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Analysis of Lossless color image compression context adaptive Huffman Coding


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Abstract:

In this project we present a new lossless color image compression algorithm based on the hierarchical prediction and context-adaptive arithmetic coding. For the lossless compression of an RGB image it is first de-correlated by a reversible color transform and then Y component is encoded by a conventional lossless grayscale image compression method. For encoding the chrominance images we develop a hierarchical scheme that enables the use of upper, left, and lower pixels for the pixel prediction, whereas the conventional raster scan prediction methods use upper and left pixels.

An appropriate context model for the prediction error is also defined and the arithmetic coding is applied to the error signal corresponding to each context. For several sets of images, it is shown that the proposed method further reduces the bit rates compared with JPEG2000 and JPEG-XR.

Image Compression Standards

There are many methods available for lossy and lossless, image compression. The efficiency of these coding standardized by some Organizations. The International Standardization Organization (ISO) and Consultative Committee of the International Telephone and Telegraph (CCITT) are defined the image compression standards for both binary and continuous tone (monochrome and Colour) images. Some of the Image Compression Standards are:

1. JBIG1
2. JBIG2
3. JPEG-LS
4. DCT based JPEG
5. Wavelet based JPEG2000

Currently, JPEG2000 [3] is widely used because; the JPEG-2000 standard supports lossy and lossless compression of single-component (e.g., grayscale) and multicomponent (e.g., color) imagery. In addition to this basic compression functionality, however, numerous other features are provided, including: 1) progressive recovery of an image by fidelity or resolution; 2) region of interest coding, whereby different parts of an image can be coded with differing fidelity; 3) random access to particular regions of an image without the needed to decode the entire code stream; 4) a flexible file format with provisions for specifying opacity information and image sequences; and 5) good error resilience. Due to its excellent coding performance and many attractive features, JPEG 2000 has a very large potential application base. Some possible application areas include: image archiving, Internet, web browsing, document imaging, digital photography, medical imaging, remote sensing, and desktop publishing.

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The main advantage of JPEG2000 over other standards, First, it would addresses a number of weaknesses in the existing JPEG standard. Second, it would provide a number of new features not available in the JPEG standard.

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, 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 adaptivity hereof consists that, the system can choose different update filters in two ways;

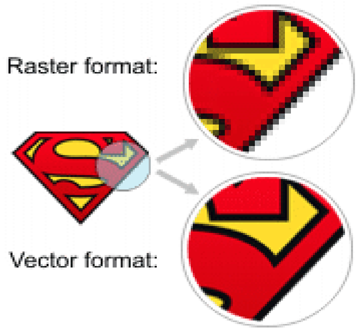
i) the choice is triggered by combining the different norms,

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.

IMAGE FILE FORMATS:

Image file formats are standardized means of organizing and storing images. This entry is about digital image formats used to store photographic and other images. Image files are composed of either pixel or vector (geometric) data that are rasterized to pixels when displayed (with few exceptions) in a vector graphic display. Including proprietary types, there are hundreds of image file types. The PNG, JPEG, and GIF formats are most often used to display images on the Internet.



In addition to straight image formats, Metafile formats are portable formats which can include both raster and vector information. The metafile format is an intermediate format. Most Windows applications open metafiles and then save them in their own native format.

FUNDAMENTAL STEPS IN DIGITAL IMAGE PROCESSING:

