An Integrated and Efficient Approach for Enhanced Medical Image Compression using SPIHT and LZW Coding

G.Prabhakar, B.Ramasubramanian

Abstract— This paper proposes the efficient medical image compression as a combined approach of SPIHT and Lempel Ziv Welch coding. This novel method consists of steps such as splitting the image into bit planes and enhancing each bit plane image using the histogram equalization technique, and then it is decomposed by using 2D Fast wavelet transform and gets compressed by the Set Partitioning in Hierarchal tress algorithm. The SPIHT algorithm results in a large amount of seriate '0' situation. Hence finally it is again encoded with the effective LZW technique to improve the compression ratio and also to increase the picture to signal noise ratio. This combined approach is applied for both colour & gray scale images which also helps in increasing the quality of picture.

Index Terms— Dynamic histogram equalization, LZW, SPIHT, Redundancy, Bit Plane Slicing.

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1 INTRODUCTION

N OW a day's medical filed is urging towards the new technical innovation to analyses the diseases more accurately and precisely. Medical images obtained from the computerised tomography, X-rays, Magnetic Resonance Imaging and ultra sonography are needed to transfer from one location to another to discuss with the physicians. But the size of uncompressed images is so high. Therefore there is a need to compress those medical images before transmission to a distant place or due to the bandwidth or storage limitations. Applications such as Telemedicine are also an important reason to compress the medical images. Reduction in the time of transmission is also important during transmission of medical images. Compression is used to reduce the volume of information to be stored into storages or to reduce the communication bandwidth for its transmission over the networks. Compression coding schemes are of two types such as lossless and lossy compression. Lossless compression requires the original data to be reconstructed without any distortion after inverse operation. Lossy compression does not guarantee that the original and recovered data are identical, but it often provides better performance than lossless methods. This can be applied to voice, image, and video media applications because they do not necessarily require perfect recovery if the reconstructed quality is good enough for human perception [1][11][13]. Lossless data compression algorithms mainly include Lempel and Ziv (LZ) codes [6], Huffman codes [12], and others such as [23] and [11].

The LZW data compression algorithm is a powerful technique for lossless data compression that gives high compression efficiency for text as well as image data [22]. In this paper, we don't consider the Huffman code due to its inherent feature of being required to know a priori probability of the input symbols.

2 METHODS OF ENHANCEMENT & COMPRESSION

Histogram Equalisation technique can be applied in many fields such as in medical image processing, radar image processing, and sonar image processing. The basic idea of HE method is to re-map the gray levels of an image based on the image's gray levels cumulative density function. HE flattens and stretches the dynamic range of the resultant image histogram and it enhances the contrast of the image consequently and gives an overall contrast improvement [16]. The JPEG [15] compression algorithm can be lossless or lossy, and it was developed for both grey scale and colour images, however, this compression leads to some blocking artefacts near boundaries at high compression rate. Wavelet compression techniques (lossy compression) are now used to overcome this problem. The wavelet-based image compression standard is JPEG 2000 [16]. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. The wavelet-based compression engine combined with the concept of region-of-interest (ROI) was also included in JPEG2000 standard. But now it has advanced towards a research about exploring its applicability also for medical images [17-18]. Lossless compression guarantees that the original information can be exactly reproduced from the compressed data. The drawback of Huffman coding and arithmetic coding needs two scan, one scan to find the the probability and the other to code the text. The dictionary coding may be static or adaptive.

