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The size of typical still image (1200x1600)

 $1200 \times 1600 \times 3byte = 5760000byte$

= 5,760*Kbyte* = 5.76*Mbyte*

The size of two hours standard television (720x480) movies

 $30 \frac{frame}{\text{sec}} \times (760 \times 480) \frac{pixels}{frame} \times 3 \frac{bytes}{pixel} = 31,104,000 bytes / \text{sec}$ $31,104,000 \times \frac{bytes}{\text{sec}} \times (60 \times 60) \frac{\text{sec}}{hour} \times 2hours = 2.24 \times 10^{11} bytes$ = 224GByte.



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Data, Information, and Redundancy

- Information
- **Data** is used to represent information
- Redundancy in data representation of an information provides no relevant information or repeats a stated information
- Let n1, and n2 are data represents the same information. Then, the relative data redundancy R of the n1 is defined as
 R = 1 1/C where C = n1/n2



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- Redundancy in Digital Images
 - Coding redundancy

usually appear as results of the uniform representation of each pixel

Spatial/Temopral redundancy

because the adjacent pixels tend to have similarity in practical.

– Irrelevant Information

Image contain information which are ignored by the human visual system.



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Coding Redundancy

Spatial Redundancy

Irrelevant Information



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Coding Redundancy

- Assume the discrete random variable for r_k in the interval [0,1] that represent the gray levels. Each r_k occurs with probability p_k
- If the number of bits used to represent each value of r_k by $l(r_k)$ then L-1

$$L_{avg} = \sum_{k=0}^{L-1} l(r_k) p(r_k)$$

- The average code bits assigned to the gray level values.
- The length of the code should be inverse proportional to its probability (occurrence).



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Examples of variable length encoding

r_k	$p_r(r_k)$	Code 1	$l_1(r_k)$	Code 2	$l_2(\mathbf{r}_k)$
$r_{87} = 87$	0.25	01010111	8	01	2
$r_{128} = 128$	0.47	1000000	8	1	1
$r_{186} = 186$	0.25	11000100	8	000	3
$r_{255} = 255$	0.03	11111111	8	001	3
r_k for $k \neq 87, 128, 186, 255$	0	—	8	—	0



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Spatial/Temopral Redundancy

- Internal Correlation between the pixel result from
 - Respective Autocorrelation
 - Structural Relationship
 - Geometric Relation ship
- The value of a pixel can be reasonably predicted from the values of its neighbors.
- To reduce the inter-pixel redundancies in an image the 2D array is transformed (*mapped*) into more efficient format (Frequency Domain etc.)



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Irrelevant information and Psycho-Visual Redundancy

- The brightness of a region depend on other factors that the light reflection
- The perceived intensity of the eye is limited an non linear
- Certain information has less relative importance that other information in normal visual processing
- In general, observer searches for distinguishing features such as edges and textural regions.



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Measuring Information

- A random even E that occurs with probability P(E) is said to contain I(E) information where I(E) is defined as I(E) = log(1/P(E)) = -log(P(E))
- P(E) = 1 contain no information
- $P(E) = \frac{1}{2}$ requires one bit of information.



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Measuring Information

- For a source of events $a_0, a_1, a_2, ..., a_k$ with associated probability $P(a_0), P(a_1), P(a_2), ..., P(a_k)$.
- The average information per source (entropy) is $H = -\sum_{j=0}^{k} P(a_j) \log(P(a_j))$

For image, we use the normalized histogram to generate the source probability, which leas to the entropy

$$\widetilde{H} = -\sum_{i=0}^{L-1} p_r(r_i) \log(p_r(r_i))$$



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Fidelity Criteria

- Objective Fidelity Criteria
 - The information loss can be expressed as a function of the encoded and decoded images.
 - For image I (x,y) and its decoded approximation I'(x,y)
 - For any value of x and y, the error e(x,y) could be defined as e(x, y) = I'(x, y) - I(x, y)
 - For the entire Image

$$\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I'(x, y) - I(x, y)$$



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Fidelity Criteria

• The mean-square-error, e_{rms} is

$$e_{rms} = \sqrt{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left[I'(x, y) - I(x, y) \right]^2}$$

The mean-square-error signal-to-noise ratio SNR_{ms} is

$$SNR_{ms} = \frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I'(x, y)^2}{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [I'(x, y) - I(x, y)]^2}$$

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Value	Rating	Description
1	Excellent	An image of extremely high quality, as good as you could desire.
2	Fine	An image of high quality, providing enjoyable viewing. Interference is not objectionable.
3	Passable	An image of acceptable quality. Interference is not objectionable.
4	Marginal	An image of poor quality; you wish you could improve it. Interference is somewhat objectionable.
5	Inferior	A very poor image, but you could watch it. Objectionable interference is definitely present.
6	Unusable	An image so bad that you could not watch it.