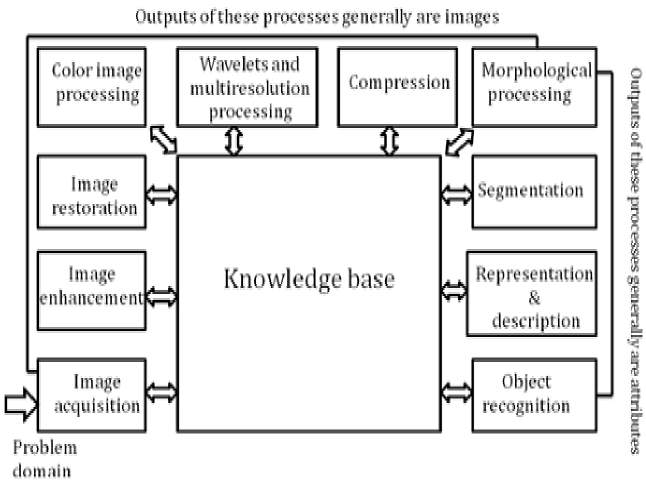
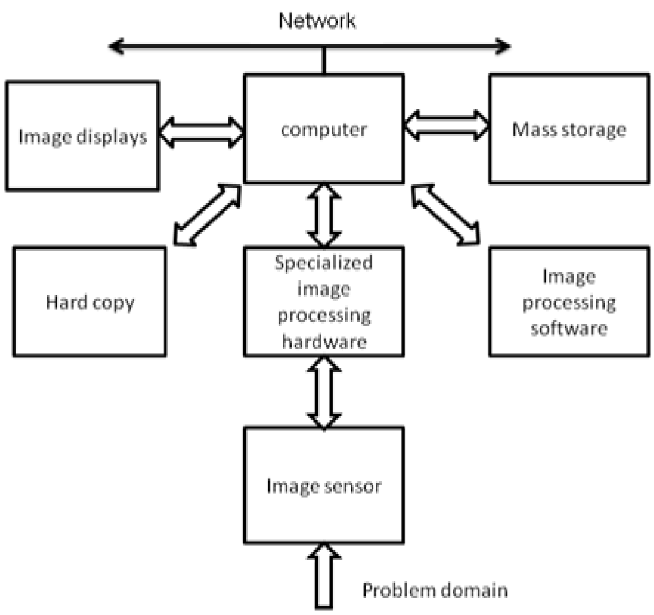


Fig: Fundamental steps in digital image processing

COMPONENTS OF AN IMAGE PROCESSING SYSTEM:

As recently as the mid-1980s, numerous models of image processing systems being sold throughout the world were rather substantial peripheral devices that attached to equally substantial host computers. Late in the 1980s and early in the 1990s, the market shifted to image processing hardware in the form of single boards designed to be compatible with industry standard buses and to fit into engineering workstation cabinets and personal computers. In addition to lowering costs, this market shift also served as a catalyst for a significant number of new companies whose specialty is the development of software written specifically for image processing.



Although large-scale image processing systems still are being sold for massive imaging applications, such as processing of satellite images, the trend continues toward miniaturizing and blending of general-purpose small computers with specialized image processing hardware. Figure 1.24 shows the basic components comprising a typical general-purpose system used for digital image processing. The function of each component is discussed in the following paragraphs, starting with image sensing.

The wavelet transform involves projecting a signal onto a complete set of translated and dilated versions of a mother wavelet Ψ(t). The strict definition of a mother wavelet will be dealt with later so that the form of the wavelet transform can be examined first. For now, assume the loose requirement that Ψ(t) has compact temporal and spectral support (limited by the uncertainty principle of course), upon which set of basis functions can be defined.

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

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

------------ (2.2)

The variable 'a' (inverse of frequency) reflects the scale (width) of a particular basis function such that its large value gives low frequencies and small value gives high frequencies. The variable 'b' specifies its translation along x-axis in time. The term $1/\sqrt{a}$ is used for normalization.

WAVELET TRANSFORM

1-D Continuous wavelet transform

The 1-D continuous wavelet transform is given by:

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \qquad \text{--(2.3)}$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)db\frac{da}{a^2} \qquad \text{-- (2.4)}$$

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

$\Psi(\omega)$ is the Fourier transform of the mother wavelet Ψ(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.

1-D Discrete wavelet transform

The discrete wavelets transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discretize the

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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 $-\infty < m, n < \infty$ -------- (2.5)

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

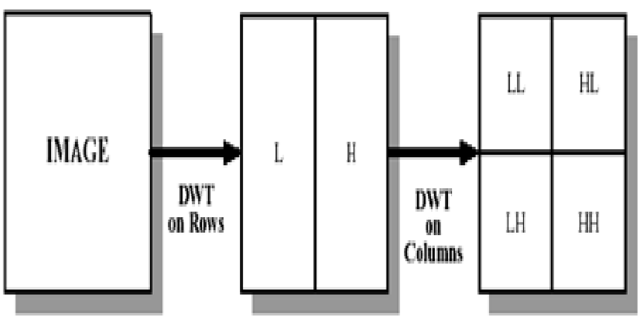
$W_{m,n} = \langle x(t), \psi_{m,n}(t) \rangle$; $m, n \in Z$ ------------ (2.6)

The 1-D inverse DWT is given as:

$x(t) = \sum_m \sum_n W_{m,n} \psi_{m,n}(t)$; $m, n \in Z$ ------------- (2.7)

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 2.1(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.



