Wavelet Identical Learning Neural Network–Based Image (JPG-JPEG) compression [+]

التدريب الأمثل للشبكة العصبية بأستخدام المويجة في ضغط مجموعة حزم الصور الفوتوغرافية والفديوية

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Abstract:

The best image quality at a given bit-rate (or compression rate) is the main goal of image compression to create much smaller files that use less space to store and less time to send. This demand is to increase the bandwidth to all users. The quality reduction achieved by manipulation of the bit stream or file without decompression and re-compression refers to scalability. In this paper the names for scalability are progressive coding or embedded bit streams, especially with a lossless compression found in a form of coarse-to-fine pixel scans. A fast scheme with a wavelet neural network fast forward multi- layer perceptron is used to recognize the quality or layer and resolution component progressive, (the highest possible compression rate without visual loss of image quality). Hence, the bit stream successively refines the reconstructed image by encoding the lower image resolution, then encoding the difference to high resolution. By encoding both grey and color pixels. With lossy compression of the image the quality of the compression procedure is measured by the Peak signal-to-noise ratio. In this paper a high resolution digital camera (DSC-W-100, 8.1 Mega Pixels) with a (2448x3264x3) or the total grand is (23970816) elements using (23970816) bytes for my baby photo. The language used is (Mat-Lab languages).

Keyword: JPEG(Joint Photographic Experts Group);JPG(Joint Photographic Group);SBC(Sub-Band-Coding); DWT(Discrete Wavelet Transform);MPEG(Moving Picture Expert Group);MLP(Multi Layer Perceptons).

المستخلص:

الهدف الرئيس لضغط الصور هو مقياس التحديد لمعامل الجودة عن طريق الوصول الى ادق التفاصيل لمعلومات الصورة بعد تقطيعها.يعتبر ضغط الصورةهو الوصول الى ملف بأقل مساحة ممكنة للخزن وبفترة ارسال قليلة، عليه يتطلب زيادة عرض النطاق الترددي لضمان تحقيق الأرسال لكل المستخدمين . فجودة الصور تنخفض بأستمرارية التعامل مع التحليل للمستويات الأقل للأجزاء المقطوعة، أي مع الفايلات غير المضغوطة. في هذا البحث تم اعتماد التسلق بأستمرارية تشفير أو اخفاء السيل المستمر لأدق التفاصيل ولأقل مستوى من التحليل لتقطيع الصورة، وبالأخص مع المسح الغليظ (الخشن) ، أي الضغط المسبوق بفقد. أعتمد برنامج سريع بأستخدام المويجة مع الشبكة العصبية متعددة الطبقات ومن نوع المتجه الأمامي للتدريب للوصول الى دقة في تفاصيل التقطيع ، أي اعلى مستوى للضغط وبدون فقد يذكر . عليه فأن تكرار تدفق

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الأجزاء المتواصل يسهل من اعادة استخلاص الصور عن طريق تشفير ادنى مستوى لتفاصيل الصورة ومن ثم التدرج بأعلى المستويات من التحليل ابتداءا" بتشفير التدرج بمستوى الأبيض والأسود ومن ثم التدرج بالألوان.مقياس جودة الصورة المضغوطة والمسبقة بفقد يتم عن طريق اعتمادة نسبة الأشارة الى الضوضاء . في هذا البحث اسخدمت كاميرا رقمية عالية الدقة(٨،١ ميكا بيكسل) بمعدل تفاصيل للصورة يصل الى (٢٣٩٧٠٨١٦ عنصر) لصورة طفلتي (صفا) بأعتماد برنامج الماتلاب.