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Three approximations of the same image





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Huffman coding is an entropy encoding algorithm used for lossless data compression. The term refers to the use of a variablelength code table for encoding a source symbol (such as a character in a file) where the variable-length code table has been derived in a particular way based on the estimated probability of occurrence for each possible value of the source symbol.



Origin	al source	Source reduction					
Symbol	Probability	1	2	3	4		
$ \begin{array}{c} a_2\\ a_6\\ a_1\\ a_4\\ a_3 \end{array} $	0.4 0.3 0.1 0.1 0.06	$\begin{array}{c} 0.4 \\ 0.3 \\ 0.1 \\ 0.1 \\ 0.1 \\ 0.1 \end{array}$	0.4 0.3 → 0.2 0.1	0.4 0.3 • 0.3	► 0.6 0.4		
a5	0.04 —						



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Huffman coding Assignment procedure

C	Original source Source reduction								
Symbol	Probability	Code	1	1	2	2		3	4
$a_2 \\ a_6 \\ a_1 \\ a_4 \\ a_3 \\ a_5$	0.4 0.3 0.1 0.1 0.06 0.04	1 00 011 0100 01010 - 01011 -	0.4 0.3 0.1 0.1 	1 00 011 0100 - 0101 -	$0.4 \\ 0.3 \\ -0.2 \\ 0.1$	1 00 010 ← 011 ←	0.4 0.3 	1 00 - 01 -	$ \begin{array}{ccc} -0.6 & 0 \\ 0.4 & 1 \end{array} $



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Arithmetic coding is a form of variable-length entropy encoding. A string is converted to arithmetic encoding, usually characters are stored with fewer bits Arithmetic coding encodes the entire message into a single number, a fraction *n* where (0.0 $\leq n < 1.0$).



Source Symbol	Probability	Initial Subinterval
<i>a</i> ₁	0.2	[0.0, 0.2)
a_2	0.2	[0.2, 0.4)
<i>a</i> ₃	0.4	[0.4, 0.8)
a_4	0.2	[0.8, 1.0)



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Compression Algorithms



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Symbol compression

This approaches determine a set of symbols that constitute the image, and take advantage of their multiple appearance. It convert each symbol into token, generate a token table and represent the compressed image as a list of tokens.

This approach is good for document images.



FIGURE 8.30 Discrete-cosine basis functions for N = 4. The origin of each block is at its top left.

where

	$\int \sqrt{\frac{1}{N}}$	for $u = 0$	
$\alpha(u) =$	$\sqrt{\frac{2}{N}}$	for $u = 1, 2,, N = 1$	(8.5-33)

and similarly for $\alpha(v)$. Figure 8.30 shows g(x, y, u, v) for the case N = 4. The computation follows the same format as explained for Fig. 8.29, with the difference that the values of g are not integers. In Fig. 8.30, the lighter gray levels correspond to larger values of g.

■ Figures 8.31(a), (c), and (c) show three approximations of the 512 × 512 monochrome image in Fig. 8.23. These pictures were obtained by dividing the original image into subinages of size 8 × 8, representing each subinage using with the DFT, one of the transforms just described (i.e., the DFT, WHT, or DCT transform), truncating 50% of the resulting coefficients, and taking the inverse transform of the truncated coefficient arrays.

In each case, the 32 retained coefficients were selected on the basis of maximum magnitude. When we disregard any quantization or coding issues, this process amounts to compressing the original image by a factor of 2. Note that in all cases, the 32 discarded coefficients had little visual impact on reconstructed image quality. Their elimination, however, was accompanied by some mean square error, which can be seen in the scaled error images of Figs. 8.31(b), (d), and (f). The actual rms errors were 1.28, 0.86, and 0.68 gray levels, respectively.



r N = 4.Tl



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a b c

FIGURE 8.17 (a) A bi-level document, (b) symbol dictionary, and (c) the triplets used to locate the symbols in the document.





