RESEARCH PAPER | Engineering | Volume : 3 | Issue : 7 | July 2013 | ISSN - 2249-555X

Still Image Compression by Using New Wavelet Bi-Orthogonal Filter Coefficients

KEYWORDS: Image compression, Wavelet Transform, Bi orthogonal wavelet, Mean Square Error

SWETHA K P

597,MUDDANNA GARDEN ,BEHIND RAILWAY STATION , KENGERI,BANGALORE -60

ABSTRACT *In this paper new wavelet bi-orthogonal filter coefficients for wavelet decomposition and reconstruction of image are introduced for better image compression.*

Digital imaging has had an enormous impact on, scientific and industrial applications. Uncompressed images require considerable storage capacity and transmission bandwidth. The solution to this problem is to compress an image for desired application.

Since last two decade the discrete wavelet transform (DWT) has witnessed great success for image compression. The proposed work reviews the various wavelet based image compression techniques. New wavelet bi-orthogonal filter coefficients for wavelet decomposition and reconstruction of image are introduced for better image compression, when the image is compressed by using the new proposed filter coefficient in DWT-SPIHT schema then it performs better than DWT-SPIHT schema with wavelet 9/7 filter and wavelet 5/3 filter. The compression result by using these filter coefficient show that the reconstructed image has higher Peak signal-to-noise ratio and low Mean Square Error than wavelet 9/7 filter and wavelet 5/3 filter.

1. INTRODUCTION

In the last decade, there has been a lot of technological transformation in the way we communicate. This transformation includes the ever present, ever growing internet, the explosive development in mobile communication and ever increasing importance of video communication. Data Compression is one of the technologies for each of the aspect of this multimedia revolution. Cellular phones would not be able to provide communication with increasing clarity without data compression. Data compression is art and science of representing information in compact form.

Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available technologies. In a distributed environment large image files remain a major bottleneck within systems. Image Compression is an important component of the solutions available for creating image file sizes of manageable and transmittable dimensions. Platform portability and performance are important in the selection of the compression/decompression technique to be employed.

There are two types of algorithms that are used in data compression. . These algorithms fall into two broad types, lossless algorithms and lossy algorithms. A lossless algorithm reproduces the original exactly. A lossy algorithm, as its name implies, loses some data. Data loss may be unacceptable in many applications. In image compression, for example, the exact reconstructed value of each sample of the image is not necessary. Depending on the quality required of the reconstructed image, varying amounts of loss of information can be accepted.

For image compression, loss of some information is acceptable. Among all of the above lossy compression methods, vector quantization requires many computational resources for large vectors; fractal compression is time consuming for coding; predictive coding has inferior compression ratio and worse reconstructed image quality than those of transform based coding. So, transform based compression methods are generally best for image compression.

For transform based compression, JPEG compression schemes based on DCT (Discrete Cosine Transform) have some advantages such as simplicity, satisfactory performance, and availability of special purpose hardware for implementation. However, because the input image is blocked, correlation across the block boundaries cannot be eliminated and this results in noticeable and annoying "blocking artifacts"' particularly at low bit rate.

Over the past ten years, the wavelet transform has been widely used in signal processing research, particularly, in image compression. In many applications, wavelet-based schemes achieve better performance than other coding schemes like the one based on DCT. Since there is no need to block the input image and its basis functions have variable length, wavelet based coding schemes can avoid blocking artifacts. Wavelet based coding also facilitates progressive transmission of images.

2. ERROR METRICS

Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$\text{MSE} = \frac{1}{MN}\sum_{Y=1}^{M}\sum_{X=1}^{N}[I(x,y) - I'(x,y)]^2$$

$$\text{PSNR} = 20 * \log10\ (255 / \text{sqrt(MSE)})$$

where I(x,y) is the original image, I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognise that it is a better one. [6]

3. PREVIOUS WORKS

Over the past decade many image compression techniques have been developed. Among those Wavelet transform has

Volume : 3 | Issue : 7 | July 2013 | ISSN - 2249-555X

emerged as a very powerful tool for data compression It provides a vehicle for image processing applications, because it has ability of taking into account Human Visual System (HVS) characteristics, good energy compaction capabilities, and under transmission, decoding, and also it is more robust under transmission & decoding error, which results in a high compression ratio.

