A New Wavelet Based Algorithm for Image Denoising and Compression

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Abstract

Considerable interest has arisen in recent years regarding wavelet as a new transform technique for both image and speech processing application. In this paper, an efficient wavelet based algorithm for image denoising and compression has been proposed. The algorithm consists of two functional units. An image Denoising technique has been used as pre-processing unit and the SPIHT algorithm has been used as a compression unit. The objective of adding a pre-processing unit is to restore a noisy image. Also this unit provides gain in compression ratio. Comparative results obtained show that the proposed algorithm supersedes various other algorithms given so far for noisy and noiseless images.

Keywords: Discrete Fourier Transform, Discrete Cosine Transform, Discrete Wavelet Transform, Hierarchical Trees.

1. Introduction

The introduction of Discrete Cosine Transform (DCT) in 1974 was an important achievement for the research community working on image compression. The DCT can be regarded as a discrete-time version of the Fourier-Cosine series [1]. Unlike DFT, DCT is real-valued and provides a better approximation of a signal with fewer coefficients. However, the input image needs to be divided into blocks using DCT in compression, and the correlation across the block boundaries is not eliminated. This results in noticeable and annoying 'blocking artifacts' particularly at low bit rates.

Wavelets are being used for image processing since 1980s when David Marr gave the first wavelet based image processing algorithm [2,3]. The first area in which wavelets were applied was image compression because it was similar to sub-band coding techniques used at that time. Various wavelet based algorithms have been for image compression, such as embedded zero wavelet, trellis coded quantization and set partitioning in hierarchical treestc. Also wavelets have been applied to image denoising applications recently. There are three main wavelet based techniques for image Denoising: VisuShrink, SureShrink and Bayes [2]. The first significant algorithm was Shapiro's EZW algorithm for image compression in 1993 [4]. EZW method is the first high level wavelet-based method that gives really good improvement from the compression point of view, compared to the DCT-based coding methods, mainly JPEG. It also introduces the Embedded-coding feature, important for some actual applications. It has been observed that wavelet based coding provides subsequent improvement in picture quality at higher compression ratios due to the better energy compaction property of wavelet transform. Wavelet-based coders for images have been implemented with both scalar quantization and vector quantization during recent years, with different interesting features; sometimes the quantization could be deployed by successive approximations. Another possible solution is the Trellis-coded quantization; this is an effective scheme for quantizing sources with moderate complexity [5]. All thc different quantization methods have a common problem that appears with coarse quantization: the distortion of the image structure. SPIHT technique given by Said and Pearlman outperformed both EZW and trellis coded quantization [6]. In SPIHT algorithm, crucial parts of the coding process are fundamentally different from EZW, because in EZW the arithmetic coding of the bitstream was essential to compress the ordering information. In SPIHT the subset partitioning is instead so effective and the significance information so compact that even binary uuencoded transmission achieves about the same or better performance than EZW. The SPIHT coding and decoding procedures are actually extremely fast, and they could be made even faster by omitting entropy coding with only a small loss in performance. SPIHT is a very efficient and popular algorithm that has been recently been applied to ECG signal compression . It has also been applied to audio coding [7]. It is being studied for application to speech compression. SPIHT algorithm has also been implemented on a real time DSP chip [8]. The new modified EZW algorithm given recently by Tanzeem Muzaffar and T.S. Choi achieves greater compression but at the cost of PSNR [9].

Wavelets have been applied to image denoising also and they have proven to be efficient than other filtering methods. There are three main techniques for wavelet based image-denoising: VisuShrink, SureShrink and BayesShrink. VisuShrink employs a universal threshold, proposed by Donoho and Johnstone [10]. The Universal threshold is derived under the constraint that with high probability the estimate should be at least as smooth as the signal. However, VisuShrink yields an overly smoothed estimate. The SureShrink employs a subband adaptive threshold where threshold value is different for each subband of wavelet coefficients [11]. In BayesShrink the threshold for each subband is determined by assuming a generalized Gaussian distribution [12]. It also provides compression using quantization schemes.The new proposed algorithm has been discussed in next section followed by the conclusion and future scope.

2. New Proposed Algorithm

The block diagram of encoding stage of proposed algorithm is as shown below. The encoding process is shown in Fig. 1(a) and decoding is shown in Fig. 1(b).

