SSIM based Image Quality Assessment for Lossy Image Compression

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Abstract---With the wide use of computers and consequently need for large scale storage and transmission of data efficient ways of storing of data have become necessary. With the growth of technology and entrance into the Digital Age the world has found itself amid a vast amount of information. Dealing with such enormous information can often present difficulties. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages.JPEG and JPEG 2000 are two important techniques used for image compression. Both are Lossy compression scheme that are often used to compress information such as digital images. Image processing is the latest field of research now days. Image Compression is the field of Image processing which includes the compression of Images and is chosen for the thesis work. JPEG 2000 image compression standard makes use of DWT (Discrete Wavelet Transform). DWT can be used to reduce the image size without losing much of the resolutions computed and values less than a pre-specified threshold are discarded. Thus it reduces the amount of memory required to represent given image. Recently discrete wavelet transform has emerged as popular techniques for image compression. The wavelet transform is one of the major processing components of image compression. For image compression, it is desirable that the selection of transform should be responsible for reducing the size of resultant data set as compared to source data set. This thesis is focused on parameter related to image such as compression ratio, PSNR, MSE, Global thresholding and SSIM.

Keywords: wavelet transforms, DCT, image coding, transform coding, Image compression, Peak to signal ratio, compression ratio, and Mean square error, structural similarity measurement index (SSIM).

I. INTRODUCTION

In recent years, many studies have been made on wavelets. An excellent overview of what wavelets have brought to the fields as diverse as biomedical applications, wireless communications, computer graphics or turbulence, is given in [1]. Image compression is one of the most visible applications of wavelets. The rapid increase in the range and use of electronic imaging justifies attention for systematic design of an image compression system and for providing the image quality needed in different applications. A typical still image contains a large amount of spatial redundancy in plain areas where adjacent picture elements (pixels) have almost the same values. It means that the pixel values are highly correlated [2]. In addition, a still image can contain subjective redundancy, which is determined by properties of a human visual system (HVS) [3]. An HVS presents some tolerance to distortion, depending upon the image content and viewing conditions. Consequently, pixels must not always be reproduced exactly as originated and the HVS will not detect the difference between original image and reproduced image. The redundancy (both statistical and subjective) can be removed to achieve compression of the image data. The basic measure for the performance of a compression algorithm is compression ratio (CR), defined as a ratio between original data size and compressed data size. In a Lossy compression scheme, the image compression algorithm should achieve a tradeoff between compression ratio and image quality [4]. Higher compression ratios will produce lower image quality and vice versa. Quality and compression can also vary according to input image characteristics and content. Transform coding is a widely used method of compression image information. In a transform-based compression system two-dimensional (2-D) images are transformed from the spatial domain to the frequency domain. An effective transform will concentrate useful information into a few of the low-frequency transform coefficients. An HVS is more sensitive to energy with low spatial frequency than with high spatial frequency. Therefore, compression can be achieved by quantizing the coefficients, so that important coefficients (low-frequency coefficients) are transmitted and the remaining coefficients are discarded. Very effective and popular ways to achieve compression of image data are based on the discrete cosine transform (DCT) and discrete wavelet transform (DWT).In recent times, much of the research activities in image coding have been focused on the DWT, which has become a standard tool in image compression applications because of their data reduction capability [10]–[12]. In a wavelet compression system, the entire image is transformed and compressed as a single data object rather than block by block as in a DCT-based compression system. It allows a uniform distribution of compression error across the entire image. DWT offers adaptive spatial-frequency resolution (better spatial resolution at high frequencies and better frequency resolution at low frequencies) that is well suited to the properties of an HVS. It can provide better image quality than DCT, especially on a higher compression ratio [13]. However, the implementation of the DCT is less expensive than that of the DWT. For example, the most efficient algorithm for 2-D 8x8 DCT requires only 54 multiplications [14], while the complexity of calculating the DWT depends on the length of wavelet filters.

A wavelet image compression system can be created by selecting a type of wavelet function, quantizer, and statistical coder. In this paper, we do not intend to give a technical description of a wavelet image compression system. We used a few general types of wavelets and compared the effects of wavelet analysis and representation, compression ratio, image content, and resolution to image quality. According to this analysis, we show that searching for the optimal wavelet needs to be done taking into account not only objective picture quality measures, but also subjective measures. We highlight the performance gain of the DWT over the DCT. Quantizers for the DCT and wavelet compression systems should be tailored to the transform structure, which is quite different for the DCT and the DWT. The representative quantizer for the DCT is a uniform quantizer in baseline JPEG [5], and for the DWT, it is Shapiro's zero tree quantizer [15], [16]. Hence, we did not take into account the influence of the quantizer and entropy coder, in order to accurately characterize the difference of compression performance due to the transforms.