Introduction:

Compressing an image is significantly different than compressing raw binary data. General purpose Compression programs can be used to compress images, but the result is less than optimal. This is because Images have certain statistical properties which can be exploited by encoders specifically designed for them. An approximation of the original image is enough for most purposes, as long as the error between the original and the compressed image is tolerable. Wavelets are a transformation of an image into its component parts as a frequency representation (i.e., how fast things change in certain repetitive patterns: waves). JPEG_S use different basis functions that are claimed to be better than the Discrete Cosine Transform (DCT) [1]. DCT algorithms such as JPEG and MPEG are all special cases of Wavelet transforms uses what are called Multi-resolution Motion Estimation Technique (MRME).They are excellent for computer graphics. JPEGs support 24-bits of color depth or 16.7 million colours (2^24=16,777,216 colors).JPEG is lossy compression algorithm that works by converting the spatial image representation into a frequency map [2]. A Discrete Cosine Transform (DCT) separates the high- and low-frequency information present in the image. The high frequency information is then selectively discarded, depending on the quality setting. Usually a technique like integer to integer wavelet compression is applied to a large data set (like an image) as the first step in the compression process. A second data coding step is applied. Ideally the first step will result in repeated value (either sequential repeats or multiple occurrences of a given value), so additional compression can be achieved by a coding algorithm like Huffman or run length coding. Wavelet compression is a form of predictive compression. Predictive compression algorithms can be used to estimate the amount of noise in the data set, relative to the predictive function. Turning this around, wavelet compression, especially wavelet packet compression can be used to estimate the amount of determinism in a data set. This can be useful in time series forecasting, since a region with low noise and high determinism may be a region that is more predictable. In terms of wavelet compression, a region that is relatively compressible may be more predictable. The first step in the wavelet compression process is to digitize the image. The digitized image can be characterized by its intensity levels, or scales of gray which range from 0 (black) to 255 (white), and its resolution, or how many pixels per square inch. The wavelet transform takes an input data set and maps it to a transformed data set [3]. When a floating point wavelet transform is applied to an integer data set, the transform maps the integer data into a real data set. The object of a compression algorithm is to represent the original data in fewer bits; a set of floating point results may require more bits than were needed to represent the original integer data set. If the compression algorithm is lossy, the result of the wavelet transform can be rounded to integer values or small values may be set to zero. Lossy compression does not provide as good an estimate for calculating the amount of deterministic information in a time series, since some information has been discarded.

Forward transform: [3].

$$D_{J+1,i} - S_{J,2i} \tag{1}$$

$$S_{J+1,i} = S_{J,2i} + \left| d_{j+1,i}/2 \right| \tag{2}$$

Inverse transform:

$$S_{J-1,2i} = S_{J,i} - \left| d_{j,i}/2 \right| \tag{3}$$

$$S_{J-1,2i+1} = d_{J,i} + S_{J-1,2i} \tag{4}$$

The integer version of the linear interpolation wavelet transforms "predicts" that an odd element will be on a line between its two even neighbors. The difference between this "prediction" and the actual value becomes the wavelet coefficient (sometimes called the detail coefficient). The scaling function is simply the average of the original even and odd elements.

Forward transform:

$$D_{J+1,i} = S_{J,2i+1} - \left| S_{j,2i} + S_{j,2i+2}/2 + 0.5 \right| \tag{5}$$

$$S_{J+1,i} = S_{J,2i} + \left| d_{j+1,i-1} + d_{j+1,i}/4 + 0.5 \right| \tag{6}$$

Inverse transform:

$$S_{J-1,2i} = S_{J,i} - \left| d_{j,i-1} + d_{j,i}/4 + 0.5 \right| \tag{7}$$

$$S_{J-1,2i+1} = S_{J,2i+1} + \left| S_{j,i} + S_{j,i+2}/2 + 0.5 \right| \tag{8}$$

Where, *D, S* is forward wavelet detail and scaling coefficients. While,*d,s* are inverse once.

