

# IMAGE COMPRESSION-II

Week IX

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## IMAGE COMPRESSION

- Data redundancy
- Self-information and Entropy
- Error-free and lossy compression
- Huffman coding
- Predictive coding
- Transform coding

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### Data Redundancy

- **CODING**: Fewer bits to represent frequent symbols.
- **INTERPIXEL / INTERFRAME**: Neighboring pixels have similar values.
- **PSYCHOVISUAL**: Human visual system can not simultaneously distinguish all colors.

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### Coding Redundancy (contd.)

- Consider equation (A): It makes sense to assign fewer bits to those  $r_k$  for which  $p_r(r_k)$  are large in order to reduce the sum.
- this achieves data compression and results in a variable length code.
- More probable gray levels will have fewer # of bits.

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

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### General Model

**General compression model**

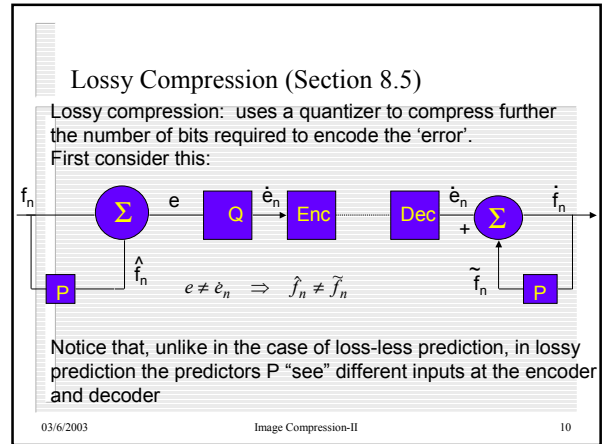
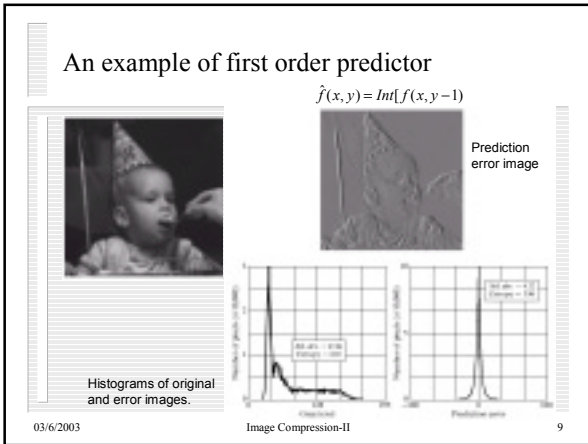
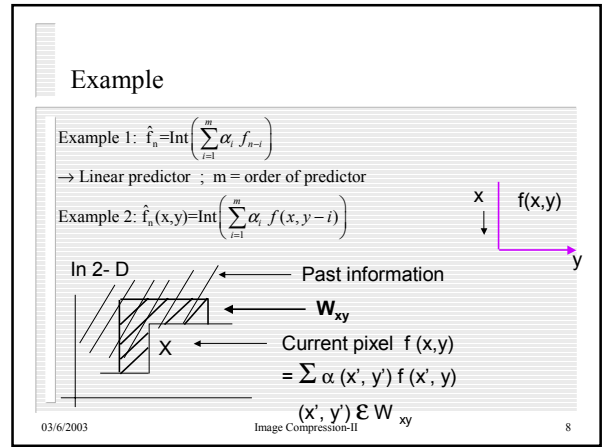
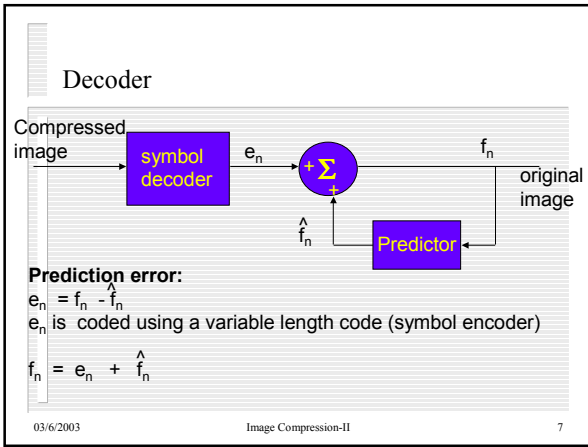
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### Predictive coding