II. WAVELETS

A wavelet is a "small wave", which has its energy concentrated in time. It gives a tool for the analysis of mandatory, non-stationary. It is also known as wave-like oscillations with amplitude which increases with zero and decreases up to zero. This is also known as one complete cycle it not only has an oscillating wave like characteristic but also has the ability to allow simultaneous time and frequency analysis with a flexible mathematical foundation. Wavelets are mainly design for specific purpose that makes them useful for signal processing and image processing. Convolution is the techniques that can combine using revert, shift, multiply and sum.

A. *Mathematical description*

Wavelets are generated from one single function (basis function) called the mother wavelet. Mother Wavelet is a prototype for generating the other window functions. The mother wavelet is scaled (or dilated) by a factor of and translated (or shifted) by a factor of b to give (under Morlet's original formulation):

$$\Psi a,b = (1/\sqrt{\,|a|\,})\Psi(t-b)/a \qquad (1.1)$$

Where, a and b are two arbitrary real numbers. 'A' and 'b' represent the dilations and translations parameters respectively in the time axis. The parameter 'a' contracts Ψ (t) in the time axis when a <1 and expands or stretches when a >1. Hence 'a' is called the dilation (scaling) parameter. Mathematically, when 't' is replaced in equation by (t - b) it causes a translation or shift in the time axis resulting in the wavelet function[6].

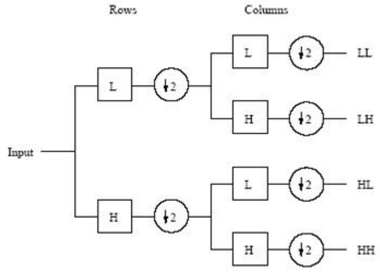


Fig. 1: 2-D DWT for Image [6]

III. STRUCTURAL SIMILARITY INDEX MEASUREMENT (SSIM)

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human eye perception.

The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies array important information about the structure of the objects in the visual scene.

Structural Similarity Index Measurement (SSIM) an objective image quality metric. Objective methods for assessing perceptual image quality traditionally attempted to quantify the visibility of errors (differences) between a distorted image and a reference image using a variety of known properties of the human visual system. Under the assumption that human visual perception is highly adapted for extracting structural information from a scene, it is an alternative complementary framework for quality assessment based on the degradation of structural information [9].

Natural image signals are highly structured: their pixels exhibit strong dependencies, especially when they are spatially proximate, and these dependencies array important information about the structure of the objects in the visual scene. The Minkowski error metric is based on point wise signal differences, which are independent of the underlying signal structure. Although most quality measures based on error sensitivity decompose image signals using linear transformations, these do not remove the strong dependencies. The motivation of our new approach is to find a more direct way to compare the structures of the reference and the distorted signals [9].

A. *The SSIM Index*

Digital images and videos are prone to different kinds of distortions during different phases like acquisition, processing, compression, storage, transmission, and reproduction [8]. This degradation results in poor visual quality. There are several metrics which are widely used to quantify the image quality like FSIM, SSIM, bitrates, PSNR and MSE [17, 8,18, and 19]. This work is primarily focus on metrics like SSIM, FSIM and bitrates. The other conventional metrics like PSNR and MSE will not be measured as they are directly dependent on the intensity of an image and do not correlate with the subjective fidelity ratings [20]. MSE cannot model the human visual system very accurately [21].

SSIM is the quality assessment of an image based on the degradation of structural information [8]. The SSIM takes an approach that the human visual system is adapted to extract structural information from images [19]. Thus, it is important to retain the structural signal for image fidelity measurement. Figure below shows the difference between nonstructural and structural distortions. The nonstructural distortions are changes in parameter like luminance, contrast, gamma distortion, and spatial shift and are usually caused by environmental and instrumental conditions occurred during image acquisition and display [19]. On the other hand, structural distortion embraces additive noise, blur, and Lossy compression [19]. The structural distortions change the structure of an image [21].