The forward wavelet transform takes *N* elements in step *j* and calculates *N/2* detail coefficients (shown as ***d*** above) and *N/2* scaled values (shown as ***s*** above). The scaled values become the input for the next step of the wavelet transform in the next step, $N_{j+1} = N_j/2$.The inverse wavelet transform in step *j* rebuilds the $s_{j-1,\ i}$ and $s_{j-1,\ i+1}$ (even and odd elements) from the d_j and s_j values. Compression is usually applied to large data sets. The estimation of the power of the compression algorithm is based on the number of bits needed to represent the compressed data set. The wavelet result for a relatively small data set (say 64 or 128 values) will tend to have few repeat values (e.g., a frequency close to *1/N* for each value, in the case of N values). The number of bits needed to represent the data set after the transform to estimate the amount determinism in the data set. When a high degree of compression is achieved (100% compression) hence, the wavelet algorithm closely approximated the original data set, leaving only small residual values. This indicates that there was a high degree of determinism, relative to the wavelet function. The total number of bits needed for to represent the wavelet result is the sum of the bit widths for each element [4]. In a real compression algorithm a sub-sequence of values would be allocated in a common number of bits per value.

The compression features of a given wavelet basis are primarily linked to the relative scarceness of the Wavelet domain representation for the signal. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using the following elements: A small number of approximation coefficients (at a suitably chosen level) and some of the detail Coefficients. The procedure contains three steps[5].

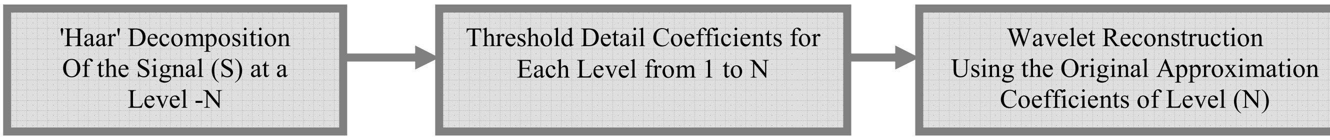


Fig. 1 The steps procedure of compression.

There are two compression approaches available [5]. The first consists of taking the wavelet expansion of the signal and keeping the largest absolute value coefficients. In this case, you can set a global threshold, a compression performance, or a relative square norm recovery performance. Thus, only a signal parameter needs to be selected. The second approach consists of applying visually determined level-dependent thresholds. Data that is compressed via a lossless compression algorithm can be exactly recovered by the decompression algorithm. Lossless compression algorithms are used to compress data where loss cannot be tolerated. Lossy compression algorithms are not perfectly invertible. The decompressed result of a lossy compression algorithm is an approximation of the original data. Lossy compression algorithms are frequently used to compress images. In many 2-D image compression algorithms, the first step of the compression algorithm converts the 2-D image data into a linear vector. In practice, a compression algorithm uses, at most, a small set of approximation functions (i.e. polynomial and spline interpolations). This function is used to "predict" values in the data set from earlier values. For example, we might choose a linear compression function that predicts that the value s_{i+1} will be equal to s_i. The difference between this prediction function and the data set is the incompressible information. This is the Lifting Scheme version of the Haar wavelet transform. Another compression function might be chosen which predicts that the point s_i lies on a line running between the point's s_{i-1} and s_{i+1}. The difference between the predicted value at s_i and the actual value at s_i is the incompressible data. This is the linear interpolation wavelet. Other prediction functions include 4-point polynomial interpolation and spline interpolation. In wavelet terminology, the predictive function is referred to as the wavelet function. The wavelet function is paired with a scaling function. The wavelet function acts as a high pass filter. The scaling function acts as a low pass filter, which avoids aliasing (large jumps in data values).Fig (2) shows the final steps needed to compress an image:

