JPEG 2000 Performance Evaluation

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Abstract— **JPEG 2000, the new ISO / ITU-T standard for still image coding, is about to be finished. Another standard has been popular in recent years, namely JPEG. This paper compares the set of features offered by JPEG 2000, and how well they are fulfilled, versus JPEG. The study concentrates on functionality set, while addressing other aspects such as Region of Interest coding (ROI), superior low bit rate performance, memory requirements. Also, compressed image quality is evaluated using various algorithms. The principles behind each algorithm are briefly described. The results show that the JPEG 2000 supports a wide set of features that JPEG can either not address efficiently or not address at all.**

I. Introduction

With the increasing use of multimedia technologies, image compression requires higher technology as well as new features. To address this needs in the specific area of still image encoding, a new standard is currently being developed the JPEG 2000. It is not only intended to provide rate-distortion and subjective image quality performance superior to existing standards, but also to provide functionalities that current standards can either not address efficiently or not address at all. JPEG 2000 image compression standard is the new future of digital imaging. Now JPEG 2000 is in its final stage to become an International Standard (IS). A great effort has been made to deliver this new standard for today's and tomorrow's applications. Now that the new standard is nearing finalization, a trivial question would be: what are the features offered by JPEG 2000 and also how well are they fulfilled when compared to the popular JPEG standard. This paper aims at providing an answer to this simple but somewhat complex question. Section 2 provides a brief overview of JPEG, and JPEG 2000 techniques. Section 3 explains most of the JPEG 2000 features. Section 4 explains the comparison methodology employed. The results and conclusions are drawn in section 5.

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II. Overview of JPEG, and JPEG 2000

For the purpose of this study we compare the coding algorithm of JPEG, and JPEG 2000 standards. The reasons behind this choice is as follows: JPEG is one of the most popular coding techniques in imaging applications ranging from Internet to digital photography. It is only logical to compare the set of features of JPEG 2000 standard to that of JPEG standard.

A. JPEG

This is the very well known ISO/ITU-T standard created in the late 1980s. There are several modes defined for JPEG, including baseline, lossless, progressive and hierarchical.

The baseline mode is the most popular one and supports lossy coding only. The lossless mode is not popular but provides for lossless coding, although it does not support lossy. In the baseline mode, the image is divided in 8x8 blocks and each of these is transformed with the DCT. The transformed blocks are quantized with a uniform scalar quantizer, zig-zag scanned and entropy coded with Huffman coding. The quantization step size for each of the 64 DCT coefficients is specified in a quantization table, which remains the same for all blocks. The DC coefficients of all blocks are coded separately, using a predictive scheme. We refer to this mode simply as JPEG [1], [2].

The lossless mode is based on a completely different algorithm, which uses a predictive scheme. The prediction is based on the nearest three causal neighbors and seven different predictors are defined (the same one is used for all samples). The prediction error is entropy coded with Huffman coding. We refer to this mode as L-JPEG [1], [2].

The progressive and hierarchical modes of JPEG are both lossy and differ only in the way the DCT coefficients are coded or computed, respectively, when compared to the baseline mode. They allow a reconstruction of a lower quality or lower resolution version of the image, respectively, by partial decoding of the compressed bitstream. Progressive mode encodes the quantized coefficients by a mixture of spectral selection and successive approximation, while hierarchical mode uses a pyramidal approach to computing the DCT coefficients in a multi-resolution way [1], [2].

B. JPEG 2000

JPEG 2000, is the next ISO/ITU-T standard for still image coding. JPEG 2000 is based on the discrete wavelet transform (DWT), scalar quantization, context modeling, arithmetic coding and post-compression rate allocation. The DWT is dyadic and can be performed with either the reversible (5,3) taps filter, which provides for lossless coding, or the non-reversible (9,7) taps biorthogonal one, which provides for higher compression but does not do lossless [3]. The quantizer follows an embedded dead-zone scalar approach and is independent for each sub-band. Each sub-band is divided into rectangular blocks (called code-blocks in JPEG 2000), typically 64x64, and entropy coded using context modelling and bit-plane arithmetic coding. The coded data is organized in so called layers, which are quality levels, using the post-compression rate allocation and output to the code-stream in packets [4]. The generated code-stream is parsable and can be resolution, or quality progressive, or any combination thereof. JPEG 2000 also supports a number of functionalities, many of which are inherent from the algorithm itself. Examples of this is random access, which is possible because of the independent coding of the code-blocks and the packetized structure of the code stream. Another such functionality is the possibility to encode images with arbitrarily shaped Regions of Interest (ROI), lossless and lossy compression in one system, and error resilience.