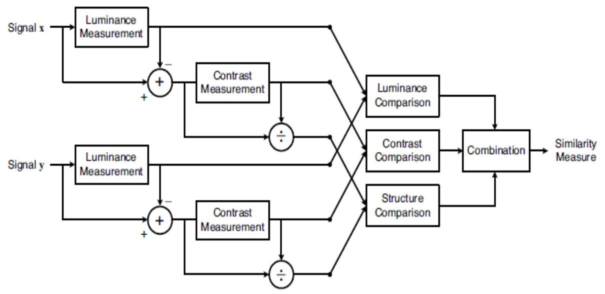


Fig. 2: Block diagram of SSIM measurement system [8]

SSIM is based on the evaluation of three different metrics like luminance, contrast and structure which are described mathematically by equations (1.2), (1.3), and (1.4) respectively [22].

$$l(x,y) = \frac{2\mu x \mu y + C1}{\mu^2 x + \mu^2 y + C1} \qquad \text{-------------------- --- (1.2)}$$

$$c(x,y) = \frac{\sigma_x \sigma_y + C_2}{\sigma^2{}_x + \sigma^2{}_y + C_2} \qquad \text{-------------------- --- (1.3)}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3} \qquad \text{-------------------- --- (1.4)}$$

Here,

- μ_x and μ_y= local sample means of x and y respectively
- σ_x and σ_y= local sample standard deviations of x and y respectively
- σ_{xy} = local sample correlation coefficient between x and y
- C_1, C_2, and C_3 = constants that stabilize the computations when denominators become small
- General form of SSIM index can be obtained by combining equations (1.2), (1.3), and (1.4) [22].
- $c_1=(k_1L)^2$, $c_2=(k_2L)^2$two variables to stabilize the division with weak denominator;
- $L$the dynamic range of the pixel-values;
- $k_1=0.01$ And $k_2=0.03$by default.

SSIM(x, y) =$[l(x,y)]^{\alpha}.[c(X,Y)]^{\beta}.[s(X,Y)]^{\gamma}$........ (1.5)

Here, α, β, and γ are parameters that mediate the relative importance of those three components. Using α = β = γ = 1 and C_3=C_2/2. We get (1.3),

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(\sigma_{xy+}C_2)}{(\mu^2{}_x+\mu^2{}_y+C_1)\ (\sigma^2{}_x+\sigma^2{}_y+c_2)} \ldots (1.6)$$

IV. RESULTS AND DISCUSSION

Analysis of Rose and Lena Images with global Thresholding Firstly we will take the sample image. i.e., Rose and Lena then apply the proposed algorithm for this image and analyzed the different wavelet function in terms of MSE, PSNR, CR and SSIM. Table below: Analysis of MSE, PSNR, CR and SSIM for Rose and Lena image using different decomposition level, different wavelet families and global threshold value.

FILTER	PSNR	RMSE	CR	SSIM
Db4	17.548	33.817	69.334	0.922
Sym5	17.574	33.715	68.742	0.922
Coif3	17.429	34.283	66.714	0.920
Bior2.4	17.856	32.641	68.774	0.927
Haar	17.550	33.809	70.793	0.921
Rbio4.4	17.490	34.044	68.822	0.920

Table. 1: Level-1 for Rose

Bior2.4 Haar Rbio4.4

Fig. 3: Level -1 for Rose using different wavelet filter

FILTER	PSNR	RMSE	CR	SSIM
Db4	17.468	34.132	80.925	0.917
Sym5	17.596	33.631	80.387	0.920
Coif3	17.305	34.777	77.998	0.915
Bior2.4	18.060	31.881	80.465	0.928
Haar	17.505	33.983	82.703	0.915
Rbio4.4	17.516	33.942	80.453	0.918

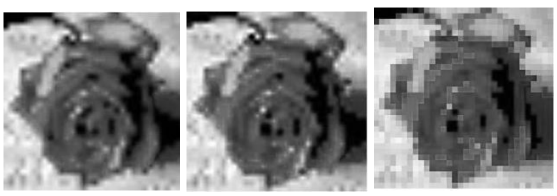
Table. 2: Level-2 for Rose

Bior2.4 Haar Rbio4.4

Fig. 4: Level -2 for Rose using different wavelet filter

FILTER	PSNR	RMSE	CR	SSIM
Db4	16.600	37.717	84.499	0.896
Sym5	16.836	36.706	84.020	0.900
Coif3	16.562	37.883	81.638	0.896
Bior2.4	17.519	33.929	84.061	0.914
Haar	16.752	37.061	86.216	0.892
Rbio4.4	16.720	37.201	84.068	0.987

Table. 3: Level-3 for Rose



Bior2.4 Rbio4.4 Haar

Fig. 5: Level -3 for Rose using different wavelet filter

FILTER	PSNR	RMSE	CR	SSIM
Db4	18.751	29.445	89.367	0.939
Sym5	18.745	29.466	89.283	0.939
Coif3	18.927	28.853	88.751	0.942
Bior2.4	19.293	27.662	89.298	0.945
Haar	18.167	31.490	89.747	0.930
Rbio4.4	18.626	29.870	89.269	0.937