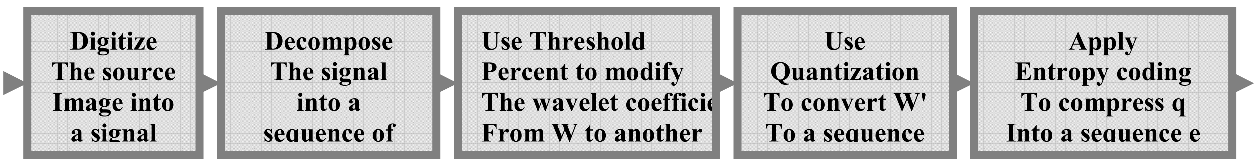
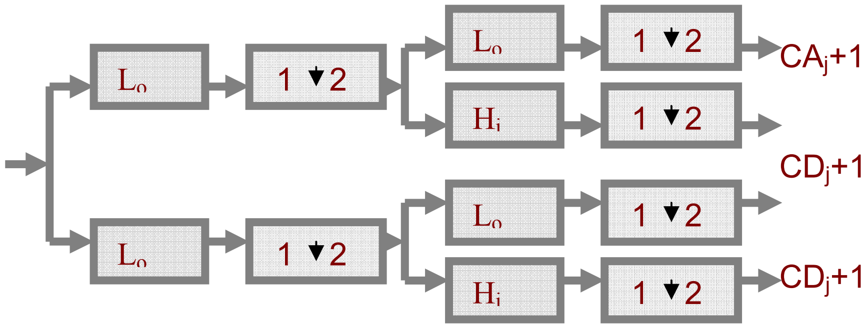


Fig. 2 A Typical Lossy Compression Image Encoder

Sub-band Coding

The fundamental concept behind Sub- band Coding (SBC) is to split up the frequency band of a signal and then to code each sub- band using a coder and bit rate accurately matched to the statistics of the band [6].



Haar" D

Fig. 4 The Safa image 400x300 Pixels, 24-Depth colour.

Fig. 5 The Safa hue bit colour, 400x300 pixels, 24-depth colour .

The process can be iterate to obtain higher band decomposition filter trees. At the decoder, the sub band signals are decoded, up sampled and passed through a bank of synthesis filters and properly summed up to yield the reconstructed image.

From Sub band to Wavelet Coding

There have been many efforts leading to improved and efficient design of filter banks and sub band coding techniques. Methods very similar and closely related to sub band coding have been proposed under the name of *Wavelet Coding* (WC) using filters specifically designed for this purpose. Such filters must meet additional and often conflicting requirements. These include short impulse response of the analysis filters to preserve the localization of image features as well as to have fast computation, short impulse response of the synthesis filters to prevent spreading of artifacts (ringing around edges) resulting from quantization errors, and linear phase of both types of filters since nonlinear phase introduces unpleasant waveform distortions around edges. Orthogonally is another useful requirement since orthogonal filters, in addition to preservation of energy, implement a unitary transform between the input and the sub bands.

Fig (4, 5) an image with it[s] hue bit color can be decomposed as a signal into various sub bands. These include uniform decomposition, octave-band decomposition, and adaptive or wavelet-packet decomposition. Out of these, octave-band decomposition is the most widely used. This is a non-uniform band splitting method that decomposes the lower frequency part into narrower bands and the high-pass output at each level is left without any further decomposition. While fig (6) shows the various sub band images of a 3-level 'Haar' decomposition. The interplay between the three components of any image coder cannot be over-emphasized since a properly designed quantizer and entropy encoder are absolutely necessary along with optimum signal transformation to get the best possible compression [7]. These have lead to improved results in terms of lower bit rates for a required image quality and better image quality for a given bit rate.

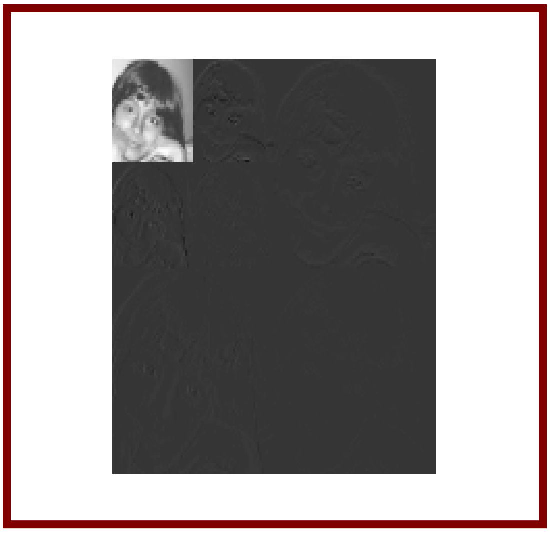


Fig. 6 The safa image 400x300 pixels, 24-depth colour, 3-levels 'Haar' decomposition.