III. JPEG 2000 Features

A. Lossless and lossy compression in one system.

Two wavelet filters are used in JPEG 2000 Part I. The daub 9/7 wavelet which contain floating filter coefficients is used for lossy coding. The integer wavelet 5/3 is used for both lossless and lossy. These applications that can use this feature: medical images where loss is not always tolerated, image archival applications where the highest quality is vital for preservation but not necessary for display, network applications that supply devices with different capabilities and resources, and pre-press imagery [4].

B. Region of Interest (ROI).

The ROI is important in applications where certain parts of the image is more important than others. In this case, these regions need to be encoded at higher quality than the background. During the transmission of the image, these regions need to be transmitted first or at a higher priority, as in the case of progressive transmission.

The ROI coding in part I of the standard is based on the so called MAXSHIFT method, which is an extension of the general ROI scaling based method. The principle of the general ROI scaling based method is to scale (shift) coefficients so that the bits associated with the ROI are placed in higher bit planes than the bits associated with the background fig.1 shows the scaling of the ROI coefficients.

Then during the embedded coding process, the most significant ROI bit planes are placed in the bit stream before any background bit planes of the image. Depending on the scaling value, some bits of the ROI coefficients might be encoded together with non ROI coefficients. Thus, the ROI will be decoded before the rest of the image. If the bit stream is truncated, or the encoded process is terminated before the image is fully encoded, the ROI will be of higher fidelity than the rest of the image.

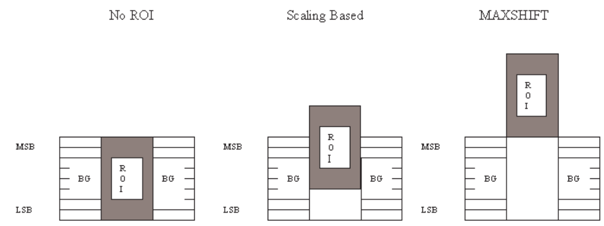

Fig. 1. Scaling of the ROI coefficients.

In JPEG 2000, the general scaling based method is implemented as follows:

1) The wavelet transform is calculated.

2) If an ROI has been defined, then a ROI mask is derived, indicating a set of coefficients that are required for lossless ROI reconstruction.

3) The wavelet coefficients are quantized. Quantized coefficients are stored in sign magnitude representation. Magnitude bits comprise the most significant part of the implementation precision used.

4) The coefficients that lay outside the ROI are down scaled by a specific scaling value.

5) The resulting coefficients are progressively entropy encoded.

The decoder reverses the steps above to reconstruct the image (step 2 is still performed before step 3). As an overhead information, the scaling value assigned to the ROI and the coordinates of the ROI are added to the bit stream. The decoder performs also the ROI mask generation but scales up the background coefficients in order to reconstruct the image.

According to the MAXSHIFT method, which is used in part I of the JPEG 2000 standard, the scaling value is computed in such a way that it makes possible to have arbitrary shaped ROIs without the need of transmitting shape information to the decoder. This means also that the decoder will not need to make ROI mask generation. The encoder scans the quantized coefficients and chooses a scaling value S such that the minimum coefficient belonging to the ROI is larger than the maximum coefficient belonging to the background. The decoder receives the bit stream and starts the decoding process. Every coefficient smaller than S belongs to the background and is therefore scaled up. The decoder needs only to up scale the background coefficients. In the MAXSHIFT method, since the bit planes with information belonging to the ROI are completely separated from those belonging to the background, the number of bit planes for the ROI and for the background are chosen independently. This gives the possibility to choose different bit rates for the ROI and for the background. To do this, it is sufficient to discard the lest significant bit planes of the ROI and the background. With the general scaling method we can't do this [3]. An example of image the girl with a region of interest is shown in fig.2.