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minges of size minuges of size just described just described esulting coeffic esulting coeffic esulting coeffic nt arrays. nt arrays. retained coeffi retained coeffi en we disregar en we disregar



a b c

FIGURE 8.18 JBIG2

compression comparison: (a) lossless compression and reconstruction; (b) perceptually lossless: and (c) the scaled difference between the two.













FIGURE 8.19 (a) A 256-bit

monochrome image. (b)–(h) The four most significant binary and Gray-coded bit planes of the image in (a).









- a b c d e f

- g h

FIGURE 8.20

(a)–(h) The four least significant binary (left column) and Gray-coded (right column) bit planes of the image in Fig. 8.19(a).

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FIGURE 8.22 Walsh-Hadamard basis functions for n = 4. The origin of each block is at its top left.



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FIGURE 8.23

Discrete-cosine basis functions for n = 4. The origin of each block is at its top left.



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a b c d e f

FIGURE 8.24 Approximations of Fig. 8.9(a) using the (a) Fourier, (b) Walsh-Hadamard, and (c) cosine transforms, together with the corresponding scaled error images in (d)-(f).



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DFT and DCT

The periodicity implicit in the 1-D DFT and DCT. The DCT provide better continuity that the general DFT.





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Bock Size vs. Reconstruction Error

The DCT provide the least error at almost any sub-image size.

The error takes its minimum at sub-images of sizes between 16 and 32.





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a b c d

FIGURE 8.27 Approximations of Fig. 8.27(a) using 25% of the DCT coefficients and (b) 2×2 subimages, (c) 4×4 subimages, and (d) 8×8 subimages. The original image in (a) is a zoomed section of Fig. 8.9(a).



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a b c d

FIGURE 8.28 Approximations of Fig. 8.9(a) using 12.5% of the 8×8 DCT coefficients: (a) – (b) threshold coding results; (c) – (d) zonal coding results. The difference images are scaled by 4.



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1	1	1	1	1	0	0	0	8	7	6	4	3	2	1	0
1	1	1	1	0	0	0	0	7	6	5	4	3	2	1	0
1	1	1	0	0	0	0	0	6	5	4	3	3	1	1	0
1	1	0	0	0	0	0	0	4	4	3	3	2	1	0	0
1	0	0	0	0	0	0	0	3	3	3	2	1	1	0	0
0	0	0	0	0	0	0	0	2	2	1	1	1	0	0	0
0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	1	1	0	0	0	0	1	5	6	14	15	27	28
1	1	1	1	0	0	0	0	2	4	7	13	16	26	29	42
1	1	0	0	0	0	0	0	3	8	12	17	25	30	41	43
1	0	0	0	0	0	0	0	9	11	18	24	31	40	44	53
0	0	0	0	0	0	0	0	10	19	23	32	39	45	52	54
0	1	0	0	0	0	0	0	20	22	33	38	46	51	55	60
0	0	0	0	0	0	0	0	21	34	37	47	50	56	59	61
	Ŭ	-													

a b c d

FIGURE 8.29

A typical (a) zonal mask, (b) zonal bit allocation, (c) threshold mask, and (d) thresholded coefficient ordering sequence. Shading highlights the coefficients that are retained.



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11	10	16	24	40	51	61
12	14	19	26	58	60	55
13	16	24	40	57	69	56
17	22	29	51	87	80	62
22	37	56	68	109	103	77
35	55	64	81	104	113	92
64	78	87	103	121	120	101
92	95	98	112	100	103	99
	11 12 13 17 22 35 64 92	11101214131617222237355564789295	111016121419131624172229223756355564647887929598	111016241214192613162440172229512237566835556481647887103929598112	11 10 16 24 40 12 14 19 26 58 13 16 24 40 57 17 22 29 51 87 22 37 56 68 109 35 55 64 81 104 64 78 87 103 121 92 95 98 112 100	11 10 16 24 40 51 12 14 19 26 58 60 13 16 24 40 57 69 17 22 29 51 87 80 22 37 56 68 109 103 35 55 64 81 104 113 64 78 87 103 121 120 92 95 98 112 100 103

a b

FIGURE 8.30 (a) A threshold coding quantization curve [see Eq. (8.2-29)]. (b) A typical normalization matrix.