To reach high image resolution and minimum number of coefficients that contain both the lost blocks and those surrounding them; decompose the original image into a large number of frame pixels, this is done by dividing the selected image into at least four sub-band images. In addition, sometimes the decomposition is constructed in a form of sum of two functions with different basic characteristics. One will capture the basic image structure and another will capture the texture [8]. Fig (7) shows the decomposition pattern of level-2 while Fig (8) and Fig (9) shows the splitting 'Haar' 3-Levels decomposition

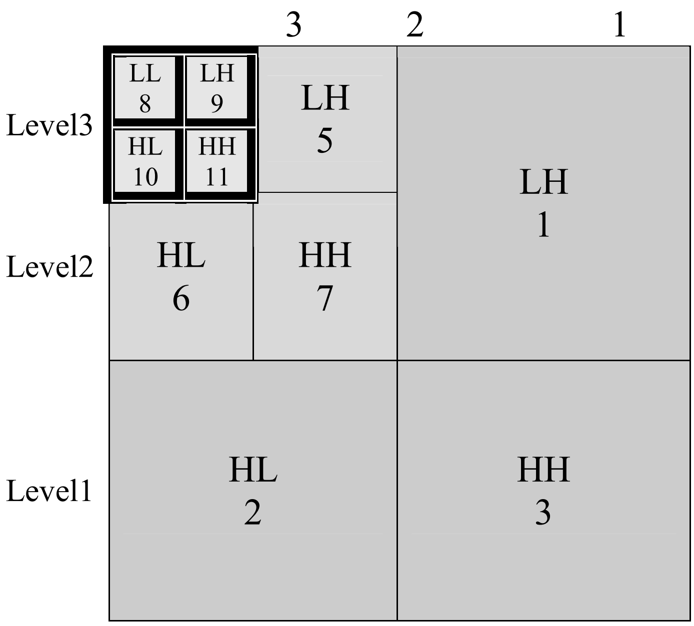


Fig. 7 The 3-Level Decomposition Pattern.

Fig. 8 The safa image 400x300 pixels, 3-levels "Haar" decomposition, in the first quadrant form.

Fig. 9 The safa image 400x300 pixels, 3-levels "Haar" decomposition, the second quadrant form.

To improve the coding performance, a fast Multi-resolution Motion Estimation (MRME) is used [9]. The set of wavelet components at each level of the pyramid are combined into a single all-orientation sub image. And the motion estimation is performed only on the all orientation
Sub images. In the standard feed forward Multi- Layer- Perceptrons (MLP) network back propagation
Solve the sub- images compression process to the hidden layers, neither the input to nor the reference
Signals for the hidden layers are known [10].
Single Neuron with output $y_{i;}$ then

$$Y_i = (1 - \exp(-2\lambda_i * X_i)) / (1 + \exp(-2\lambda_i * X_i)) = X_i \tag{9}$$

In which:

$$X_i = \sum_{i=1}^{n} W_{ij} u_j + W_o \tag{10}$$

Where, W_o is bias term and $\lambda$is the type of sigmoid function applied. The squared error of the output
Signal is given by:

$$E_i = 0.5(y_d - y_i)^2 = 0.5 e_i{}^2 \tag{11}$$

By a suitable choice of the weighting coefficients W_{ij} is desired to minimize the E_i. *E (w)* by means of
an iterative procedure generating a number of search points, *W (k)*, such that:

$$W(K+1) = W(K) + \eta(K) d(K) \tag{12}$$

The term d (k) indicates the search direction where's $\eta(k)$ indicates the length of search step or the amount of learning to be carried out. For the steepest descent method the search direction is given by:

$$D(K) = -\nabla E(W(K)) \tag{13}$$

Where, ∇indicates the derivative, or gradient of the error function. Figures (10, 11, and 12) are the proposed sub-images compression process. While figure (13) shows the proposed selected images with 65% compression steps.