C. Error Resilience.

Error resilience is one of the most desirable properties in mobile and internet applications. JPEG 2000 uses a variable

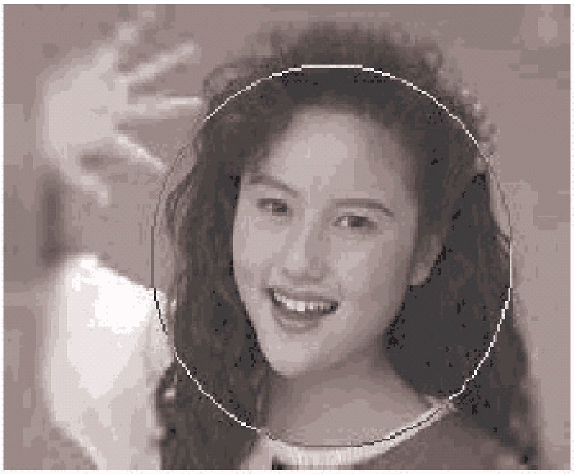

Fig. 2. Image Girl with a ROI.

Fig. 3. Compressed image Lina (a)JPEG 2000 at 0.125 bpp. (b)JPEG at 0.125 bpp.

length coder (an arithmetic coder) to compress the quantized wavelet coefficients. variable length coder is known to be prone to channel or transmission errors. A bit error may result in reducing decoder synchronization and the reconstructed image can be damaged. To improve the transmission over an error prone channel, error resilience tools are included in the standard. It deals with the channel error using the following approaches: data partitioning and resynchronization, error detection and concealment. Error resilience is achieved at the entropy encoder level and at the packet level.

Entropy encoding of quantized coefficients are performed within code blocks. Since encoding and decoding of the code blocks are independent processes, bit error of the bit stream of a code block will be restricted within that code block. To increase error resilience, termination of the arithmetic coder is allowed at the end of every coding pass and the context may be reset after every coding pass. This allows the decoder to continue the decoding process even if an error has occurred. At the packet level, a packet with a re-synchronization marker allow spatial partitioning and re-synchronization. This is placed in front of every packet in a tile with a sequence number starting at zero and incremented with each packet [3].

IV. Comparison Methodology

Here we compare the performance of JPEG and JPEG 2000 according to: low bit-rate performance, tilling artifacts, scalability, image quality, and memory requirements.

A. Superior low bit-rate performance

This standard offers performance superior to the current standards at low bit-rates (e.g. below 0.25bpp). Fig.3 a,b compare the performance between JPEG and JPEG 2000 at the same bit-rate on the same image (Lena). The JPEG compressed image is visually unacceptable while the JPEG 2000 compressed image is pretty good.

B. Tilling artifacts

In JPEG the image is divided into 8×8 blocks and JPEG compression engine deals with each block individually (transform it by DCT, encode it, and decode it). As a result blocking artifacts appears in the reconstructed image. While JPEG 2000 compression engine divides the image into packets, and then the packets into code blocks. A bit stream is created for each code block, but it takes into account the relation ship between neighboring pixels. For coding a pixel in a code block the engine doesn't only compute the significance of that pixel but also the significance of it's 8 immediate neighbors, also it takes into account the pixels that exist on the edges of the code block. This eliminates the effect of tilling artifacts that exist in JPEG images. Fig 4 a,b compares the performance of JPEG and JPEG 2000 for the same image (The Girl) at the same bit rate 0.125 bpp.

The JPEG compressed image is visually unaccepted because of tilling artifacts while JPEG 2000 image is pretty good.

C. Scalability.

Scalability of still image the ability of coding with more than one quality and/or resolution simultaneously. Scalable image coding involves generating a coded representation in a manner which facilitates the derivation of images of more than one quality and/or resolution by scalable decoding. A key advantage of scalable compression is that the target bit rate or reconstruction resolution need not be known at the time of compression. Also, scalable coding provide resilience to transmission errors, as the most important data at the lower layers can be send over the channel with better error performance, while the less important data can be sent with poor error performance.