Said A. and Pearlman W.A [20] developed a new fast and efficient image coder based on Set Partitioning in Hierarchical Trees (SPIHT). This technique is the advanced wavelet techniques to provide better image quality than JPEG especially at high compression ratios. Megibow et. al. [19] examined the effects of various compression levels on the diagnostic interpretation of appendicitis on CT images. This study is based on the use of ROC methodology to assess observer performance using a lossy wavelet-based algorithm (Embedded Predictive Wavelet Image Coder) in 2002. Sudhakar et al [21] proposed a method for Image compression using coding of wavelet coefficients in 2006. In 2006, Sunil Kumar Pattanaik, K. K. Mahapatra, and G. Panda [9] introduced a novel lossless image compression using arithmetic modulo operation. Suneetha Agarwal et al [10] designed a model for compressing a medical using simple arithmetic operation in 2007. Yet still, traditional approach has its limitations: poor image quality and large computational time.
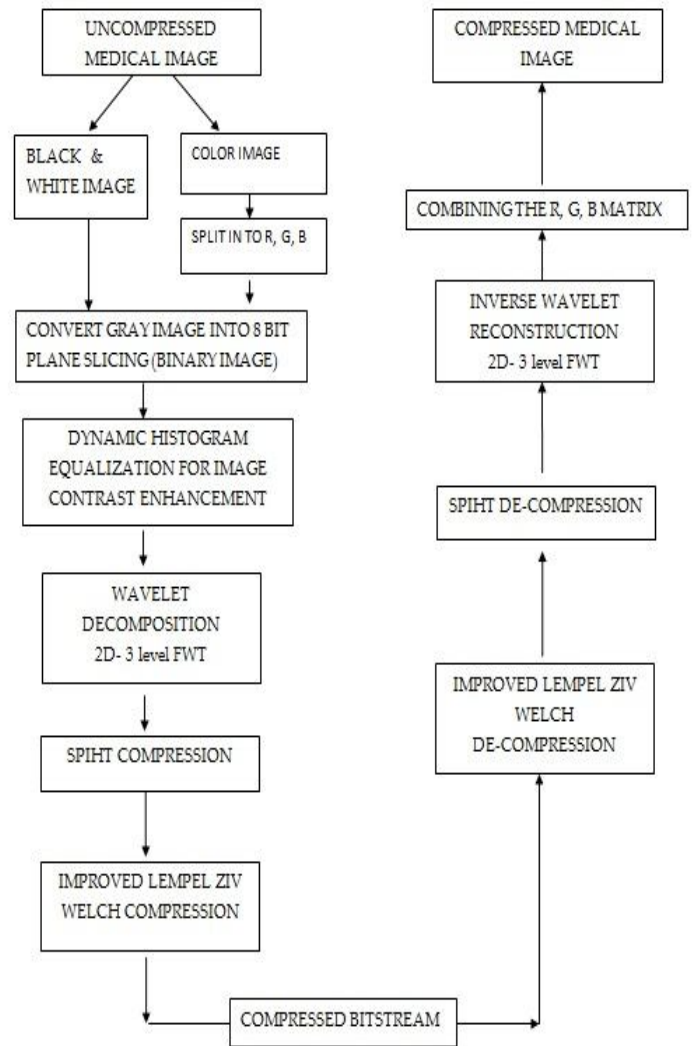
3 PROPOSED METHOD

Fig. 1. Proposed Block Diagram

3.1 Bit-Plane Slicing

Highlighting the contribution made to the total image appearance by specific bits. The Assumption here is that each pixel is represented by 8-bits and the image is composed of eight 1-bit planes. Plane (0) contains the least significant bit and plane (7) contains the most significant bit. The higher order bits only (top four) contain the majority visually significant data. The remaining bit planes contribute the more subtle details. It is useful for analyzing the relative importance played by each bit of the image [6] [13].

The first step is to slice the grayscale images into eight binary monochrome images by using bit-plane slicing. The colored images are represented by the tristimulus red, green, and blue signals. Each of which is gray scale image will be sliced into eight binary (monochrome) images by using bit-plane slicing. The separation of the input image can be done through color separation or through semantic separation [7][8]. The generated binary images contain redundant bits. Because the number of color decreases to 2 colors black (0) and white (1).

3.2 Dynamic Histogram Equalization for Image Contrast

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Enhancement

The main purpose of image enhancement is to bring out the detail that is hidden in an image or to increase the contrast in a low contrast image. Histogram equalisation is one of the well known image enhancement technique. Brightness preservation is the most important area of the image enhancement. Dynamic histogram equalization for image contrast enhancement employs a partitioning operation over the input histogram to chop it into some sub histograms so that they have no dominating component in them. When each sub-histogram goes through histogram equalisation technique and it is allowed to occupy a specified gray level range in the enhanced output image. Therefore the better overall contrast enhancement is attained by DHE with controlled dynamic range of gray levels and eliminating the possibility of the low histogram components being compressed that may cause some part of the image to have washed out appearance.