Embedded zero-tree wavelet (EZW) coding introduced by J.M. Shapiro [7], is a simple and effective technique for image compression. This method is based on three steps. First, the image is partial ordering of the transformed image elements by magnitude, with transmission of order by a subset partitioning algorithm. Second, the method arranges the bit plane transmission of the refinement bits. Third, it exploits the self-similarity of the image wavelet transform across different scales. Amir Said and William Pearlman [8] proposed a new and different implementation providing even better performance than the EZW. This method is called Set Partitioning in Hierarchical Trees (SPIHT); the core of the Embedded Image Coding using Zero Blocks of Sub-band / Wavelet Coefficients and Context Modelling (EZBC) [9] approach is also based on the idea of hierarchical set partitioning on bitplanes for individual sub-band. EZMC is shown to be superior to the Embedded Block Coding with Optimized Truncation (EBCOT) [10].

Jurate Puniene et al [11] presented compression techniques to improve the ultrasound and angio images by applying the wavelet transform outperforms the discrete cosine transform. Hyung Jun Kim and Li, C, C [12] presented a fast image compressor using biorthogonal wavelet transform which gives high computational speed and excellent compression performance. Angelidis, P, A [13] presented a technique for MR image compression based on a transform coding scheme using the wavelet transform and vector quantization.

Chandandeep Kaur, Sumit Budhiraj [14], surveys various improvements in SPIHT in certain fields as speed, redundancy, quality, error resilience, complexity, memory requirement and compression ratio.

The popular 9/7 filter is one of the bi-orthogonal wavelet filters proposed by Cohen, Daubechies and Feauveau [15] in 1992. This filter has been used as the default filter in the irreversible wavelet transform of the upcoming new still image compression standard PEG2000 [16]. The implementation of the wavelet transform with the 9/7 filter has two modes: convolution-based implementation [17] and lifting-based implementation (LBI) [18]. The former has a higher commutation cost than the latter. It is reported that the JPEG200 decoder takes approximately 34 times longer than the JPEG encoder [15].

4. METHODOLOGY

This work introduces new wavelet based bi-orthogonal filter coefficient that can give better result in case of PSNR and MSE comparison to wavelet 9/7 filter and wavelet 5/3 filter. The image compression new filter coefficients for proposed schema is shown in table:

TABLE-1 TABLE CONTAINS 9/7 FILTER COEFFICIENT AND PROPOSED FILTER COEFFICIENTS

9/7 Filter Coefficient		Proposed Filter Coefficient	
Low Pass Filter	High Pass Filter	Low Pass Filter	High Pass Filter
0	0	-0.0015	0.0015
0.0378	-0.0645	0.0027	0.0027
-0.0238	0.0407	0.0049	-0.0049
-0.1106	0.4181	-0.0128	-0.0128
0.3774	-0.7885	-0.0025	0.0025
0.8527	0.4181	0.0264	0.0264
0.3774	0.0407	-0.0050	0.0050
-0.1106	-0.0645	-0.0455	-0.0455
-0.0238	0	0.0211	-0.0211
0.0378	0	0.0756	0.0756
		-0.0568	0.0568
		-0.1404	-0.1404
		0.1817	-0.1817
		0.6594	0.6594
		0.6594	-0.6594
		0.1817	0.1817
		-0.1404	0.1404
		-0.0568	-0.0568
		0.0756	-0.0756
		0.0211	0.0211
		-0.0455	0.0455
		-0.0050	-0.0050
		0.0264	-0.0264
		-0.0025	-0.0025
		-0.0128	0.0128
		0.0049	0.0049
		0.0027	-0.0027
		-0.0015	-0.0015

This work introduces new wavelet based bi-orthogonal filter coefficient that can give better result in case of PSNR and MSE comparison to wavelet 9/7 filter and wavelet 5/3 filter. The image compression algorithm for proposed schema has following steps:

(A) Compression:

1. Firstly image is converted in digital form and read by respective software (MATLAB).
2. The RGB image is converted into YCbCr format.
3. Separate Y, Cb and Cr component of image.
4. Decompose each component by using 2-DWT with proposed filter coefficient schema.
5. Code the coefficient of each component by using SPIHT coder.

(B) Decompression:

1. Read the coded image.
2. Decode the coded image by using SPIHT encoder.
3. Pass the decoded image through inverse DWT with proposed filter coefficient.
4. Covert the image from YCbCr to RGB format.
5. Measure MSE and PSNR for the image.
6. Repeat compression and decompression process by using wavelet 9/7 filter coefficient.
7. Compare the result for both the cases.

5. RESULTS

The image coding results are compared in this section between DWT-SPIHT with wavelet 9/7 filter coefficient and DWT-SPIHT with proposed filter coefficient.