To reduce / eliminate interpixel redundancies

**Lossless predictive coding: ENCODER**

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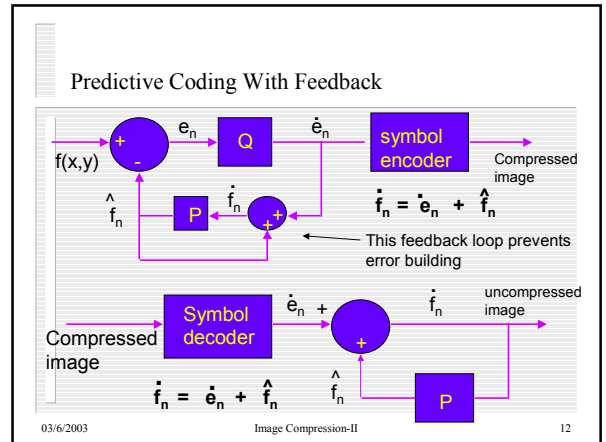


### Quantization error

This results in a gradual buildup of error which is due to the quantization error at the encoder site.  
 In order to minimize this buildup of error due to quantization we should ensure that 'Ps' have the same input in both the cases.

$f_n$	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$\hat{f}_n = f_{n-1}$															
$e_n$	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
$\hat{e}_n$	0	2	2	2	2	2	2	2	2	2	2	2	2	2	2
$\hat{f}_n$	0	2	4	6	8	10	10	10	10	10	10	10	10	10	10

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### Example

**Example:**

$$\hat{f}_n = \alpha \hat{f}_{n-1}$$

$$\text{and } \dot{e}_n = \begin{cases} +\xi & e_n > 0 \\ -\xi & e_n < 0 \end{cases} \quad 0 < \alpha < 1 \quad \text{prediction coefficient}$$

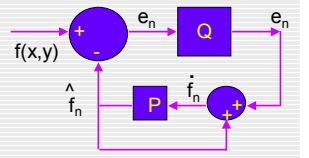
$$\hat{f}_n = \dot{e}_n + \hat{f}_{n-1}$$

$$= \dot{e}_n + \alpha \hat{f}_{n-1}$$

### Example

with feedback

$f_n$	=	0	1	2	3	4
$e_n$	=	-	1	2	1	2
$\dot{e}_n$	=	-	0	2	0	2
$\hat{f}_n$	=	0	0	2	2	4
$\hat{f}_n$	=	-	0	0	2	2



Note: The quantizer used here is-- floor( $e_n/2$ )\*2. This is different from the one used in the earlier example. Note that this would result in a worse response if used without Feedback (output will be flat at "0").

### Another example

{14, 15, 14, 15, 13, 15, 15, 14, 20, 26, 27, 28, 27, 29, 37, 37, 62, 75, 77, 78, 79, 80, 81, 81, 82, 82}



Input	Encoder			Decoder			Error
$x$	$\hat{x}$	$\dot{x}$	$\hat{x}$	$\hat{x}$	$\hat{x}$	$(x - \hat{x})$	
14	14	-	14	14	14	0	0.0
15	15	1	15	15	15	0	0.0
14	14	0	14	14	14	0	0.0
15	15	1	15	15	15	0	0.0
13	13	-	13	13	13	0	0.0
15	15	1	15	15	15	0	0.0
15	15	1	15	15	15	0	0.0
14	14	0	14	14	14	0	0.0
20	20	0	20	20	20	0	0.0
26	26	0	26	26	26	0	0.0
27	27	0	27	27	27	0	0.0
28	28	0	28	28	28	0	0.0
27	27	0	27	27	27	0	0.0
29	29	0	29	29	29	0	0.0
37	37	0	37	37	37	0	0.0
37	37	0	37	37	37	0	0.0
62	62	0	62	62	62	0	0.0
75	75	0	75	75	75	0	0.0
77	77	0	77	77	77	0	0.0
78	78	0	78	78	78	0	0.0
79	79	0	79	79	79	0	0.0
80	80	0	80	80	80	0	0.0
81	81	0	81	81	81	0	0.0
81	81	0	81	81	81	0	0.0
82	82	0	82	82	82	0	0.0
82	82	0	82	82	82	0	0.0