Algorithm Steps:

3.2.1 Histogram Partition

DHE partitions the histogram based on local minima. DHE applies first as a one-dimensional smoothing filter of size 1 x 3 on the histogram to get rid of insignificant minima. After making partitions (sub-histograms), it takes the portion of histogram that falls between two local minima (the first and the last non-zero histogram components are considered as minima). Mathematically, if m0, m1, …, mn are (n+1) gray levels (GL) that correspond to (n+1) local minima in the image histogram. The first sub-histogram will take the histogram components of the GL range [m0, m1] and the second one will take [m1+1, m2] and so on. This histogram partitioning helps toprevent someparts of the histogram from being dominated by others.

3.2.2 Gray Scale Allocation:

DHE allocates a particular range of GLs for each sub-histogram over which it may span in output image histogram. Decision is mainly based on the ratio of the span of gray levels that the sub-histograms occupy in the input image histogram. Thus the forward approach is Spani= mi-mi-1.

$$\text{Range}_i = \frac{\text{Span}_i}{\sum \text{span}_i} * (L-1)$$

Where, spani = dynamic GL range used by subhistogram i in input image. mi = ith local minima in the input image histogram. range i = dynamic gray level range for sub-histogram i in output image. The allocated order of gray levels for the sub-histograms in output image histogram are maintained in the same order as they are in the input image, if sub-histogram i is allocated the gray levels from [istart, iend], then istart = (i-1) end + 1 and iend= istart + rangei. For the first sub-histogram, j, jstart = r0.

3.2.3 Histogram Equalization:

Each sub-histogram goes through the process of conventional HE. But its span in the output image histogram is allowed to confine within the allocated GL range that is designated to it. Hence any part of the input image histogram is not allowed to dominate in HE.
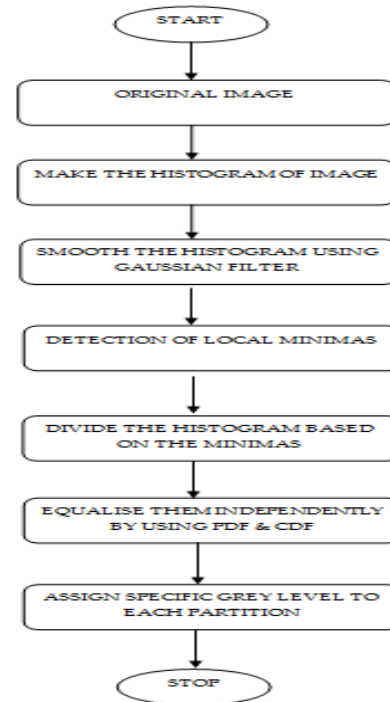

Fig. 2. Process Flow Chart of Histogram Equalisation

3.3 2D- Fast Wavelet Transform

Wavelet transform has a good localisation property in the frequency domain & time domain [6]. It is used in the image processing for the purpose of compression. The DWT decomposes the input image into four frequency subbands such as LL, LH, HL, and HH. The remaining subbands will have the edge information. This paper uses the 2D fast wavelet transform to decompose the medical image. This result in 4 quarter-size decomposition outputs such as the approximation and horizontal, vertical and diagonal details. A similar process was used to generate the two-scale FWT. But the input to the filter bank was changed to the quarter-size approximation subimage from the upper left hand corner of the image. Then the quarter size subimage was then replaced by the 4 quarter size decomposition results that were generated in the second filtering pass (now 1/16th of the size of the original image). Final image is the 3-scale FWT that resulted when the subimage from the upper left hand corner of the processed image. Each

pass through the filter bank produced 4 quarter size output images that were substituted for the input from which they were derived.