JPEG image compression system divides the file into a series of scans. The first scan shows the image at the equivalent of a very low quality setting, and therefore it takes very little space. Following scans gradually improve the quality (SNR). Each scan adds to the data already provided, i.e. each scan increases the number of bits per pixel. So JPEG provides only progression by quality (SNR scalability).

JPEG 2000 image compression system creates a scalable bit stream, that allows decoding of an appropriate subset

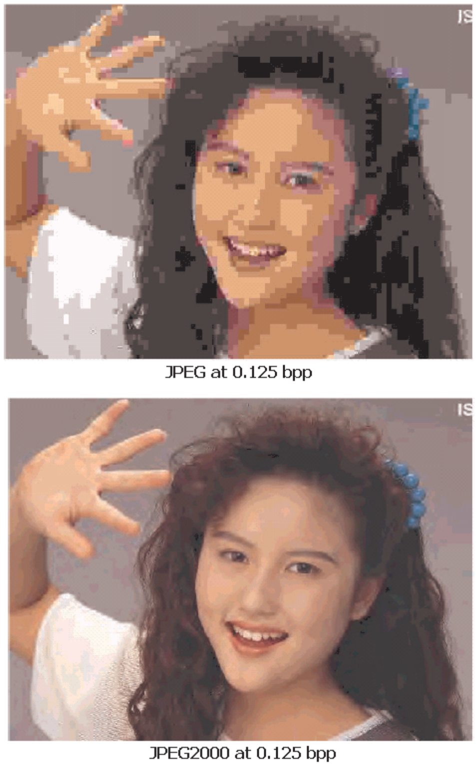

Fig. 4. Compressed image The Girl.(a) JPEG at 0.125 bpp. (b) JPEG 2000 at 0.125 bpp.

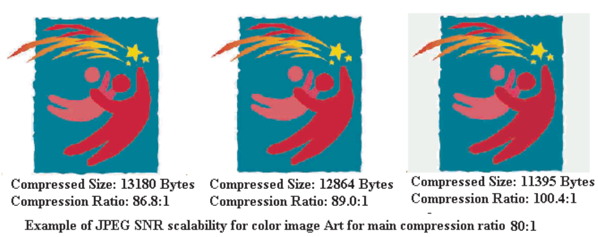

Fig. 5. JPEG SNR scalability for color image Art for main compression ratio 80:1.

of the bit stream to generate complete picture of quality and/or resolution commensurate with the proportion of the bit stream decoded. JPEG 2000 provides both SNR and resolution scalability [4].

Fig.5 shows JPEG SNR scalability for color image Art with main compression ratio $80:1$.

Fig.6 shows JPEG 2000 SNR scalability for color image Art with main compression ratio $80:1$.

Fig.7 shows resolution scalability for color image Art for main compression ratio $80:1$.

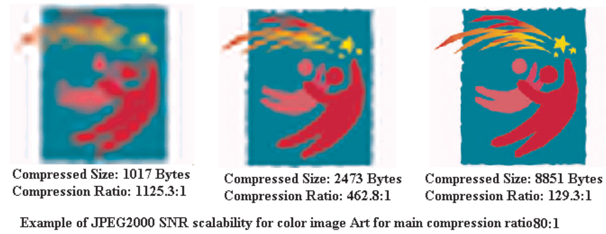

Fig. 6. JPEG 2000 SNR scalability for color image Art for main compression ratio 80:1.

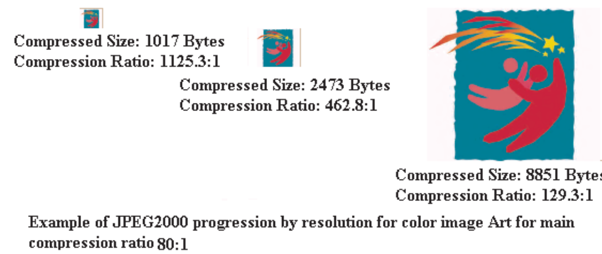

Fig. 7. JPEG 2000 progression by resolution for color image Art for main compression ratio 80:1.

