Volume 2, Issue 2, February 2012 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Lossless Image Compression Algorithm For Transmitting Over Low Bandwidth Line

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Abstract-In this paper to decrease the communication bandwidth and save the transmitting power in the wireless endoscopy capsule, this paper presents a new near-lossless image compression algorithm based on the Bayer format image suitable for hardware design. This algorithm can provide low average compression rate (2.12 bits/pixel) with high image quality (larger than 53.11 dB) for endoscopic images. Especially, it has low complexity hardware overhead (only two line buffers) and supports real-time compressing. In addition, the algorithm can provide lossless compression for the region of interest (ROI) and high-quality compression for other regions. The ROI can be selected arbitrarily by varying ROI parameters. The proposed technique produces a bit stream that results in a progressive and ultimately lossless reconstruction of an image similar to what one can obtain with a reversible wavelet codec. In addition, the proposed scheme provides near-lossless reconstruction with respect to a given bound after decoding of each layer of the successively refundable bit stream. We formulate the image data compression problem as one of successively refining the probability density function (pdf) estimate of each pixel. Experimental results for both lossless and near-lossless cases indicate that the proposed compression scheme, that innovatively combines lossless, near-lossless and progressive coding attributes, gives competitive performance in comparison to state-of-the-art compression schemes.

Key word: Image compression, Image quality, Image compressor configuration Huffman coding

I. INTRODUCTION

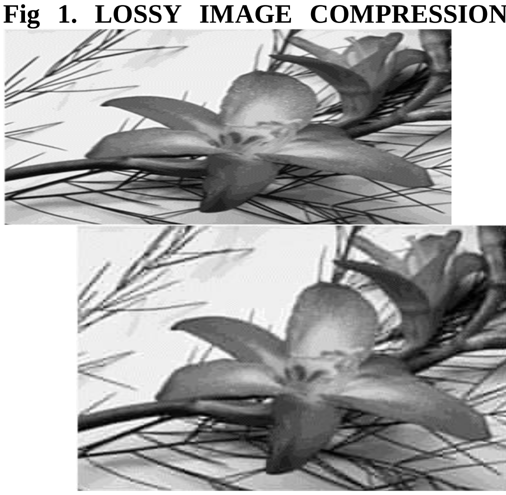
Lossless or reversible compression refers to compression techniques in which the reconstructed data exactly matches the original. Near-lossless compression denotes compression methods, which give quantitative bounds on the nature of the loss that is introduced. Such compression techniques provide the guarantee that no pixel difference between the original and the compressed image is above a given value. Both lossless and near-lossless compression find potential applications in remote sensing, medical and space imaging, and multispectral image archiving. In these applications the volume of the data would call for lossy compression for practical storage or transmission. However, the necessity to preserve the validity and precision of data for subsequent recognized diagnosis operations, forensic analysis, as well as scientific or clinical measurements, often imposes strict constraints on the reconstruction error. In such situations near-lossless compression becomes a viable solution, as, on the one hand, it provides significantly higher compression gains lossless algorithms, and on the other hand it provides guaranteed bounds on the nature of loss introduced by compression.

Another way to deal with the lossy-lossless dilemma faced in applications such as medical imaging and remote sensing is to use a successively refundable compression technique that provides a bit stream that leads to a progressive reconstruction of the image. Using wavelets, for example, one can obtain an embedded bit stream from which various levels of rate and distortion can be obtained. In fact with reversible integer wavelets, one gets a progressive reconstruction capability all the way to lossless recovery of the original. Such techniques have been explored for potential use in tele-radiology where a physician typically requests portions of an image at increased quality (including lossless reconstruction) while accepting initial renderings and unimportant portions at lower quality, and thus reducing the overall bandwidth requirements. In fact, the new still image compression standard, JPEG 2000, provides such features.