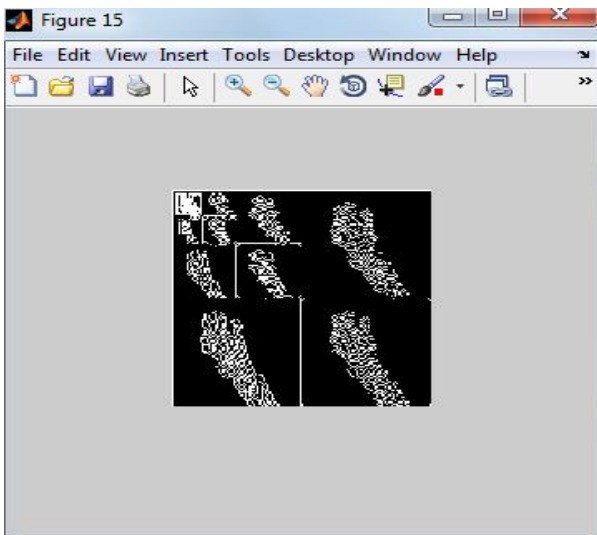Fig. 3. Three Level FWT Decomposed Structure

Fig. 4. Simulated 3 Levels FWT Decomposed MRI Leg Image

3.4 The SPIHT Algorithm

The most efficient algorithm in the area of image compression is the Set Partitioning in Hierarchical Trees (SPIHT) [20]. It uses a sub-band coder which produces a pyramid structure where an image is decomposed sequentially by applying power complementary low pass and high pass filters and then decimating the resulting images. These filters are one-dimensional filters that are applied in cascade (row then column) to an image whereby creating the four-way decomposition such as LL (low-pass then another low pass), LH (low pass then high pass), HL (high and low pass) and finally HH (high pass then another high pass). Such resulting LL version is again four-way decomposed. This procedure is repeated until the top of the pyramid is reached.
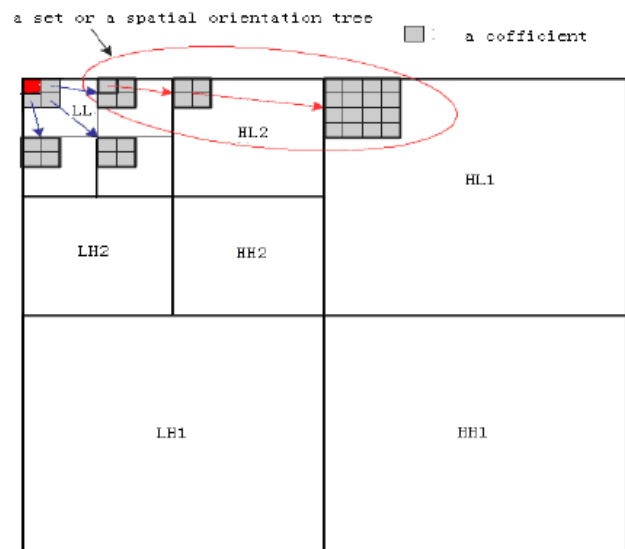

Fig. 5. FWT Decomposed with SPIHT Tree Descendants

There exists a spatial relationship among the coefficients at different levels and frequency sub-bands in the pyramid structure. A wavelet coefficient at location (i,j) in the pyramid representation has four direct descendants (off-springs) at locations:

$$O\ (i,j)=\{(2i,2j),\ (2i,2j+1),\ (2i+1,2j),\ (2i+1,2j+1)\} \quad (1)$$

And each of them recursively maintains a spatial similarity to its corresponding four off-spring. The structure of pyramid is commonly known as spatial orientation tree. The Figure shows the similarity among sub-bands within levels in the wavelet space If a given coefficient at location (i,j) is significant in magnitude then some of its descendants will also probably be significant in magnitude. It takes advantage of the spatial similarity present in the wavelet space to optimally find the location of the wavelet coefficient that is significant by means of a binary search algorithm.

The SPIHT algorithm sends the top coefficients in the pyramid structure using a progressive transmission method. This method allows obtaining a high quality version of the original image from the minimal amount of transmitted data. The pyramid wavelet coefficients are ordered by magnitude and then the most significant bits are transmitted first and then are followed by the next bit plane and so on until the lowest bit plane is reached. This progressive transmission can significantly reduce the Mean Square Error (MSE) distortion for every bit-plane sent.