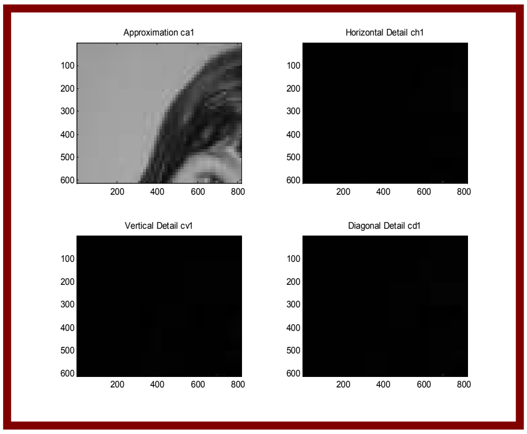


Fig. 10 The (‘safa.jpg’ 400x300 24-bits colour), 3-levels, first quadrant "Haar" decomposition compression process

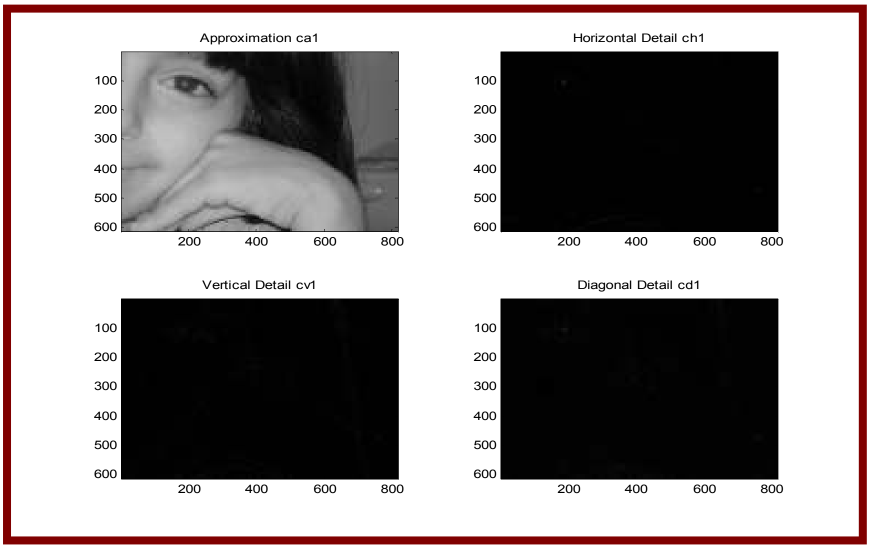
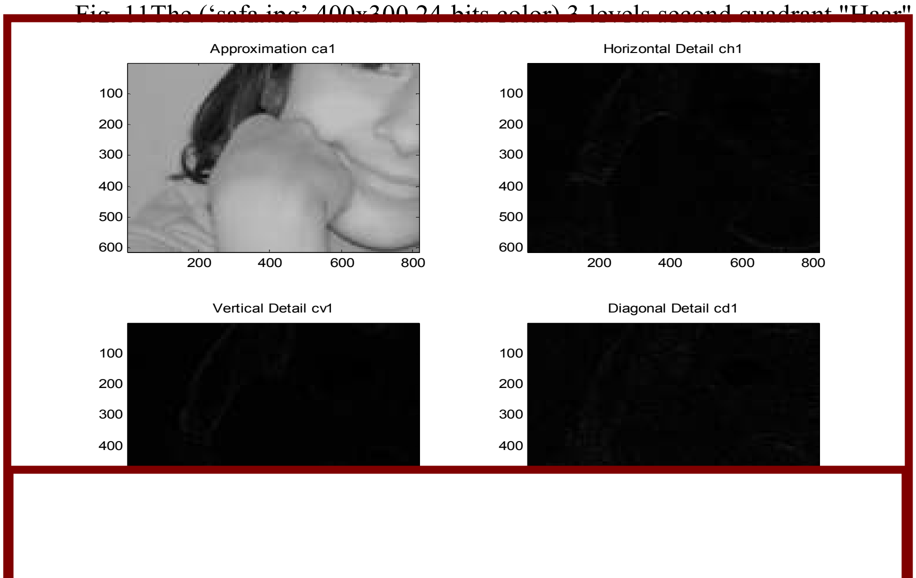