LIFTING USING HARR

The lifting scheme is a useful way of looking at discrete wavelet transform. It is easy to understand, since it performs all operations in the time domain, rather than in the frequency domain, and has other advantages as well. This section illustrates the lifting approach using the Haar Transform [6].

The Haar transform is based on the calculations of the averages (approximation co-efficient) and differences (detail co-efficient). Given two adjacent pixels a and b, the principle is to calculate the average $s = \frac{(a+b)}{2}$ and the difference $d = a - b$. If a and b are similar, s will be similar to both and d will be small, i.e., require few bits to represent. This transform is reversible, since $a = s - \frac{d}{2}$ and $b = s + \frac{d}{2}$ and it can be written using matrix notation as

$$(s,d) = (a,b)\begin{pmatrix} 1/2 & -1 \\ 1/2 & 1 \end{pmatrix} = (a,b)A,$$

$$(a,b) = (s,d)\begin{pmatrix} 1 & 1 \\ -1/2 & 1/2 \end{pmatrix} = (s,d)A^{-1}$$

Consider a row of 2^n pixels values $S_{n,l}$ for $0 \le l < 2^n$. There are 2^{n-1} pairs of pixels $S_{n,2l}, S_{n,2l+1}\, for\, l = 0,2,4,\ldots,2^{n-2}$. Each pair is transformed into an average $S_{n-1,1} = (S_{n,2l} + S_{n,2l+1})/2$ and the difference $d_{n-1,l} = S_{n,2l+1} - S_{n,2l}$. The result is a set $S_{n-1}\, of\, 2^{n-1}$ averages and a set $d_{n-1}\, of\, 2^{n-1}$ differences.

Algorithm:

1) Initialization: output n $= \lfloor \log_2(\max_{(i,j)}\{|c_{i,j}|\}) \rfloor$; set the LSP as an empty list, and add the coordinates (i, j) ∈H to the LIP, and only those with descendants also to the LIS, as type A entries.

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Sorting Pass:

for each entry (i,j) in the LIP do:

2.1.1) output $S_n(i, j)$;

2.1.2) if $S_n(i, j) = 1$ then move (i, j) to the LSP and

output the sign of $c_{i,j}$;

For each entry (i, j) in the LIS do:

2.2.1) if the entry is of type A then

- output S_n(D(i,j)) ;
- if S_n(D(z, 1)) = 1 then
  - ❖ for each (k , I) ∊ O(i,j) do:
    - output S_n(k, l);
    - if S_n(k, I) = 1 then add (k ,l) to the LSB and sign of $c_{i,j}$
    - if S,(k, 1) = 0 then add (k ,l) to the end of LIP.
  - ❖ if l(i, j) # 0 then move (i, j) to the end of the LIS, as an entry of type B, and go to Step 2.2.2); otherwise, remove entry (i, j) from the LIS;

if the entry is of type B then

- output Sn(L(2, J)) ;
- if S_n(L(I, j)) = 1 then
  * add each (k , I) ∊ O(z, j) to the end of the LIS as an entry of type A;
  * remove (i, j) from the LIS.

Refinement Pass: for each entry (i, j) in the LSP, except those included in the last sorting pass (i.e., with same n), output the nth most significant bit of $|c_{i,j}|$;

Quantization-Step Update: decrement n by 1 and go to Step 2.