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FIGURE 8.31 Approximations of Fig. 8.9(a) using the DCT and normalization array of Fig. 8.30(b): (a) \mathbb{Z} , (b) 2 \mathbb{Z} , (c) 4 \mathbb{Z} , (d) 8 \mathbb{Z} , (e) 16 \mathbb{Z} , and (f) 32 \mathbb{Z} .



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a b c

d e f

FIGURE 8.32 Two JPEG approximations of Fig. 8.9(a). Each row contains a result after compression and reconstruction, the scaled difference between the result and the original image, and a zoomed portion of the reconstructed image.



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Lossless Predictive coding

The encoder expects a discrete sample of a signal f(n).

- 1. A predictor is applied and its output is rounded to the nearest integer. $\hat{f}(n)$
- 2. The error is estimated as $e(n) = f(n) - \hat{f}(n)$
- 3. The compressed stream consist of first sample and the errors, encoded using variable length coding



The decoder uses the predictor and the error stream to reconstructs the original signal f(n).

- 1. The predictor is initialized using the first sample.
- 2. The received error is added to predictor result.

 $f(n) = \hat{f}(n) + e(n)$



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Lossless Predictive coding

Linear predictors usually have the form:

$$\hat{f}(n) = round\left[\sum_{i=0}^{m} a_i f(n-i)\right]$$

Original Image (view of the earth). The prediction error and its histogram.

- 1. The error is small in uniform regions
- 2. Large close to edges and sharp changes in pixel intensities





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Lossy Predictive coding

The encoder expects a discrete samples of a signal f(n).

- 1. A predictor is applied and its output is rounded to the nearest $\hat{f}(n)$
- 2. The error is mapped into limited rage of values (quantized) $\dot{e}(n)$
- 3. The compressed stream consist of first sample and the mapped errors, encoded using variable length coding





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Lossy Predictive coding

The decoder uses error stream to reconstructs an approximation of the original signal, $\dot{f}(n)$

- 1. The predictor is initialized using the first sample.
- 2. The received error is added to predictor result.

$$\dot{f}(n) = \dot{e}(n) + \hat{f}(n)$$

$$\dot{e}(n) = \begin{cases} +\zeta & e(n) > 0 \\ -\xi & otherwise \end{cases}$$





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In	put		Enc	coder		Dec	oder	Error	
п	f(n)	$\hat{f}(n)$	e(n)	$\dot{e}(n)$	$\dot{f}(n)$	$\hat{f}(n)$	$\dot{f}(n)$	$f(n) - \dot{f}(n)$	
0	14				14.0		14.0	0.0	
1	15	14.0	1.0	6.5	20.5	14.0	20.5	-5.5	
2	14	20.5	-6.5	-6.5	14.0	20.5	14.0	0.0	
3	15	14.0	1.0	6.5	20.5	14.0	20.5	-5.5	
	•	-	•						
•		•		•		-	•	•	
14	29	20.5	8.5	6.5	27.0	20.5	27.0	2.0	
15	37	27.0	10.0	6.5	33.5	27.0	33.5	3.5	
16	47	33.5	13.5	6.5	40.0	33.5	40.0	7.0	
17	62	40.0	22.0	6.5	46.5	40.0	46.5	15.5	
18	75	46.5	28.5	6.5	53.0	46.5	53.0	22.0	
19	77	53.0	24.0	6.5	59.6	53.0	59.6	17.5	
•	•	•	•	•	•	•		•	
•	•	•	•	•	•	•	•	•	



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Prediction Error

The following images show the prediction error of the predictor $\hat{f}(x, y) = 0.97 f(x, y-1)$ $\hat{f}(x, y) = 0.5f(x, y-1) + 0.5f(x-1, y)$ $\hat{f}(x, y) = 0.75f(x, y-1) + 0.75f(x-1, y) - 0.5f(x-1, y-1)$ $\hat{f}(x, y) = \begin{cases} 0.97f(x, y-1) & \Delta h \le \Delta v \\ 0.97f(x-1, y) & otherwise \end{cases}$ $\Delta h = |f(x-1, y) - f(x-1, y-1) \\ \Delta v = |f(x, y-1) - f(x-1, y-1) \end{cases}$