D. *Quality Measurement.*

Any lossy image compression technique results in distortion in compressed image. When compressing an image using lossy JPEG or lossy JPEG 2000, the compressed image suffers from certain amount of distortion. For comparing the performance of JPEG and JPEG 2000 compression systems, we need a reliable quality measuring tools for determining the amount of image distortion. Image quality is measured either by a subjective criteria or an objective criteria.

In subjective criteria the ultimate assessment of image quality is made by human observers. Evaluation performed by the observers take two forms: Absolute and comparative. Absolute evaluation is a process whereby the observer assigns to an image a category in a given rating scale, whereas comparative evaluation is the ranking of a set of images from best to worst. Here we are not using subjective criteria, as in many cases, subjective rating results may not be reproducible as they can be affected by a number of factors including [5]:

a)type, size and range of images.

b)observers background and motivation.

c)experimental conditions (lighting, display quality, etc.).

Objective image quality metrics can be classified according to the availability of an original (distortion-free)image, with which the distorted image is to be compared. Most existing approaches are known as full-reference, meaning that a complete reference image is assumed to be known. In many practical applications, however, the reference image is not available, and a no-reference or blindquality assessment approach is desirable. In a third type of method, the reference image is only partially available, in the form of a set of extracted features made available as side information to help evaluate the quality of the distorted image. This is referred to as reduced-reference quality assessment. Here we work with full reference image quality assessment. We use the original uncompressed image as our reference, compare it once with JPEG image, and other time with JPEG 2000 image.

The simplest and most widely used full-reference quality metric is the mean squared error (MSE), and peak signal to noise ratio (PSNR). These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization. MSE and PSNR measure only the pixel-by-pixel correspondence and doesn't account for any spatial relation ship in the image. They can't capture artifacts like blurriness. So they are not very well matched to perceived visual quality, and can't correlate well with visual error perception [5], [8].

In the last three decades, a great deal of effort has gone into the development of quality assessment methods that take advantage of known characteristics of the human visual system (HVS) [8]. The majority of the proposed perceptual quality assessment models have followed a strategy of modifying the MSE measure so that errors are penalized in accordance with their visibility.

A new philosophy in designing image quality metrics states that: The main function of the human eyes is to extract structural information from the viewing field, and the human visual system is highly adapted for this purpose. Therefore, a measurement of structural distortion should be a good approximation of perceived image distortion. A measure of structural similarity was developed that compares local patterns of pixel intensities that have been normalized for luminance and contrast. There are two image quality measures based on structural similarity criteria universal quality index (UQI), and mean structural similarity index (MSSIM) [6], [7].

1) MSE and PSNR.: MSE is used as an objective fidelity criteria. MSE is measured between two images the original uncompressed image (input image), and the compressed image (output image).

Suppose that the input image consists of the $N \times N$ array of pixels $f(x, y), x, y = 0, 1, ..., N-1$. Each pixel is an m bit binary word corresponding to one of the 2^m possible gray levels. The encoder reduces the data bulk from $N \times N \times m$ bits to a fewer number of bits. The decoder processes these bits to reconstruct the output picture consisting of the $N \times N$ array of picture elements $g(x, y), x, y = 0, 1, ..., N-1$, where each pixel is also an m bit binary word corresponding to one of the 2^m possible gray levels.

For any value x and y in the range $0, 1, ..., N-1$, the error between an input pixel and the corresponding output pixel is

$$e(x, y) = g(x, y) - f(x, y) \tag{1}$$

The squared error average over the image array is

$$\overline{e^2} = \frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} e^2(x, y) \tag{2}$$

$$= \frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} [g(x, y) - f(x, y)]^2 \tag{3}$$

and the rms error is defined as

$$e_{rms} = [\overline{e^2}]^{\frac{1}{2}} \tag{4}$$

We can also consider the difference between the output and input image to be ”noise”, so that each output signal (pixel) consists of an input signal (the corresponding input pixel) plus noise (the error), that is,

$$g(x, y) = f(x, y) + e(x, y) \tag{5}$$

The mean-square signal-to-noise ratio of the output image is defined as the average of $g^2(x, y)$ divided by the average of $e^2(x, y)$ over the image array. In other words,

$$(SNR)_{ms} = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{N-1} g^2(x, y)}{\sum_{x=0}^{N-1} \sum_{y=0}^{N-1} e^2(x, y)} \tag{6}$$

The rms value of SNR is then given by

$$(SNR)_{rms} = [\frac{\sum_{x=0}^{N-1} \sum_{y=0}^{N-1} g^2(x, y)}{\sum_{x=0}^{N-1} \sum_{y=0}^{N-1} [g(x, y) - f(x, y)]^2}]^{\frac{1}{2}} \tag{7}$$

Where the variable term in the denominator is the noise expressed in terms of the input and output images.