1.1 METHODS FOR LOSSY COMPRESSION

Reducing the color space the most common colors in the image. The selected colors are specified in the color palette in the header of the compressed image. Each pixel just references the index of a color in the color palette. This method can be combined with dithering to avoid pasteurizations. Chrome sub sampling. This takes advantage of the fact that the human eye perceives spatial changes of brightness more sharply than those of color, by averaging or dropping some of the chrominance information in the image. Transform coding. This is the most commonly used method. A Fourier-related transform such as DCT or the wavelet transform are applied, followed by quantization and entropy coding.

Fig 1. LOSSY IMAGE COMPRESSIONRESULT



Original Image 257Kb Compressed Image 256Kb

1.2. Image Compression

Digital Image compression addresses the problem of reducing the amount of data required to represent a digital image. The underlying basis of the reduction process is removal of redundant data. From the mathematical viewpoint, this amounts to transforming a 2D pixel array into a statically uncorrelated data set. The data redundancy is not an abstract concept but a mathematically quantifiable entity. If n1 and n2 denote the number of information-carrying units in two data sets that represent the same information, the relative data redundancy R_D of the first data set (the one characterized by n1) can be defined as,

$$R_D = 1 - \frac{1}{C_R}$$

Where C_R called as compression ratio. It is defined as

$$C_R = \frac{n1}{n2}$$

In image compression, three basic data redundancies can be identified and exploited: redundancy. Image compression is achieved when one or more of these redundancies are reduced or eliminated.

The image compression is mainly used for image transmission and storage. Image transmission applications are in broadcast television; remote sensing via satellite, air-craft, radar, or sonar; teleconferencing; computer communications; and facsimile transmission. Image storage is required most commonly for educational and business documents, medical images that arise in computer tomography (CT), magnetic resonance imaging (MRI) and digital radiology, motion pictures, satellite images, weather maps, geological surveys, and so on.

II. PROPOSED SYSTEM

2.1. SIGNIFICANCE OF THIS WORK

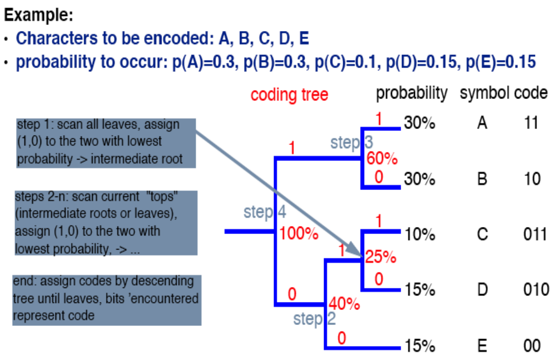
In this project, Image compression based on adaptive wavelet decomposition is presented. Adaptive wavelet decomposition is very useful in various applications, such as image analysis, compression, and feature extraction and denoising. For such task, it is important that multiresolution representations take into account the characteristics of the underlying signal and do leave intact important signal characteristics, such as sharp transitions, edges, singularities, and other region of interests. The adaptive lifting technique includes an adaptive update lifting and fixed prediction lifting step. The adaptively hereof consists that, the system can choose different update filters in two ways; i) the choice is triggered by combining the different norms, ii) Based on the arbitrary Threshold.

This image compression based on adaptive wavelet decomposition is implemented using MATLAB programs, and the results compared with Non-adaptive (‘Harr’) decomposition.

III. . HUFFMAN CODING

Huffman coding is based on the frequency of occurrence of a data item (pixel in images). The principle is to use a lower number of bits to encode the data that occurs more frequently. Codes are stored in a Code Book which may be constructed for each image or a set of images. In all cases the code book plus encoded data must be transmitted to enable decoding.

Decoding for the above two algorithms is trivial as long as the coding table (the statistics) is sent before the data. (There is a bit overhead for sending this, negligible if the data file is big.) Unique Prefix Property. No code is a prefix to any other code (all symbols are at the leaf nodes) great for decoder, unambiguous. If prior statistics are available and accurate, then Huffman coding is very good.