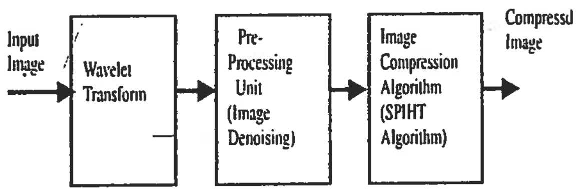

Figure 1 (a): Block Diagram of proposed algrithm. (Encoding)

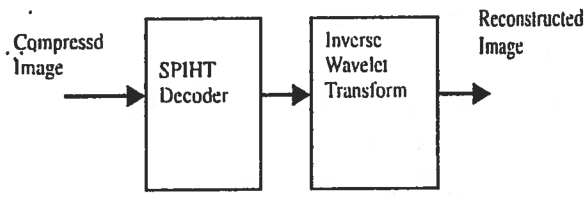

Figure 1 (b): Decoding stage.

In this algorithm, first of all, two dimensional discrete wavelet transform of the input image is performed. It is followed by a pre-processing unit, in which a threshold value based on image denoising technique is selected and applied using soft or hard or custom shrinkage function. Then SPIHT encoding is performed. In the decoding process there is a SPIHT decoder first. Then inverse wavelet transform is calculated to get the reconstructed image. Salient features of The proposed algorithm are given below:

- It uses Bayesian technique as a pre-processing unit, which filters noise of noisy images and acts like almost an all pass filter for noiseless images.

- The proposed algorithm is applicable to both noisy and noiseless images.

- The proposed algorithm provides variable compression ratio.

2.1 Pre-Processing Unit of the Proposed Algorithm

Image pre-processing unit consists of a wavelet based denoising technique. The idea is to restore a noisy image and enhance a noiseless to achieve compression. There are two subband adaptive techniques BayesShrink and SureShrink for image Denoising. BayesShrink has been chosen to be implemented and used as pre-processing unit in the proposed algorithm.

BayesShrink is a subband adaptive technique given by Chang and Vetterli [13]. In this technique, the noise variance σ^2 is estimated first. In some situations, it may be possible to measure σ^2 based on the information other than the corrupted image. If such is not the case, it is estimated from the subband HH_1 by robust mean estimator;

$$\sigma^2 = \text{Median}(|Y_{ij}|)/0.6745 \quad , Y_{ij} \text{ belongs to subband } HH_1 \qquad (1)$$

The observation model is Y = X + V; where X is the noiseless image, V is the random Gaussian Noise and Y is the noisy image. It should be noted that X and V independent of each other. Hence,

$$\sigma^2_y = \sigma^2_x + \sigma^2$$

where σ^2_y is the variance of Y. Since Y is modeled as zero mean σ^2_y can be found empirically by

$$\hat{\sigma}_y^2 = \frac{1}{n}\sum_{i,j=1}^{n} Y_{i,j}^2$$

where n x n is the size of subband under consideration. Thus threshold TB is given by:

$$\hat{T}_n(\hat{\sigma}_x) = \frac{\hat{\sigma}^2}{\hat{\sigma}_x} \qquad (4)$$

where

$$\hat{\sigma}_x = \sqrt{\max(\hat{\sigma}_Y^2 - \hat{\sigma}^2, 0)} \qquad (5)$$

Thus threshold TB is not only nearly optimal but also has intuitive appeal. The normalized threshold TB /σ, is inversely proportional to σx, the standard deviation of X and proportional to σ, the noise standard deviation. When σ/σx<<1, the signal is much stronger than noise , TB /σ is chosen to be small in order to preserve most of the signal and remove some of the noise; vice versa, when σ/σx>>1, the noise dominates and the normalized threshold is chosen to be large to remove the noise which has overwhelmed the signal. Thus this threshold choice adapts to both the signal and noise characteristics as reflected in the parameters σ and σ+.

2.2 Image compression unit of proposed algorithm

One of the most efficient algorithms in the area of image compression is Set Partitioning in Hierarchical Trees (SPIHT) [6]. This provides an alternative explanation of the principles of the operation of EZW and a new, and quite different, implementation based on set partitioning in hierarchical trees. This results in higher performance than EZW. SPIHT algorithm has been used as the compression unit in the proposed algorithm. In SPIHT algorithm, crucial parts of the coding process are fundamentally different from EZW, because in EZW the arithmetic coding of the bitstream was essential to compress the ordering information as conveyed by the results of the significance tests. In SPIHT the subset partitioning is instead so effective and the significance information so compact that even binary unencoded transmission achieves about the same or better performance than EZW. The SPIHT coding and decoding procedures are actually extremely fast, and they could be made even faster by omitting entropy coding with only a small loss in performance. However the utilization of arithmetic coding usually increases the PSNR by 0.3-0.6 dB. As for EZW, the transmitted code, and so the compressed image file, is completely embedded so the file could be truncated at various points to obtain a series of reconstructed images at lower rates. EZW could not give its best performance with a single embedded file, because it requires for each rate the optimization of some parameters. SPIHT solves this problem by changing the transmission priority and yields, with one embedded file, its top performance for all rates.