RESULTS AND COMPARISONS

QUALITY MEASURES FOR IMAGE:

The Quality of the reconstructed image is measured interms of mean square error (MSE) and peak signal to noise ratio (PSNR) ratio [12]. The MSE is often called **reconstruction error variance σ_q^2**. The MSE between the original image ***f*** and the reconstructed image ***g*** at decoder is defined as:

$$\textbf{MSE} = \sigma_q^2 = \frac{1}{N}\sum_{j,k}(f[j,k]-g[j,k])^2$$

Where the sum over j, k denotes the sum over all pixels in the image and N is the number of pixels in each image. From that the peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance. The PSNR between two images having 8 bits per pixel in terms of decibels (dBs) [12] is given by: PSNR

$$= 10\log_{10}\left(\frac{255^2}{MSE}\right)$$

Generally when PSNR is 40 dB or greater, then the original and the reconstructed images are virtually indistinguishable by human eyes.

SIMULATION RESULTS

INPUT IMAGE:

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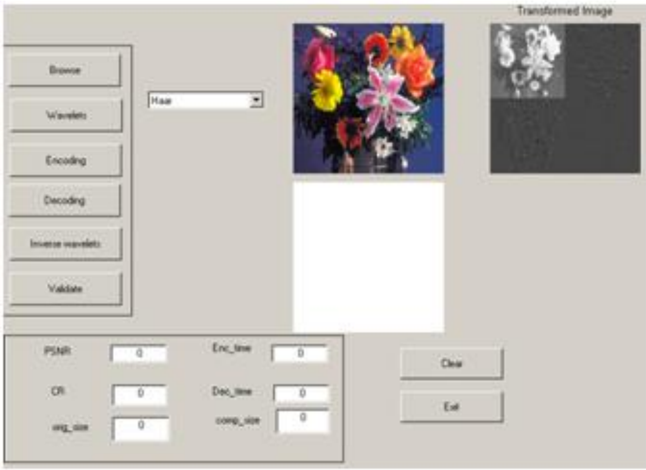
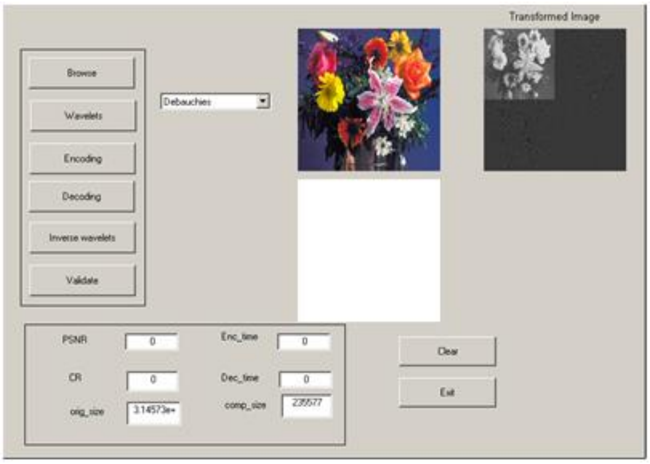
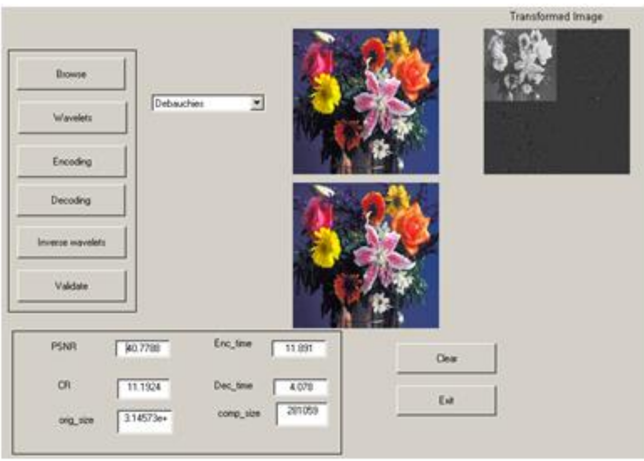
Haar Transformed Image



DEBAUCHIES TRANSFORMED IMAGE:



OUTPUT



CONCLUSION AND FUTURE WORK

In this project, Image compression based on adaptive and non-adaptive wavelets decomposition is presented. The adaptive lifting technique includes an adaptive update lifting and fixed prediction lifting step. The adaptivity here of 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.

The results of adaptive and Non-adaptive based image compression are compared. From the results the adaptive wavelet decomposition works better than non-adaptive wavelet decomposition.

Future work aims at extending this frame work for colour video compressions, and Denoising applications.

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