IV. WAVELET APPROACH

Storage constrains and bandwidth limitations in communication systems have necessitated the search for efficient image compression techniques. For real time video and multimedia applications where a reasonable approximation to the original signal can be tolerated, lossy compression is used. In the recent past, wavelet based image compression schemes have gained wide popularity. The characteristics of the wavelet transform provide compression results that outperform other transform techniques such as discrete cosine transform (DCT). Consequently, the JPEG2000 compression standard and FBI fingerprint compression system have adopted a wavelet approach to image compression.

The wavelet coding techniques is based on the idea that the co-efficient of a transform that decor relates the pixels of an image can be coded more efficiently than the original pixels themselves. If the transform's basis functions in this case wavelet- packs most of the important visual information into small number of co-efficient, the remaining co-efficient can be coarsely quantized or truncated to zero with little image distortion.

The still image compression, modern DWT based coders have outperformed DCT based coders providing higher compression ratio and more peak signal to noise ratio (PSNR) due to the wavelet transforms multi-resolution and energy compaction properties and the ability to handle signals.

The basis set of wavelets is generated from the mother or basic wavelet is defined as:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad ; a, b \in \Re \text{ and } a>0 \quad \text{--- (1)}$$

5.1. 1-D Continuous wavelet transforms

The 1-D continuous wavelet transform is given by:

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \qquad \text{------------ (2)}$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)db\frac{da}{a^2} \qquad \text{----- (3)}$$

$$\text{Where } C = \int_{-\infty}^{\infty}\frac{|\psi\omega)|^2}{\omega}d\omega < \infty$$

$\Psi(\omega)$ is the Fourier transform of the mother wavelet $\Psi(t)$. C is required to be finite, which leads to one of the required properties of a mother wavelet. Since C must be finite, then $\Psi(0) = 0$ to avoid a singularity in the integral, and thus the $\Psi(t)$ must have zero mean. This condition can be stated as $\int_{-\infty}^{\infty}\psi(t)dt = 0$ and known as the admissibility condition.

5.2. 1-D Discrete wavelet transforms

The discrete wavelets transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discredit the wavelet parameters, which reduce the previously continuous basis set of wavelets to a discrete and orthogonal / orthonormal set of basis wavelets.

$\psi_{m,n}(t) = 2^{m/2}\,\psi(2^m t - n)$; m, n $\in$ Z such that $-\infty <$ m, n $< \infty$ -------- (4)

The 1-D DWT is given as the inner product of the signal x(t) being transformed with each of the discrete basis functions.

$W_{m,n} = <$ x(t), $\psi_{m,n}(t) >$; m, n $\in$ Z ------------ (5)

The 1-D inverse DWT is given as:

$x(t) = \sum_m \sum_n W_{m,n}\psi_{m,n}(t)$; m, n $\in$ Z ------------- (6)

5.3. 2-D wavelet transform

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in Figure 1(c), the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

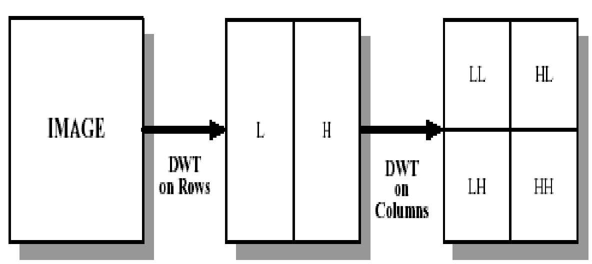


Figure 2. Block Diagram of DWT (a)Original Image (b) Output image after the 1-D applied on Row input (c) Output image after the second 1-D applied on row input

(a) (b) (c)

Figure 3. DWT for Lena image (a)Original Image (b) Output image after the 1-D applied on column input (c) Output image after the second 1-D applied on row input

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of Fig. 3(b), respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image is shown in Fig.2(c).