An alternate definition of signal-to-noise ratio is the square root of the peak value of $g(x, y)$ squared (assuming the minimum value is zero) and the rms noise; that is,

$$(SNR)_p = [\frac{[peakvalueofg(x, y)]^2}{e_{rms}}]^{\frac{1}{2}} \tag{8}$$

The peak value of $g(x, y)$ is the total dynamic range of the output image. Hence, $(SNR)_{rms}$ and $(SNR)_p$ differ by a scale constant equal to the ratio of maximum signal to level to the average signal level. Fig.8, and fig.9 respectively shows MSE and PSNR for color image the team, compressed by different compression ratio (different bit rates) once by JPEG and another time by JPEG 2000. From fig. 8, and fig.9 it is clear that JPEG compression system generates greater MSE and less PSNR than JPEG 2000 at any compression ratio (at any bit rate). i.e. JPEG 2000 compressed images have better quality, than that achieved by JPEG (when quality is evaluated by MSE or PSNR).

2) UQI and MSSIM.: This image quality measure is based on the assumption that the human visual system is highly adapted to extract structural information from the viewing field. It follows that a measure of structural information change can provide a good approximation to perceived image distortion.

The system diagram of the proposed quality assessment system is shown in Fig.10.

Suppose x and y are two image signals, which have been aligned with each other. If we consider one of the signals to have perfect quality (the uncompressed signal), then the similarity measure can serve as a quantitative measurement of the quality of the second signal (the compressed image).

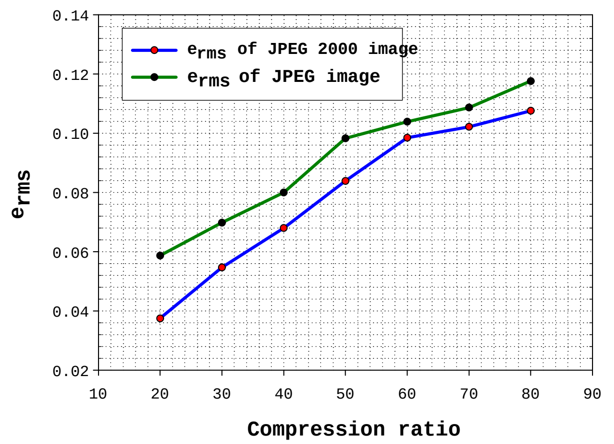

Fig. 8. MSE for color image The Team.

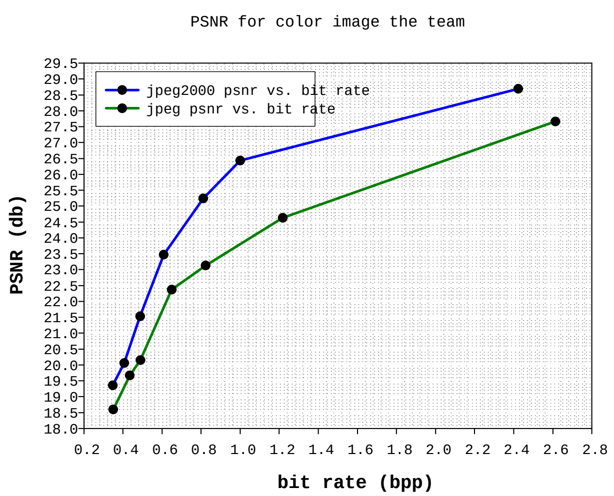

Fig. 9. PSNR for color image The Team.