### A comparison (Fig 8.23)



FIGURE 8.23 A 512 × 512-bit monochrome image.

### Four linear predictors

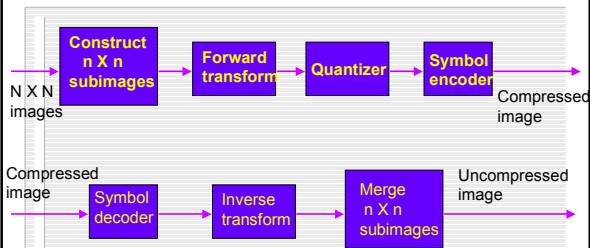
FIGURE 8.24 A comparison of four linear predictors for image.



### Transform Coding

Feb 28, 2002

## Transform coding



**Blocking artifact:** boundaries between subimages become visible

## Transform Selection

- DFT
- Discrete Cosine Transform (DCT)
- Wavelet transform
- Karhunen-Loeve Transform (KLT)
- ....

Fig 8.31

DFT,  
Hadamard  
and DCT



## Discrete Cosine Transform

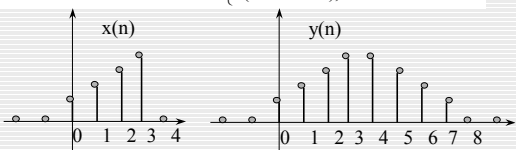
Ahmed, Natarajan, and Rao, IEEE T-Computers, pp. 90-93, 1974.

## 1-D Case: Extended 2N Point Sequence

Consider 1-D first; Let  $x(n)$  be a  $N$  point sequence  $0 \leq n \leq N-1$ .

$$x(n) \leftrightarrow \begin{matrix} 2-N \text{ point} \\ y(n) \end{matrix} \xleftrightarrow{\text{DFT}} \begin{matrix} 2-N \text{ point} \\ Y(u) \end{matrix} \leftrightarrow \begin{matrix} N \text{ point} \\ C(u) \end{matrix}$$

$$y(n) = x(n) + x(2N-1-n) = \begin{cases} x(n), & 0 \leq n \leq N-1 \\ x(2N-1-n), & N \leq n \leq 2N-1 \end{cases}$$



## DCT & DFT

$$\begin{aligned} Y(u) &= \sum_{n=0}^{2N-1} y(n) \exp\left(-j \frac{2\pi}{2N} un\right) \\ &= \sum_{n=0}^{N-1} x(n) \exp\left(-j \frac{2\pi}{2N} un\right) + \sum_{n=N}^{2N-1} x(2N-1-n) \exp\left(-j \frac{2\pi}{2N} un\right) \\ &= \sum_{n=0}^{N-1} x(n) \exp\left(-j \frac{2\pi}{2N} un\right) + \sum_{m=0}^{N-1} x(m) \exp\left(-j \frac{2\pi}{2N} u(2N-1-m)\right) \\ &= \exp\left(j \frac{\pi}{2N} u\right) \sum_{n=0}^{N-1} x(n) \exp\left(-j \frac{\pi}{2N} u - j \frac{2\pi}{2N} un\right) \\ &\quad + \exp\left(j \frac{\pi}{2N} u\right) \sum_{n=0}^{N-1} x(n) \exp\left(j \frac{\pi}{2N} u + j \frac{2\pi}{2N} un\right) \\ &= \exp\left(j \frac{\pi}{2N} u\right) \sum_{n=0}^{N-1} 2x(n) \cos\left(\frac{\pi}{2N} u(2n+1)\right). \end{aligned}$$