To take advantage of the spatial relationship among the coefficients at different levels and frequency bands. This algorithm orders the wavelets coefficient according to the significance test defined as:

$$\max_{(i,j)\ \in\ \tau_m} |C_{i,j}| \geq 2^n$$

(2)

Where $C(i,j)$ is the wavelet coefficient at the nth bit plane, at location (i,j)of the τ_m subset of pixels. It represents a parent node and its descendants. Sometimes the result of the significance test is yes an S flag is set to 1 indicating that a particular test is significant. In some other time the answer is no, if such type of result came, the S flag is set to 0. It indicates that the particular coefficient is insignificant.

$$S_n(\tau) = \begin{cases} 1, & \max_{(i,j)\in\ \tau} \left|C_{i,j}\right| \geq 2^n \\ 0, & \text{otherwise} \end{cases}$$

(3)

Wavelets coefficients which are not significant at the nth bit-plane level may be significant at (n-1)th bit-plane or lower. This type of information is arranged according to its significance, in three separate lists such as list of insignificant sets (LIS), the list of insignificant pixels (LIP) and the list of significant pixels (LSP). In the decoder, the SPIHT algorithm replicates the same number of lists. The usage of basic principle is that if the execution path of any algorithm is defined by the results on its branching points and sometimes the encoder and decoder have the same sorting algorithm then the decoder can recover the ordering information easily.

The output bit stream of SPIHT encoding consists of a large number of seriate 0 situations. To avoid these redundancy bits we go for entrophy encoding. In this paper we proposed a LZW technique to decrease the redundancy bits present in the bitstream obtained from the SPIHT encoding or compressed bitstream.

3.5 LZW Compression

LZW is an error free compression approach and it addresses spatial redundancies in an image. It assigns fixed length code words to variable length sequences of source symbols. It requires no priori knowledge of probability of occurrence of symbols to be encoded. The additional compression reduced by LZW is due to removal of some of image's spatial redundancy. Lossless Dictionary based algorithms scan a image to find out the sequences of data which occurs more than once. Then these sequences are stored in a dictionary. LZW compression replaces strings of characters with single codes. The output of LZW algorithm can be of any arbitrary length and it should have more bits in it than a single character.

The first 256 codes (when using eight bit characters) are initially assigned to the standard character set. The left out codes are assigned to strings as the algorithm proceeds. The exemplary program runs with 12 bit codes [6]. LZW is a versatile technique. When the compression algorithm runs, a changing dictionary of the strings that have appeared in the text so far is maintained. Because the dictionary is preloaded with the 256 different codes that may appear in a byte, it is guaranteed that the entire input source may be converted into a series of dictionary indexes. If "A" and "B" are two strings that are held in the dictionary, the character sequence "AB" is converted into the index of "A" followed by the index of "B". "A" greedy string matching algorithm is used for scanning the input, so if

the first character of "B" is "x", then "Ax" cannot be an element of the dictionary. The versatile nature of the algorithm is due to that fact that "A" "x" is automatically added to the dictionary if "A" is matched but "A" "x" is not matched [13]. This means codes 0-255 refer to individual bytes, while codes 256-4095 refers to substrings. LZW compression is the best technique for reducing the size of files containing more repetitive data [3] [13]. None of the contents in the file are lost during or after compression due to this lossless technique. The reverse process of compression algorithm is the process of decompression algorithm.

In this coding, dictionary is dynamically created during the encoding process and it is not required to transmit the dictionary along with the encoded bit stream. The same dictionary will be dynamically created by the decoder during decompression process. Decompression is attained by reading & translating the codes through the dictionary. This avoids insertion of large string translation table with compression data.