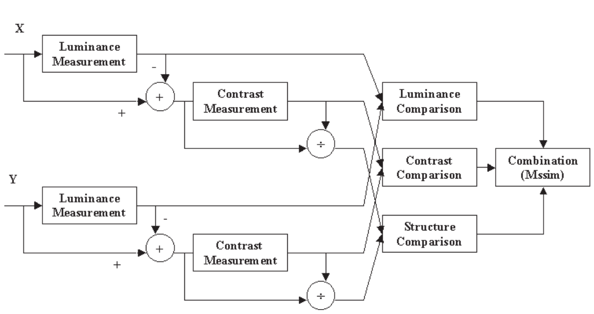

Fig. 10. Diagram of the structural similarity (SSIM) measurement system.

The system separates the task of similarity measurement into three comparisons: luminance, contrast and structure. First, the luminance of each signal is compared. Assuming discrete signals, this is estimated as the mean intensity:

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{9}$$

The luminance comparison function $l(x, y)$ is then a function of μ_x and μ_y.

Second, we remove the mean intensity from the signal. We use the standard deviation (the square root of variance) as an estimate of the signal contrast. An unbiased estimate in discrete form is given by

$$\sigma_x = \Big(\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)\Big)^{\frac{1}{2}} \tag{10}$$

The contrast comparison $c(x, y)$ is then the comparison of σ_x and σ_y.

Third, the signal is normalized (divided) by its own standard deviation, so that the two signals being compared have unit standard deviation. The structure comparison $s(x, y)$ is conducted on these normalized signals $\frac{x-\mu_x}{\sigma_x}$ and $\frac{y-\mu_y}{\sigma_y}$. Finally, the three components are combined to yield an overall similarity measure:

$$S(x, y) = f(l(x, y), c(x, y), s(x, y)) \tag{11}$$

An important point is that the three components are relatively independent. For example, the change of luminance and/or contrast will not affect the structures of images.

For luminance comparison, we define

$$l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{12}$$

where the constant C_1 is included to avoid instability when $\mu_x^2 + \mu_y^2$ is very close to zero. Specifically, we choose

$$C_1 = (K_1 L)^2 \tag{13}$$

where L is the dynamic range of the pixel values 255 for 8-bit gray scale images, and $K_1 \ll 1$ is a small constant. Similar considerations also apply to contrast comparison and structure comparison described.

The contrast comparison function takes a similar form:

$$c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{14}$$

where $C_2 = (K_2 L)^2$, and $K_2 \ll 1$.

Structure comparison is conducted after luminance subtraction and contrast normalization. We define the structure comparison function as follows:

$$s(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{15}$$

As in the luminance and contrast measures, we have introduced a small constant in both denominator and numerator. In discrete form, σ_{xy} can be estimated as:

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \tag{16}$$

Finally, we combine the three comparisons and name the resulting similarity measure the Structural SIMilarity (SSIM) index between signals x and y:

$$SSIM(x, y) = [l(x, y)]^{\alpha}.[c(x, y)]^{\beta}.[s(x, y)]^{\gamma} \tag{17}$$

where $\alpha > 0, \beta > 0, \gamma > 0$ are parameters used to adjust the relative importance of the three components. In order to simplify the expression, we set $\alpha = \beta = \gamma = 1$ and $C_3 = \frac{C_2}{2}$. This results in a specific form of the SSIM index:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{18}$$

The universal quality index (UQI) defined in [**?**] corresponds to the special case that $C_1 = C_2 = 0$, which produces unstable results when either $\mu_x^2 + \mu_y^2$ or $\sigma_x^2 + \sigma_y^2$ is very close to zero. In UQI the local statistics μ_x, σ_x and σ_{xy} are computed within a local 8×8 square window, which moves pixel-by-pixel over the entire image. At each step, the local statistics and SSIM index are calculated within the local window. One problem with this method is that the resulting SSIM index map often exhibits undesirable blocking artifacts. In SSIM index, we use an 11×11 circular-symmetric Gaussian weighting function $w = w_i = 1, 2, ..., N$, with standard deviation of 1.5 samples, normalized to unit sum $\sum_{i=1}^{N} w_i = 1$. The estimates of local statistics μ_x, σ_x and σ_{xy} are then modified accordingly as

$$\mu_x = \sum_{i=1}^{N} w_i x_i \tag{19}$$

$$\sigma_x = \Big(\sum_{i=1}^{N} w_i (x_i - \mu_x)^2\Big)^{\frac{1}{2}} \tag{20}$$

$$\sigma_{xy} = \sum_{i=1}^{N} w_i (x_i - \mu_x)(y_i - \mu_y) \tag{21}$$

The SSIM measure in this work uses the following parameter settings: $K_1 = 0.01; K_2 = 0.03$. These values are somewhat arbitrary, but we find that the performance of the SSIM index algorithm is fairly insensitive to slight variations of these values.