Table. 4: Level-1 for Lena

Bior2.4 Haar Rbio4.4

Fig. 6: Level -1 for Lena using different wavelet filter

FILTER	PSNR	RMSE	CR	SSIM
Db4	17.089	35.654	93.674	0.907
Sym5	16.959	36.190	93.604	0.905
Coif3	17.189	35.246	92.986	0.909
Bior2.4	17.595	33.640	93.613	0.914
Haar	16.585	33.218	94.105	0.892
Rbio4.4	17.011	35.975	93.599	0.905

Table. 5: Level-2 for Lena

Bior2.4 Haar Rbio4.4

Fig. 7: Level -2 for Lena using different wavelet filter

FILTER	PSNR	RMSE	CR	SSIM
Db4	15.790	41.406	94.972	0.870
Sym5	15.719	41.742	94.875	0.869
Coif3	15.983	40.493	94.277	0.875
Bior2.4	16.188	39.551	94.876	0.876
Haar	15.031	45.185	95.427	0.845
Rbio4.4	15.759	41.552	94.869	0.868

Table. 6: Level-3 for Lena

Bior2.4 Haar Rbio4.4

Fig. 8: Level -3 for Lena using different wavelet filter

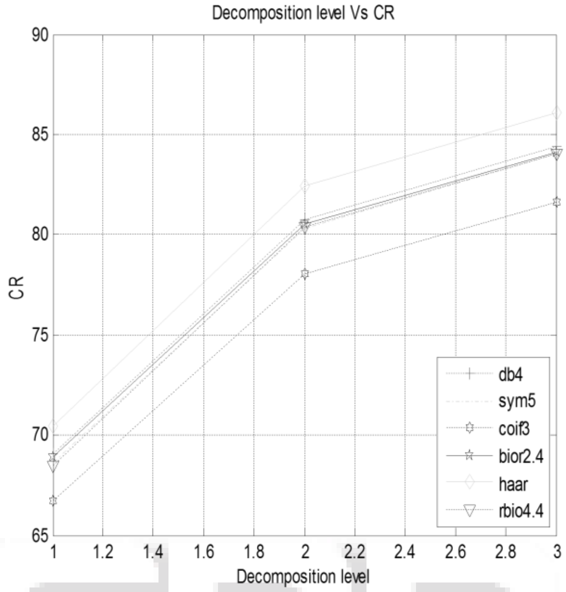


Fig. 9: Decomposition level Vs CR for Bior2.4 Wavelet Filter

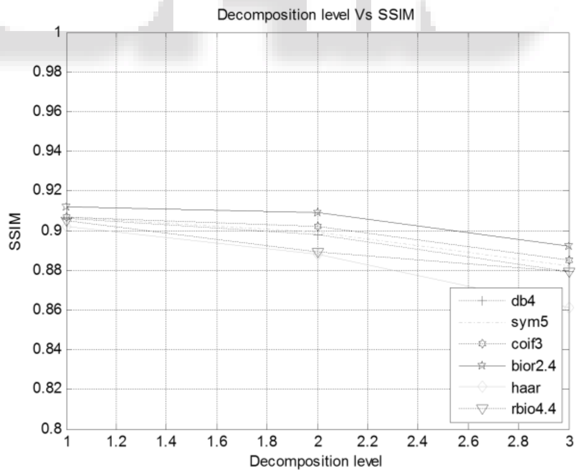


Fig. 10: Decomposition level Vs SSIM for Bior2.4 Wavelet Filter

V. SUMMARY

This study presented an analysis and comparison the wavelet families using for image compression considering PSNR, CR and visual quality of image as quality measure. A performance analysis of various wavelet families using for image compression on variety of test images has been done. The effects of Bi-Orthogonal, Daubechies, Coiflet and Symlets, haar and Rbio wavelet families on test image have been examined. We analyzed the result for wide range of wavelet families using different way just like (1) different decomposition level (2) different wavelet families (3) Global threshold value. After analysis of wavelet families using image compression and found that the bi-orthogonal and Haar wavelets give the better performance compared to other wavelet families for all variety of images. When level of decomposition increase then quality of reconstructed image and PSNR is decreased but CR is increased. The CR of Haar wavelet is much better than other wavelets and PSNR and quality of reconstructed image is better for Bi-Orthogonal and reverses Bi-Orthogonal wavelets.

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