## DCT

The  $N$ -point DCT of  $x(n)$ ,  $C(u)$ , is given by

$$C(u) = \begin{cases} \exp\left(-j\frac{\pi}{2N}u\right)Y(u), & 0 \leq u \leq N-1 \\ 0 & \text{otherwise.} \end{cases}$$

The unitary DCT transformations are:

$$F(u) = \alpha(u) \sum_{n=0}^{N-1} f(n) \cos\left(\frac{\pi}{2N}(2n+1)u\right), \quad 0 \leq u \leq N-1, \text{ where}$$

$$\alpha(0) = \frac{1}{\sqrt{N}}, \quad \alpha(u) = \sqrt{\frac{2}{N}} \text{ for } 1 \leq u \leq N-1. \text{ The inverse transformation is}$$

$$f(n) = \sum_{u=0}^{N-1} \alpha(u) F(u) \cos\left(\frac{\pi}{2N}(2n+1)u\right), \quad 0 \leq u \leq N-1.$$

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## Discrete Cosine Transform—in 2-D

$$C(u, v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

for  $u, v = 0, 1, 2, \dots, N-1$ , where

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & \text{for } u = 0 \\ \sqrt{\frac{2}{N}} & \text{for } u = 1, 2, \dots, N-1. \end{cases} \text{ and}$$

$$f(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \alpha(u)\alpha(v) C(u, v) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

for  $x, y = 0, 1, 2, \dots, N-1$

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## DCT Basis functions

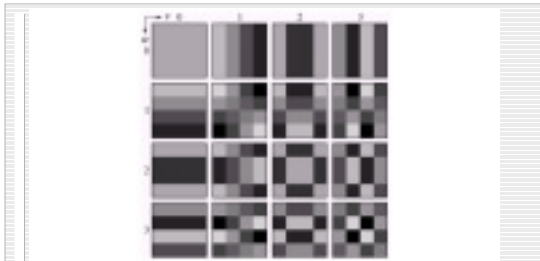


FIGURE 8.30 Discrete-cosine basis functions for  $N = 4$ . The origin of each block is at its top left.

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## Implicit Periodicity-DFT vs DCT (Fig 8.32)

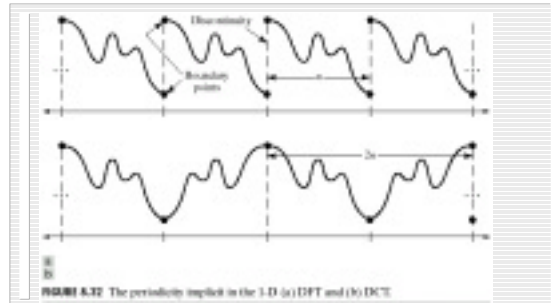


FIGURE 8.32 The periodicity implicit in the 1-D (a) DFT and (b) DCT.

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## Why DCT?

- Blocking artifacts less pronounced in DCT than in DFT.
- Good approximation to the Karhunen-Loeve Transform (KLT) but with basis vectors fixed.
- DCT is used in JPEG image compression standard.

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## Karhunen-Loeve Transform

- READ pp. 476 and Section 11.4 Text (if you are working on the face recognition project, you must!)
- Also called the Hotelling Transform.
- Transform is data dependent. Let  $X$  denote the random data, and let  $C$  be the covariance matrix of  $X$ , i.e.
 
$$C = E\{(X-m)(X-m)^T\}$$
 where  $m$  is the mean vector of the data.
 

The matrix  $C$  is real and symmetric, and hence can be diagonalized using its eigenvectors.

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## What are eigenvectors?

Let  $C = E[(x - m_x)(x - m_x)^T]$

where  $C$  is the  $N \times N$  covariance matrix,  $x$  is an  $N$ -dimensional vector, and  $m_x$  is the mean vector of the samples.