3.6 Analysis of LZW Technique

Akimov, Kolesnikov and Franti [5] worked in lossless compression of color map images by context tree modelling. They propose an n-ary context tree model with incomplete tree structure for the lossless compression of color map images. The proposed n-ary incomplete context-tree-based algorithm outperforms the competitive algorithms (MCT, PWC) by 20%, and by 6% in the case of full context tree (CT) algorithm. The proposed algorithm has some disadvantages such as Apply on map images that have few colors and the compression method was successfully applied to raster map images up to 67 colors. Cui [15] presented a new LZW compression algorithm that increases the throughput and improves the compression ratio simultaneously. The key of the proposed algorithm is designing adaptive preprocessor which decreases correlation between original input data block. A parallel VLSI architecture for the new LZW compression processor is proposed. The architecture is based on a parallel dictionary set that has the capability of parallel searching technique. This testing mechanism consisting of six text sources and six image sources is applied to the proposed architecture. The hardware cost is the first disadvantage. Moreover; the algorithm tested in six images only, which have high redundancy and the compression ratio using standard LZW is greater than two. Horspool [9] have selected two ways of improving LZC (the UNIX compress command). One, a method of loading the dictionary at a faster rate, has not been used before. The other, a method to phase in increased lengths of binary numbers gradually, is not original but is not currently used with LZC. The Disadvantages the algorithm; apply on English text files and C source code file that have high redundancy.

4 EFFECTIVE LZW

In the compression process, the repeated string patterns are replaced by the index values. Since the dictionary is dynamically created during the encoding process, it is not required that the dictionary has to be transmitted along with the encod-

ed message. The relevant dictionary will be dynamically created by the decoder also during decoding process. The output image is attained by reading and translating the codes through the dictionary. Thus the algorithm is a versatile compression algorithm. The proposed method improves LZW compression in the following ways.

The input given to the LZW is obtained from the SPIHT compressed bit stream This is to initialize LZW dictionary with two characters "0" that represent zero values for black color and "1" that represent one value for white color in monochrome image instead of (256) characters of the underlying character set.

The final step is, each output code in the dictionary associates a frequency counter to phase in binary codes progressively using Adaptive Huffman algorithm to decrease the number of bits. This way a continuous adaption will be achieved and local variations will becompensated at run time. The first step in improve LZW compression read the image then check if color or gray scale image because the color image will be divided into three components: red, green and blue before dividing it to (8) binary images. For each of binary image 2D matrix will be converted to vector, and deal with the two values (0 and 1) as a character, then, standard LZW compression is applied. The resulted code of string using Adaptive Huffman Algorithm to achieve improvement from the binary code instead of decimal number that produced by the standard LZW algorithm.

5   QUALITY MEASURES

The Picture Quality of the reconstructed image is measured in terms of mean square error (MSE) and peaksignal to noise ratio (PSNR) ratio. The MSE is often called reconstruction error variance σ_q^2. The MSE between the original image f and the reconstructed image g at decoder is defined as:

$$\text{MSE} = \sigma_q^2 = \frac{1}{N} \sum_{j,k} (f[j,k] - g[j,k])^2 \qquad (4)$$

The peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance. The PSNR value between 2 images having eight bits per pixel expressed in terms of decibels is:

$$\text{PSNR} = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \qquad (5)$$

When PSNR is 40 dB or greater, then the original and the reconstructed images are virtually indistinguishable by human vision. The compression ratio is calculated as the size of input data divided by size of output data.

6   SIMULATION RESULTS

The proposed method was tested on the uncompressed medical images acquired from the physician. All the algorithms were implemented in MATLAB 7.9 on an Intel core i5 processor with 4GB RAM and windows7 64 bit operating system.

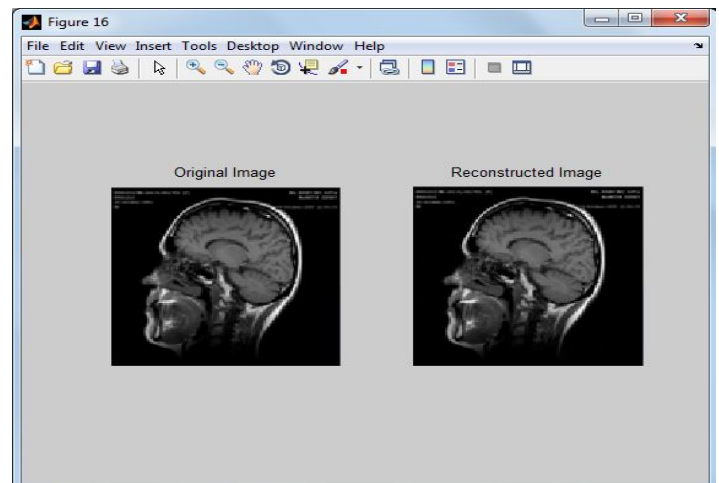Fig.6. Screen Shot of Simulated Output (MRI Leg Image)