There exists a spatial relationship among the wavelet coefficients at location (i , j) in the pyramid structure after wavelet decomposition. A wavelet coefficient at location (i , j) in the pyramid representation has four direct descendents (off-springs) at locations:

$$O(i, j) = \{(2i,2j), (2i,2j+1),(2i+1,2j),(2i+1,2j+1)\} \quad (6)$$

And each of them recursively maintains a spatial similarity to its corresponding four offsprings. If a given coefficient at location (i , j) is significant in magnitude then some of its descendents will also probably be significant in magnitude. The SPIHT algorithm takes advantage of the spatial similarity present in the wavelet space to optimally find the location of wavelet coefficients that are significant by means of a binary search algorithm.

The SPIHT algorithm sends the top coefficients in the pyramid structure using a progressive transmission scheme. From the original image, defined by a set of N pixel values p_{ij} where *i* and *j* are the coordinates of the pixel, a DWT results in a set of N transform coefficients c_{ij}, each one represented by a small number of bits, 8 or 16, that can be treated as an integer. In a progressive transmission scheme the decoder initially sets the reconstruction vector of coefficients to zero and updates it according to the coded message; after receiving the approximate or exact value of some coefficients the decoder can obtain a reconstructed image p'_{ij}. The main objective in a progressive transmission scheme is to select the most important information to be transmitted first, using the Mean-Square Error distortion measure on p_{ij} or, what in this case is the same, on c_{ij}. If the exact value of c_{ij} is sent to the decoder, the MSE decrease by $| c_{ij} |^2 / N$; for this reason the coefficients with larger magnitude should be transmitted first. The information in the value of $| c_{ij} |$ can be ranked according to its binary representation, so the most significant bits should be transmitted first. The progressive transmission scheme present in SPIHT incorporates these two concepts:

- Ordering the coefficients by magnitude
- Transmitting the most significant bits first.

The ordering information makes the uniform scalar quantization method very efficient. This scheme is a method that allows obtaining a high quality version of the 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, followed by the next bit plane and so on until the lowest bit plane is reached.

3. Implementation and Results

The new proposed algorithm has been implemented in Matlab 6.0 using two toolboxes: Wavelet toolbox and Image Processing toolbox. It has been tested with different levels of wavelet decomposition and on different wavelets. Table 1 shows Peak Signal to Noise Ratio (PSNR) values for different bits per pixel (bpp) at different levels for proposed algorithm for a standard noiseless Lena image. The wavelet used is db4 and shrinkage rule chosen is soft.

Table 1: PSNR values for different bpp forproposed algorithm

Wavelet = db4					
A Standard Noiseless Lena Image					
bpp	PSNR in decibels at level 3	PSNR in decibels at level 4	PSNR in decibels at level 5	PSNR in decibels at level 6	PSNR in decibels at level 7
0.05	18.5617	26.3888	29.234	29.2249	29.2258
0.08	23.9382	29.3031	29.234	29.2249	29.2258
0.1	26.6321	29.3031	32.4401	32.4376	32.4367
0.15	29.525	32.4669	32.4401	32.4376	32.4367
0.2	32.5857	32.4669	35.585	35.5846	35.5848
0.3	35.6535	35.5925	38.585	38.5846	35.5848
0.4	35.6535	38.616	38.6134	38.6133	38.613
0.5	38.6429	38.616	38.6134	38.6133	38.613
0.6	38.6428	38.616	38.6134	38.6133	38.613
0.7	38.6429	38.616	38.6134	38.6133	38.613