WAVELET PLANE	SP153 WAVELET(proposed method)		CDF97 WAVELET	
	MSE	PSNR	MSE	PSNR
Y PLANE	16.5937	35.9314	29.1027	33.4915
CB PLANE	19.27	35.282	18.6696	35.4195
CR PLANE	16.6474	35.9173	32.9318	32.9546

Table: MSE and PSNR values in different planes for different wavelets

Volume : 3 | Issue : 7 | July 2013 | ISSN - 2249-555X

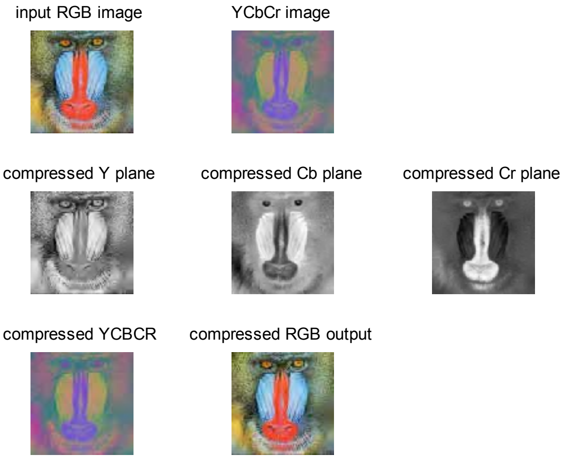

Figure Different planes compressed images

REFERENCE

[1] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955. | [2] Ms S. S. Tamboli," Compression Methods Using Wavelet Transform",International Journal of Computer Engineering and Technology, Volume 3, Issue 1, January- June (2012), pp. 314-321 | [3] Naoki Saitoi,Frequently Asked questions on Wavelets , University of California, USA, April, 2004. | [4] Martin J. Mohlenkamp "A Tutorial on Wavelets Thesis and Applications" University of Colorado at Boulder, Dept, of Applied Mathematics, MJM@colorado.edu | [5] I. Daubechies "Book reviews Ten Lecture on Wavelets" IEEE Geosciences & Remote Sensing Society Newsletter, 1992. | [6] G.M.Padmaja, P.Nirupama," Analysis of Various Image Compression Techniques", ARPN Journal of Science and Technology, VOL. 2, NO. 4, May 2012,pp 371-376 | [7] J.M. Shapiro, "Embedded image coding using zerotree of wavelet Coefficients," IEEE Trans, Signal Processing, Vol. 41 ,No. 12.Dec 1993. | [8] A. Said and W. A. Pearlman, "A new fast and efficient image codec based on set partitioning in hierarchical tree", IEEE Trans. Circuits and Systems for Video Technology, Vol.6, No.3 Jun 1996. | [9] Shih-Ta Hsiang, "Embedded image coding using zeroblocks of subband/ wavelet coefficients and context modeling," IEEE Data Compression Conference, pp. 83-92, Snow Bird, UT, Mar. 2001. | [10] D. Taubman, "High performance scalable image compression with EBCOT," IEEE Transactions on Image Processing, Vol.97, pp. 1158- 1170, Jul 2000. | [11] Jurate Puniene., Vytenis Punys and Jonas Punys "Ultrasound and angio image compression by cosine and wavelet transforms" International Journal of Medical Informatics, Vol. 64, Issues 2–3, (December 2001), pp 473–481. | [12] Hyung Jun Kim and Li, C, C "Unified Image Compression Using Reversible and Fast Biorthogonal Wavelet Transform" Proceedings IWISP '96, 4–7 (November 1996), Manchester, United Kingdom, 1996, pp 263–266 | [13] Angelidis, P, A "MR image compression using a wavelet transform coding algorithm" Magnetic Resonance Imaging, Vol. 12, Issue 7, (1994), pp 1111–1120 | [14] Chandandeep Kaur, Sumit Budhiraja ," Improvements of SPIHT in Image Compression- Survey", International Journal of Emerging Technology and Advanced Engineering, Volume 3, Issue 1, January 2013, pp 652-656 | [15] W. Ding, F. Wu, X. Wu, S. Li, and H. Li, "Adaptive directional lifting-based wavelet transform for image coding," IEEE Trans. Image Process., vol. 16, no. 2, pp. 416–427, Feb. 2007. | [16] C.-L. Chang, A. Maleki, and B. Girod, "Adaptive wavelet transform for image compression via directional quincunx lifting," in Proc. IEEE Workshop Multimedia Signal Processing, Shanghai, China, Oct. 2005. | [17] C. -. Chang and B. Girod, "Direction-adaptive discrete wavelet transform via directional lifting and band eletization," in Proc. IEEE Int.Conf. Image Processing 2006, Atlanta, GA, Oct. 2006. | [18] Weisheng Dong, Guangming Shi, Member, IEEE, and JizhengXu, Member, IEEE,"Adaptive Nonseparable Interpolation for ImageCompression With Directional Wavelet Transform" in IEEE SIGNAL PROCESSING LETTERS, VOL. 15, 2008.