Fig.7. Screen Shot of Simulated Output (MRI Brain Skull Image)

Fig.8. Screen Shot of Simulated Output (FMRI Brain Colour Image)

TABLE 1
COMPARISION CHART

IMAGES	COMPRESSION RATIO		PROPOSED METHOD PSNR VALUE (dB)
	EXISTING METHOD	PROPOSED METHOD	
MRI Leg Image	1.24	1.9	61.96
MRI Brain Skull Image	1.9	2.5	58.20
MRI Knee Image	1.8	2.23	59.13
FMRI Brain Colour Image	1.02	2.1	45.47

7 CONCLUSION & FUTURE WORKS

Thus the efficient and integrated approach for medical image compression is followed by several steps such as bit plane slicing, dynamic histogram equalization for contrast enhancement, FWT, SPIHT and finally applied with LZW coding to output the compressed image with good compression ratio and good PSNR value. The proposed method is comparatively better than the existing algorithms regarding PSNR & Compression ratio. In the future am going to apply this technique to OMAP processors to encode and decode the image in real time applications and also am trying to extend this work to compress the video.

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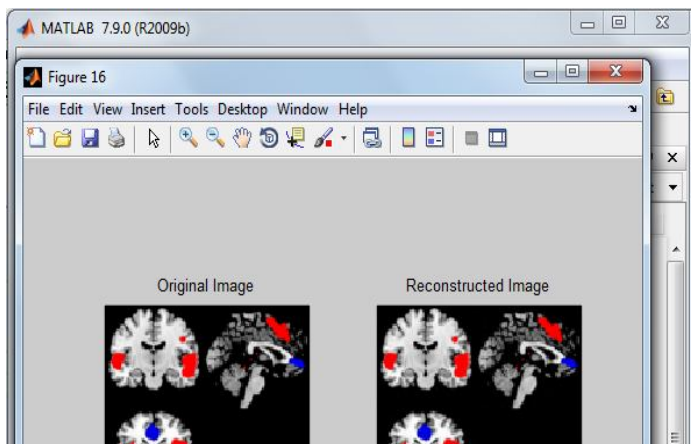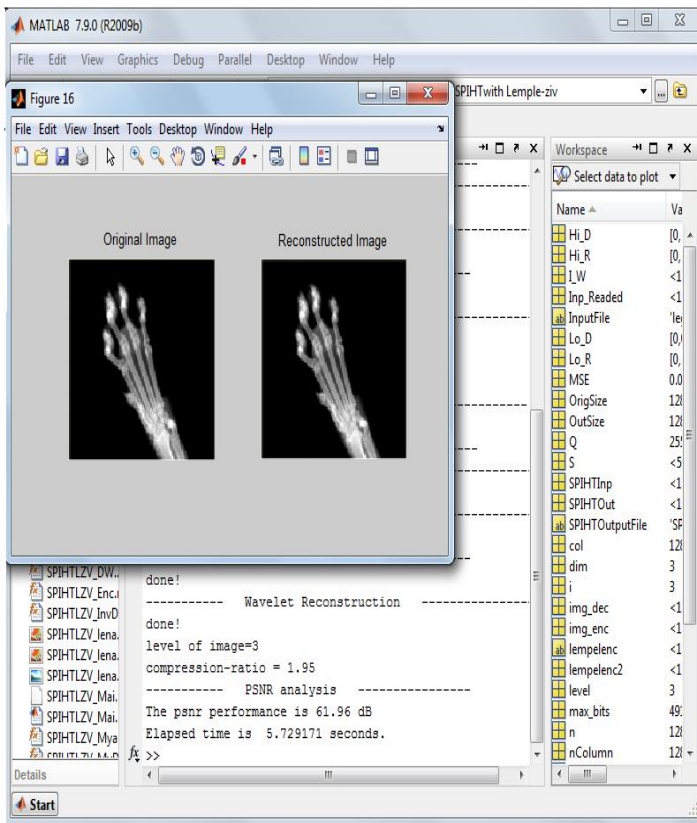
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