Fig. 11The ('safa.jpg' 400x300 24 bits color) 3-levels second quadrant "Haar"



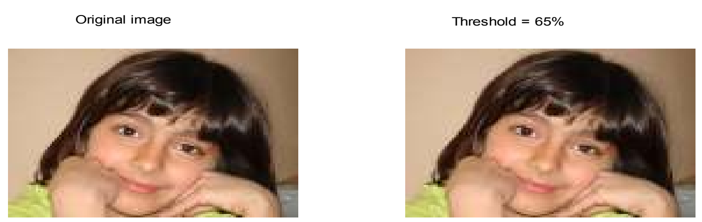


Fig. 13 The safa image 400x300 pixels, 24- depth color, in a form of 65% compression process.

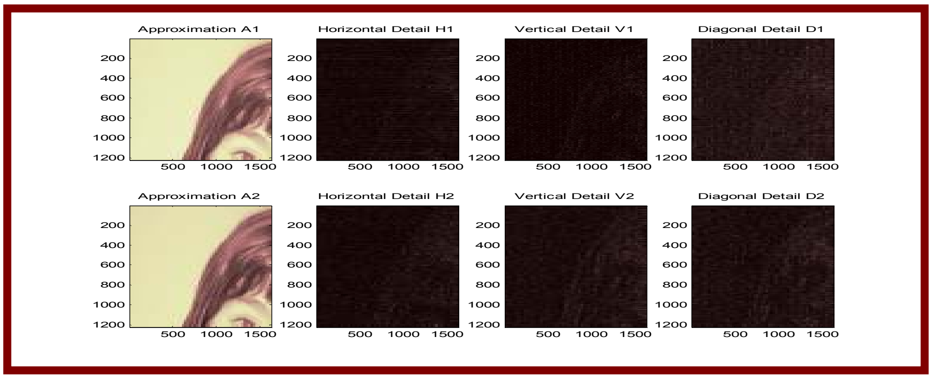


Fig. 14 The first quadrant 3-levels "Haar" decomposition
H, V, D with the approximation compression process.

The visual appearance of the image is almost exactly the same; the actual information content of the image will be reduced. High speed compression algorithm used is lossy algorithm based upon wavelet compression [11]. After conversion to a compressed image, the individual pixels are no longer discernable, because the compression technology used synthesizes a scence using full screen resolution.
The proposed 100% compression process is illustrated in (14, 15, and16).