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Optimal Predictors

What are the parameters of a linear predictor that minimize error

$$E\{e^{2}(n)\} = E\left\{\left[f(n) - \hat{f}(n)\right]^{2}\right\}$$

While taking into account

$$\dot{f}(n) = \dot{e}(n) + \hat{f}(n) \cong e(n) + \hat{f}(n) = f(n)$$

Using the definition of linear predictor

$$E\{e^{2}(n)\} = E\left\{\left[f(n) - \sum_{i=1}^{m} \alpha_{i} f(n-1)\right]^{2}\right\}$$

We assume that f(n) has a mean zero and variance σ^2

$$\alpha = R^{-1}r$$



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And R⁻¹ is the mxn autocorrelation matrix

$$R = \begin{bmatrix} E\{f(n-1)f(n-1)\} & E\{f(n-1)f(n-2)\} & \dots & E\{f(n-1)f(n-m)\}\\ E\{f(n-2)f(n-1)\} & E\{f(n-2)f(n-2)\} & \dots & E\{f(n-2)f(n-m)\}\\ \vdots & \vdots & \vdots & \vdots\\ E\{f(n-m)f(n-1)\} & E\{f(n-m)f(n-1)\} & \dots & E\{f(n-m)f(n-1)\}\end{bmatrix}$$

$$r = \begin{bmatrix} E\{f(n)f(n-1)\}\\ \vdots\\ E\{f(n-1)f(n-m)\}\end{bmatrix}$$

$$a = \begin{bmatrix} \alpha_1\\ \vdots\\ \alpha_m \end{bmatrix}$$

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Levels		2			4			8	
i	S_i		t_i	s _i		t_i	Si		t_i
1	∞		0.707	1.102		0.395	0.504		0.222
2				∞		1.810	1.181		0.785
3							2.285		1.576
4							∞		2.994
θ		1.414			1.087			0.731	

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FIGURE 8.46 Three-scale wavelet transforms of Fig. 8.9(a) with respect to (a) Haar wavelets, (b) Daubechies wavelets, (c) symlets, and (d) Cohen-Daubechies Feauveau biorthogonal wavelets.

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Wavelet	Filter Taps (Scaling + Wavelet)	Zeroed Coefficients
Haar (see Ex. 7.10)	2 + 2	33.8%
Daubechies (see Fig. 7.8)	8 + 8	40.9%
Symlet (see Fig. 7.26)	8 + 8	41.2%
Biorthogonal (see Fig. 7.39)	17 + 11	42.1%

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Decomposition Level (Scales or Filter Bank Iterations)	Approximation Coefficient Image	Truncated Coefficients (%)	Reconstruction Error (rms)
1	256×256	74.7%	3.27
2	128×128	91.7%	4.23
3	64×64	95.1%	4.54
4	32×32	95.6%	4.61
5	16×16	95.5%	4.63

TABLE 8.14

Decomposition level impact on wavelet coding the 512×512 image of Fig. 8.9(a).



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Filter Tap	Highpass Wavelet Coefficient	Lowpass Scaling Coefficient
0	-1.115087052456994	0.6029490182363579
± 1	0.5912717631142470	0.2668641184428723
± 2	0.05754352622849957	-0.07822326652898785
± 3	-0.09127176311424948	-0.01686411844287495
± 4	0	0.02674875741080976

TABLE 8.15Impulse responsesof the low- andhighpass analysisfilters for anirreversible 9-7wavelettransform.



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FIGURE 8.49 Four JPEG-2000 approximations of Fig. 8.9(a). Each row contains a result after compression and reconstruction, the scaled difference between the result and the original image, and a zoomed portion of the reconstructed image. (Compare the results in rows 1 and 2 with the JPEG results in Fig. 8.32.)

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a b c d

FIGURE 8.53 (a) and (c) Two watermarked versions of Fig. 8.9(a); (b) and (d) the differences (scaled in intensity) between the watermarked versions and the unmarked image. These two images show the intensity contribution (although scaled dramatically) of the pseudo-random watermarks on the original image.



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FIGURE 8.54 Attacks on the watermarked image in Fig. 8.53(a): (a) lossy JPEG compression and decompression with an rms error of 7 intensity levels; (b) lossy JPEG compression and decompression with an rms error of 10 intensity levels (note the blocking artifact); (c) smoothing by spatial filtering; (d) the addition of Gaussian noise; (e) histogram equalization; and (f) rotation. Each image is a modified version of the watermarked image in Fig. 8.53(a). After modification, they retain their watermarks to varying degrees, as indicated by the correlation coefficients below each image.