V. ADAPTIVENESS BASED ON COMBINING NORMS

The PSNR value for different bit rates and different decomposition levels of the sharp edge preserved images and image without sharp edge as shown in table III.

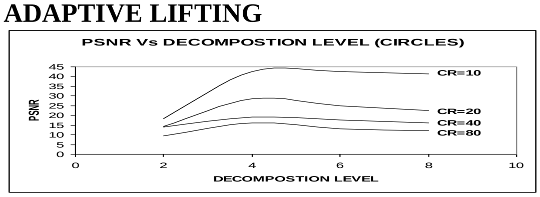
TABLE I. PEAK SIGNAL TO NOISE RATIO IMAGE: 2. Circles. raw (256 X 256)

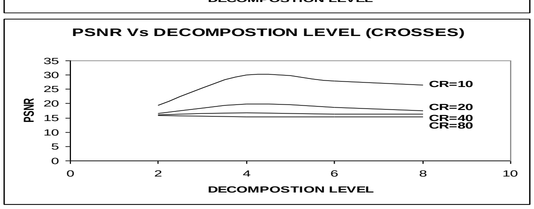
Decom Level / Bitrate	1	2	3	4	5	6	7	8
0.1	5.9648	9.4727	13.3799	16.0149	15.2286	13.0027	12.8011	12.2103
0.2	6.8893	14.0965	17.0302	19.2020	19.3243	17.5740	17.6823	16.0277
0.3	8.2989	14.1348	17.8058	21.3807	20.0473	18.3804	18.4453	16.5872
0.4	9.6339	14.2176	21.9700	28.5182	26.7580	25.0202	24.0116	22.5015
0.5	11.8215	14.2545	22.2816	31.9134	31.7764	30.6664	29.9021	27.5289
0.6	14.6586	17.8378	30.2719	33.8180	34.5754	33.7578	33.0740	30.4916
0.7	14.6649	18.0936	31.2636	40.8679	38.4586	37.0913	36.1441	33.6640
0.8	14.7378	18.2896	35.1514	42.5870	42.3540	42.4427	41.6846	41.4874
0.9	14.7601	18.3902	35.3632	43.4222	48.4813	47.8383	47.1766	46.7161
1.0	14.7759	22.1046	43.5108	49.7174	50.1181	49.8951	50.2574	48.8571

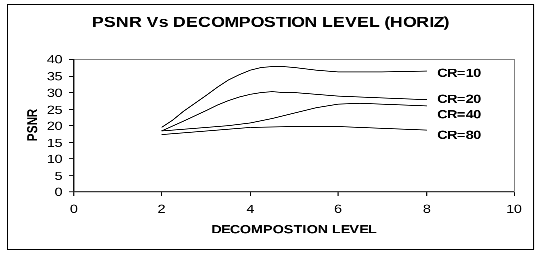
IMAGE: 3. Crosses. raw (256 X 256)

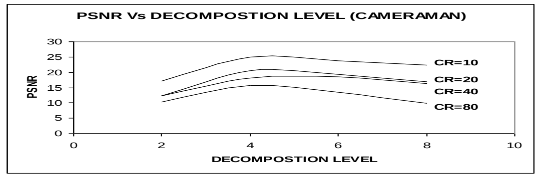
Decom Level / Bit rate	1	2	3	4	5	6	7	8
0.1	15.4471	15.9084	15.1838	15.4329	15.5005	15.4890	15.4829	15.4829
0.2	16.1007	15.9947	16.0367	16.8527	16.3261	16.3264	16.3449	16.3299
0.3	16.8185	16.3687	17.8731	17.4792	16.7924	16.8536	16.8487	16.8467
0.4	17.5390	16.6628	18.5061	19.9660	19.4335	18.7336	18.1260	17.6089
0.5	18.0404	17.1515	20.0880	20.6281	20.1048	19.3495	18.6396	18.1828
0.6	18.1029	18.1238	21.0634	20.8342	20.3102	19.5326	18.7887	18.2921
0.7	18.3167	18.8096	21.2205	29.4664	27.9392	27.7636	25.0620	26.4316
0.8	18.8289	19.3588	25.8184	30.0390	28.1793	27.9918	25.1962	26.5652
0.9	19.3566	19.7278	30.7431	33.1359	32.5961	32.2085	31.0758	29.5372
1.0	19.5210	20.4194	30.7660	33.6842	32.9818	32.4619	31.3449	29.6743