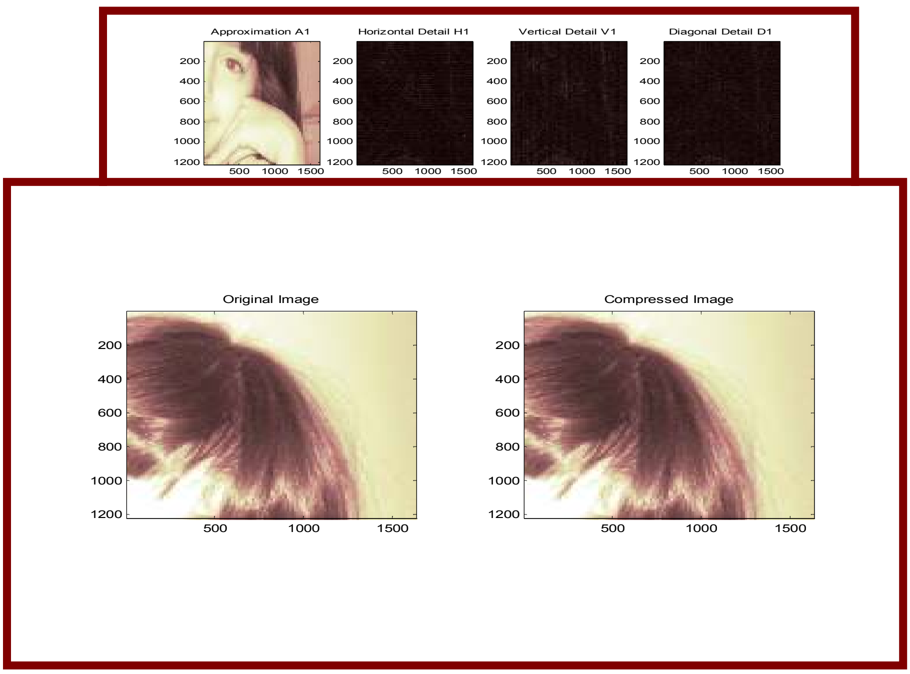


Fig. 16 The second quadrant 3-levels 100% threshold compression.

Conclusion:

Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. Several proposed systems have already demonstrated the feasibility of implementing wavelet-based system. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. The estimation of the power of the compression algorithm is based on the number of bits needed to represent the compressed data set. Our approach applies a general model to reconstruct the loss blocks before and after compression, a fast scheme for wavelet-domain interpolation of irregularly lost blocks is presented. We reconstruct the lost block in the wavelet domain using the correlation between the lost block and its neighbours. The proposed method is able to improve image quality in terms of both visual perception and image fidelity, a Neural Networks (NN) classifier can handle problems of large dimension efficiency, and hence, the classifier is combined with the wavelet domain interpolation of irregularly lost blocks. The architecture of the proposed Neural Network is a fast forward multi-layer perceptron and in its learning it uses the resilient back-propagation training. It will be seen that computation results is very closer to that Normalized desired input-output values.

References:

1. R., Ulichney, "Digital Halftoning," MIT Press, Cambridge, Mass., 1987.
2. H. sun and W. Kwok, "Concealment of Damaged Block Transform Coded Images," Using Projections onto Conves Sets, IEEE. Transactions on Image Processing vol.4, PP. 470-477, April 1995.
3. S. G. rane, Sapiro, and M. Bertalmio, "Wavelet Domain Reconstruction of Lost Blocks In Wireless Image Transmission and Packet-Switched Networks, submitted to IEEE. Transactions on Image Processing, 2002.
4. O., M., Rioul, Vetterli, "Wavelet and Signal Processing," Signal Processing magazine IEEE.Vol. 8, No.4 ISSN 1053-5888, PP. 14-37, October. 1991.

5. A. Ortega, "Optimal rate allocation under multiple rate constraints", Data compression Confernce'96,
Snowbird, UT, Mar. 1996.
6. S.S Hemami, "Digital image coding for robust multimedia transmission," in Symposium on Multimedia
Communications and Video Coding, (New York, NY), 1995.
7. Michael L. Hilton, Bjorn D. Jawerth, and Ayan Sengupta, "Compression Still and Moving Images with Wavelets," Multimedia Systems, vol.2, no.3.
8. S.G Mallat “A Theory for Multi-Resolution Signal Decomposition: The wavelet Representation,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 11, pp. 674-693, 1989.
9. 44.K., Warwick, “Neural Networks for Control: Counter Arguments,” Proc. IEE int. Conference control
94, Warwick University, PP. 95-99, 1994.
10. K. J. Hunt, D. Sbarbaro, R. Zbikowski and P.J. Gawthrop, “Neural Networks for Control Systems-
Asurvey, Automatica,”vol. 28, pp.1083-1112, 1992.
11. Z. fan and R. Eschbach, “JPEG Decompression with Reduced Artifacts,” in Proc. SPIE 1996 Symp.
Image and Video Compression, vol. 2186, PP. 50-55, Feb. 1996.