(k, l) = 0$ then add (k, l) to the end of the LIP;

  if $L(i, j) \neq 0$ then move (i, j) to the end of the LIS, as an entry of type B, and go to Step 2.2.2); otherwise, remove entry (i, j) from the LIS;

2.2.2) if the entry is of type B then
- output $S_n(L(i, j))$;
- if $S_n(L(i, j)) = 1$ then
  add each $(k, l) \in O(i, j)$ to the end of the LIS as an entry of type A;
  remove (i, j) from the LIS.

Step3: Refinement Pass: for each entry (i, j) in the LSP, except those included in the last sorting pass (i.e., with same n), output the nth most significant bit of $|c_{i,j}|$;

Step4: Quantization-Step Update: decrement n by 1 and go to Step 2).

IV. Particle Swarm Optimization

Particle swarm optimization (PSO) [8-10] is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. The PSO is a population-based optimization technique, where the population is called swarm.

The basic PSO algorithm can be described as follows: Each particle in the swarm represents a possible solution to the optimization problem existing. During PSO iteration, every particle accelerates independently in the direction of its own personal best solution found so far, as well as the direction of the global best solution discovered so far by any other particle. Therefore, if a particle finds a promising new solution, all other particles will move closer to it, exploring the solution space more thoroughly.

Let s denotes the swarm size. Each particle $1 \leq i \leq s$ is characterized by three attributes:

- The particle position vector Yi;
- The particle position change (velocity) vector Vi;
- The personal (local) best position achieved by the particle so far Ŷi. Moreover, let G denote the best particle in the swarm.

Step1. Initialize Yi and Vi, and set Ŷi = Yi for i = 1, 2… s.
Step2. Evaluate each particle Yi for i = 1, 2… s.
Step3. Let G to be the best particle in {Ŷ1, Ŷ 2... Ŷ s}
Step4. For i = 1, 2… s. do:
Update Vi according to:
V =wV +c r (Y' -Y) + c r (G-Y) - (1)
Update Yi according to:
Yi = Yi + Vi - (2)
Step5. Go to Step 3, and repeat until convergence. Where w inertia weight factor; c1, c2 self-confidence factor and swarm-confidence factor, respectively; r 1, r 2 two random numbers uniformly distributed between 0 and 1.
If Yi is better than Ŷi , then Ŷi =Yi
Step6. Go to Step 3, and repeat until convergence.

V. MODELING AND RESULTS

Image compression is very important in today's medical application because advanced Medical imaging applications require storage of large quantities of digitized clinical data and due to the constrained requirements of medical data archiving, compression is adapted in most of the storage and transmission applications. Fig. 3 shows the proposed model used for compressing medical images. Matlab software is used for simulating this work. In our testing we have used Dicom images [7]. Image is compressed using encoding and decoding process of SPIHT algorithm. But at the decoding process we have implemented particle swarm optimization algorithm which gives significant improvement in visual quality.

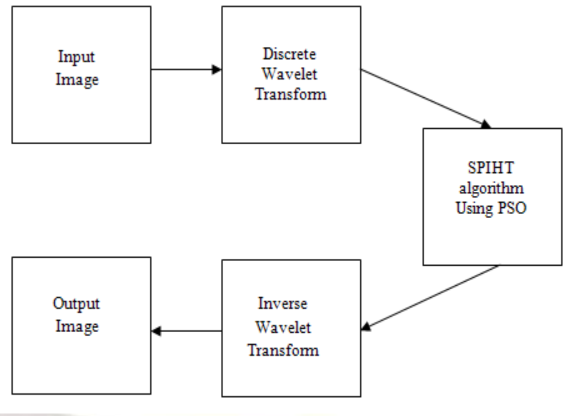

Fig. 3 Proposed Compression model of image

In order to measure the quality of the image data at the output of the decoder, mean square error (MSE) and peak to signal to noise ratio (PSNR ratio) are often used. The MSE is often called quantization error variance $\sigma^2 q$. The MSE between the original image f and the reconstructed image g at decoder is defined as:

$$MSE = \sigma^2 q = 1/N \, \Sigma \, (f\,[j, k] - g\,[j, k])^2$$

Where the sum over j, k denotes the sum over all pixels in the image and N is the no. of pixels in each image. The PSNR between two images having 8 bits per pixels or samples in term of decibels (db) is given by:

$$PSNR = 10\log_{10} (255^2 / MSE)$$

Generally when PSNR is 40 dB or greater , than the original and the reconstructed images are virtually indistinguishable by human observers.

We have implemented various wavelet families such as haar, daubechies, symlet, biorthogonal, coiflet, discrete approximation of meyer wavelet. In our testing we have considered 512* 512 Dicom images.