In practice, one usually requires a single overall quality measure of the entire image. We use a mean SSIM (MSSIM)index to evaluate the overall image quality:

$$MSSIM(X, Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j) \tag{22}$$

where X and Y are the reference and the distorted images, respectively; x_j and y_j are the image contents at the j-th local window; and M is the number of windows in the image. Fig.11 shows an evaluation of color image diagonal sand. Fig.11 shows that, for the same compression ratio, JPEG 2000 images proved to have better quality than JPEG image (when image quality is evaluated by means of UQI and MSSIM index).

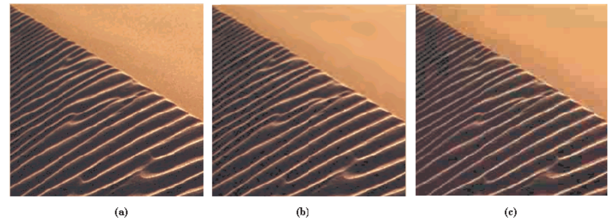

Fig. 11. Evaluation of color image "Diagonal Sand" compressed to 70:1 once by JPEG, and other time by JPEG 2000. (a) Original uncompressed image. (b) JPEG 2000 image,UQI=0.6398, MSSIM= 0.9685. (c) JPEg image, UQI=0.3950, MSSIM=0.9372 .

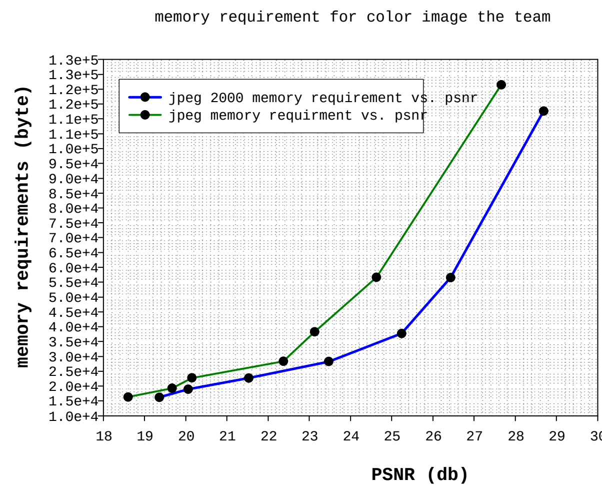

Fig. 12. Memory requirement in byte versus PSNR for color image The Team.

E. *Memory Requirements.*

One of the main aims of image compression is to reduce the storage space required to store the image file, while keeping an acceptable image quality. When an image is compressed once by JPEG 2000 and other time by JPEG, and the two images have the same quality (PSNR), JPEG 2000 image file requires from $25./.$ to $35./.$ less memory space than that required to store JPEG image. Fig.12 shows memory requirements in bytes for image the team, when compressed once by JPEG and other time by JPEG 2000. From fig. 12 it's clear that JPEG 2000 image file requires less memory space than JPEG image file.

V. CONCLUSION

This work aims at providing a comparison of the efficiency of various features that can be expected from recent and most popular still image coding algorithms JPEG, and JPEG 2000. To do so, many aspects have been considered such as low bit-rate performance, scalability, region of interest, compressed image quality, memory requirements, and so on.

The results presented in previous sections show that from a functionality point of view JPEG 2000 is a true improvement, providing lossy and lossless compression, progressive bitstreams, error resilience, region of interest, better image quality (MSE, PSNR, UQI, and MSSIM index) and other features. i.e. JPEG 2000 provides the most flexible solution, combining good compression performance with a rich set of features.

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