Fig 2: A standard Noiseless Image Lena.tif

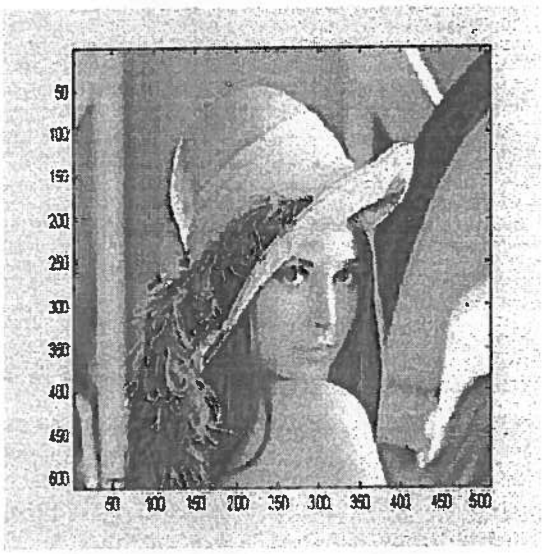

Fig. 3: Reconstructed image with proposed algorithm at 0.2 bpp

3.1 Comparative Evaluation

The best results have been obtained with haar wavelet and sym4 for proposed algorithm for noiseless images. Wavelets of Symlet family have been found to give better performance than daubechies and biorthogonal wavelets. Fig. 2 shows a standard 512 X 512 pixel test image Lena.tif. Fig. 3 shows the reconstructed image with proposed algorithm at 0.2 bpp i.e. at compression ratio of 40:1. The PSNR vs. bpp graph (Fig. 4) shows that proposed algorithm supercede various other algorithms for noiseless images.

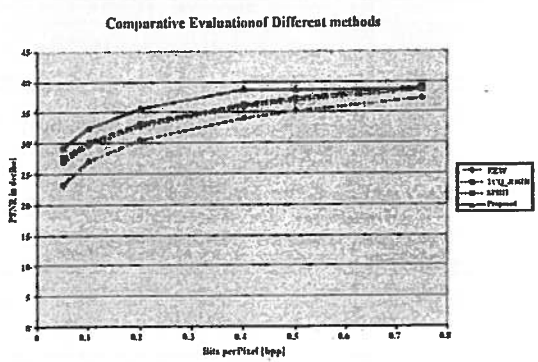

Fig. 4.: Comparative Evaluation of different algorithms

3.2 Implementation Results for Noisy images

The proposed algorithm has also been tested on noisy images corrupted by Gaussian Noise of standard deviation ó. MSE value is minimum while using db4 wavelet and also it can be seen that, it performs better than Bayes+ Comp. Method given by Chang [12] Fig. 5 shows graphical evaluation of two methods.

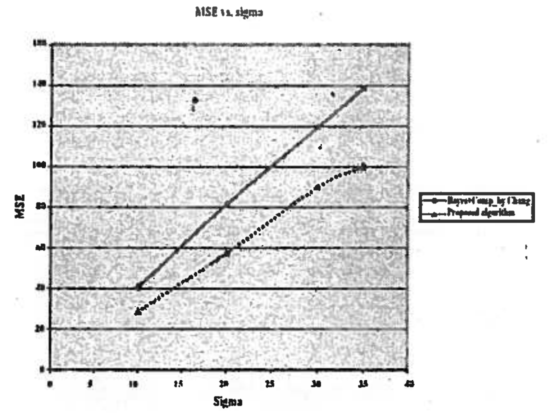

Fig 5: Comparative Evaluation for the preposedalgorithm forNoisyImages

4. Conclusion

In this paper, an efficient algorithm for image restoration and compression has been proposed. The algorithm is applicable to both noisy and noiseless gray scale images. It has been tested on some standard gray scale test images. The comparative results show that algorithm supercede various other algorithms given so far for noisy and noiseless images. The optimum numbers of decomposition levels of wavelet decomposition are 4 and 5; and recommended wavelet is sym4. For Noiseless images, the best results have been obtained with haar wavelet and sym4 for noiseless images. For Noisy images, best results have been obtained by using db4 wavelet. Wavelets of symlets family also show comparable performance. The proposed algorithm also supercedes the method Bayes+ Comp. given by Chang. It has been observed that for higher compression ratios, the execution time is less.

5. Future Scope

The algorithm can be extended for application to colour images. In this work a few wavelets have been taken. Different wavelets can be tried with the proposed algorithm and results can be found. This algorithm can be very valuable in image transmission via the Internet, because the compression / decompression execution time decreases as the compression ratio gets higher allowing for rough-scale image previews before the image is fully downloaded. The proposed algorithm can be coupled with different features like :

1) The possibility to extract objects considered interesting for recording and storage, with techniques of edge detection, object detection and pattern recognition.

2) The possibility to zoom into the image, obtaining more detailed images of the interesting objects or selecting a prescribed area of the image, and to zoom out, obtaining panoramic images of the whole area.

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