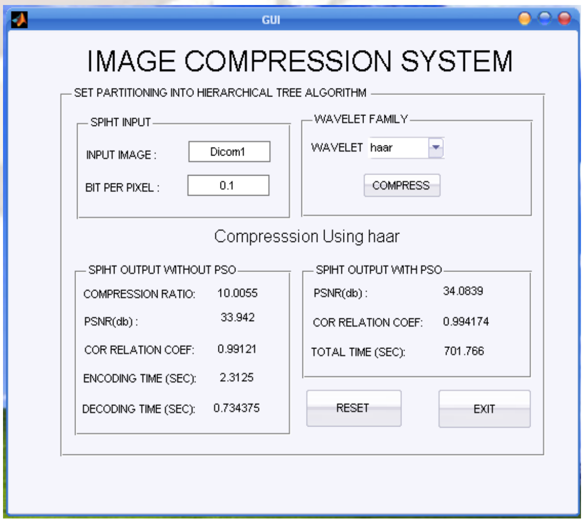

Fig. 4 GUI form of Dicom1 Image

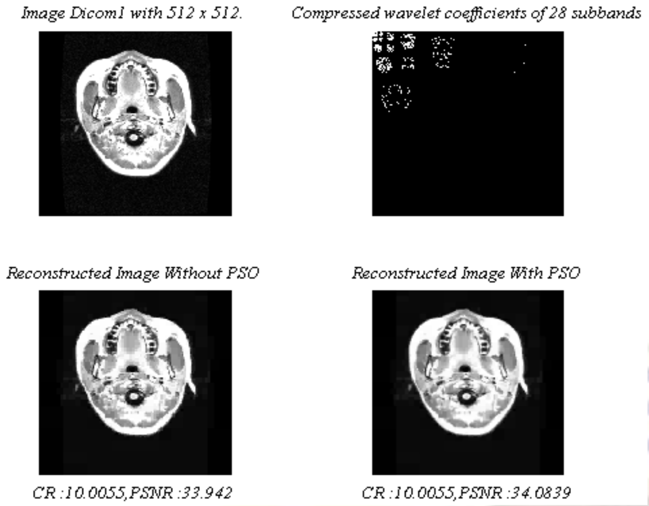

Fig. 5 Reconstucted image of Dicom1

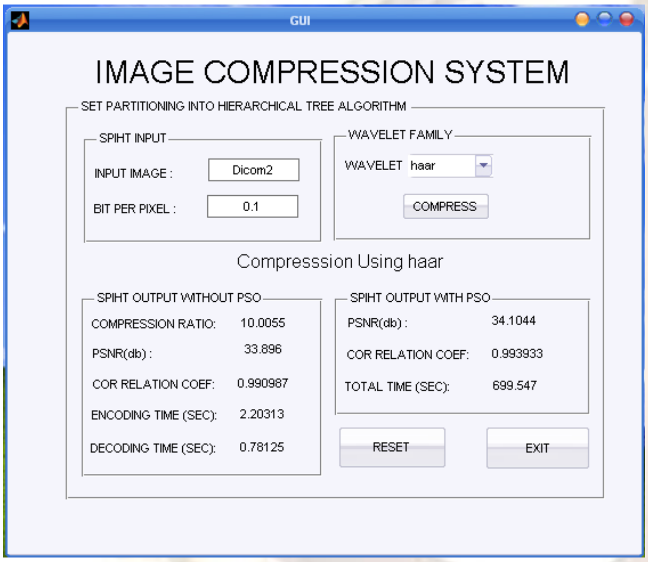

Fig. 6 GUI form of Dicom2 Image

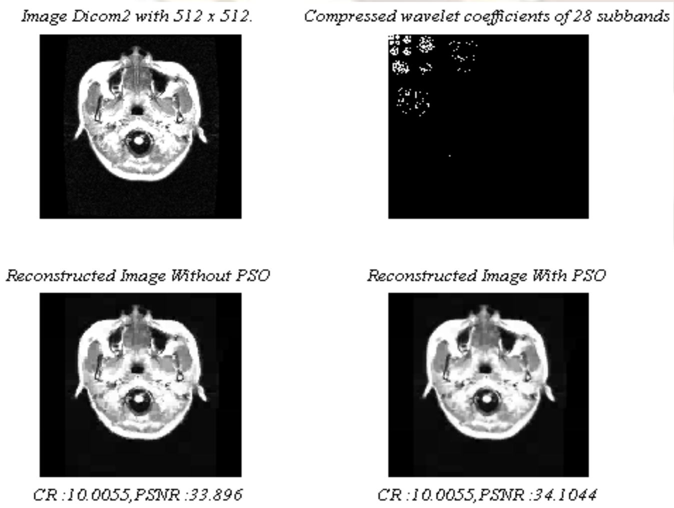

Fig. 7 Reconstucted image of Dicom2

VI. CONCLUSION

2D SPIHT algorithm can be used for image of any size. If the image size is large, time required for compression and reconstruction of the image is also more. The results show that the implementation of SPIHT algorithm using PSO obtained significant improvement in PSNR value than simple SPIHT algorithm. Execution time of the proposed algorithm may vary as system changes.

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