7.1. IMAGE COMPRESSION BASED ON ADAPTIVE LIFTING









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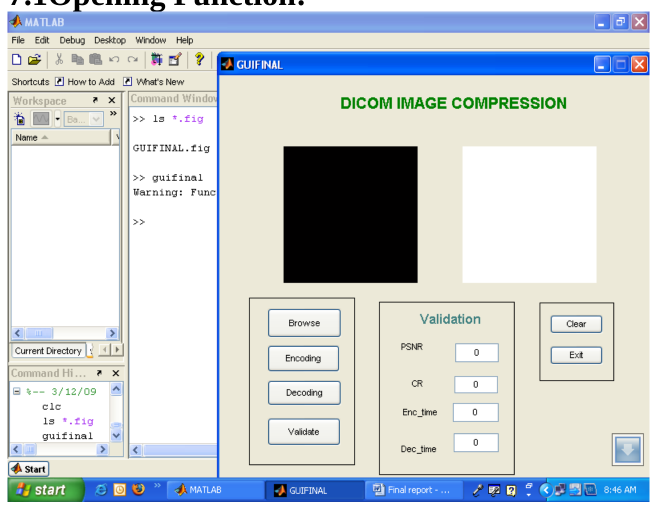
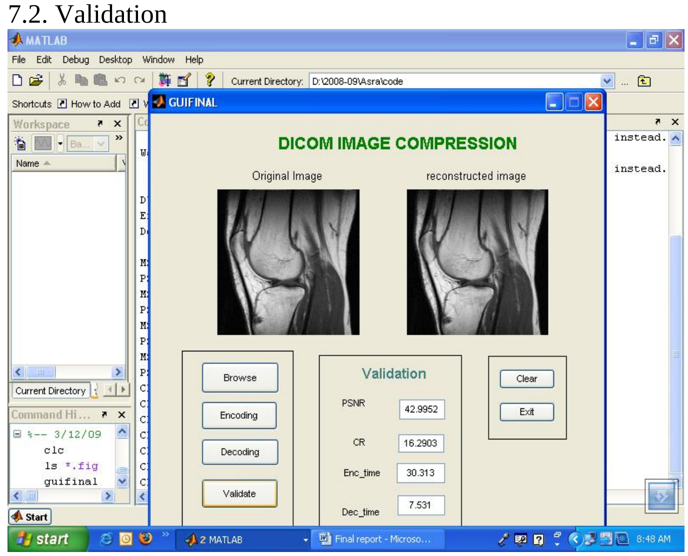
VI. EXPERIMENTAL SIMULATION RESULTS

7.1Opening Function:



7.2. Validation



VII. . CONCLUSION

This work has shown that the compression of image can be improved by considering spectral and temporal correlations as well as spatial redundancy. The efficiency of temporal prediction was found to be highly dependent on individual image sequences. Given the results from earlier work that found temporal prediction to be more useful for image, we can conclude that the relatively poor performance of temporal prediction, for some sequences, is due to spectral prediction being more efficient than temporal. Another Conclusions and Future Work finding from this work is that the extra compression available from image can be achieved without necessitating a large increase in decoder complexity. Indeed the presented scheme has a decoder that is less complex than many lossless image compression decoders, due mainly to the use of forward rather than backward adaptation. The results of adaptive and Non-adaptive based image compression are compared. From the results the adaptive wavelet decomposition works better than non-adaptive (Haar) wavelet decomposition. Future work aims at extending this frame work for color images, video compressions, and Denoising applications.

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