The eigenvectors  $e_i$  of  $C$  are given by

$$C e_i = \lambda_i e_i$$

where  $\lambda_i$  are the corresponding eigenvalues.

Now consider a matrix  $A$  whose columns correspond to the eigenvectors of  $C$ , arranged such that the first column corresponds to the eigenvector with the largest eigenvalue, and second with the second largest and so on.

Then, consider a transformation on the vectors  $x$  such that

$y = A^T(x - m_x)$ . Note that  $y$  is zero mean, and its covariance matrix is

$$C_y = E(y y^T) = E[A^T(x - m_x)(x - m_x)^T A] = A^T C A = \Lambda$$

= diagonal matrix of eigenvalues, in decreasing order.

Note that the elements of the transformed vector are uncorrelated (non-diagonal elements are zero).

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## What is KLT

- The transformation from  $X$  to  $Y$  is called the KLT. In computing the transformation matrix  $A$ , we assume that the columns are made up of orthonormal eigenvectors (i.e., the inverse of  $A$  is also its transpose.)
- Thus the basis vectors of the KLT are the orthonormal eigenvectors of the covariance matrix  $C$ .
- The KLT yields uncorrelated coefficients.
- For compression, we only keep the top  $K$  coefficients corresponding to the  $K$  largest eigenvectors.
- Then the mean squared error in reconstruction is given by

$$MSE = \sum_{j=K+1}^N \lambda_j$$

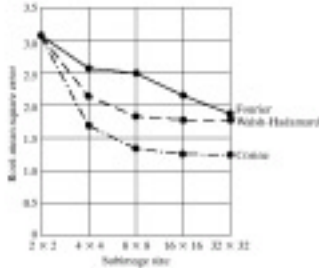
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## Sub-image size selection

FIGURE 8.33 Reconstruction error versus subimage size.



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## Different sub-image sizes



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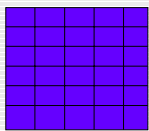
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## Bit Allocation/Threshold Coding

- # of coefficients to keep
- How to quantize them
  - Threshold coding
  - Zonal coding

### Threshold coding



- For each subimage  $i$
- Arrange the transform coefficients in decreasing order of magnitude
  - Keep only the top  $X\%$  of the coefficients and discard rest.
  - Code the retained coefficient using variable length code.

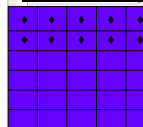
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## Zonal Coding

### Zonal coding:



$i$ th coefficient in each sub image

- (1) Compute the variance of each of the transform coeff; use the subimages to compute this.
- (2) Keep  $X\%$  of their coeff. which have maximum variance.
- (3) Variable length coding (proportional to variance)

Bit allocation: In general, let the number of bits allocated be made proportional to the variance of the coefficients. Suppose the total number of bits per block is  $B$ . Let the number of retained coefficients be  $M$ . Let  $v(i)$  be variance of the  $i$ -th coefficient. Then

$$b(i) = \frac{B}{M} + \frac{1}{2} \log_2 v(i) - \frac{1}{2M} \sum_{i=1}^M \log_2 v(i)$$

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## JPEG -color image

- RGB to Y-Cr-Cb space
  - $Y = 0.3R + 0.6G + 0.1B$
  - $Cr = 0.5(B-Y) + 0.5$
  - $Cb = (1/1.6)(R - Y) + 0.5$
- Chrominance samples are sub-sampled by 2 in both directions.

Y1	Y2	Y3	Y4	Cr1	Cr2	Cb1	Cb2
Y5	Y6	Y7	Y8	Cr3	Cr4	Cb3	Cb4
Y9	Y10	Y11	Y12				
Y13	Y14	Y15	Y16				

Non-Interleaved  
 Scan 1: Y1, Y2, ..., Y16  
 Scan 2: Cr1, Cr2, Cr3, Cr4  
 Scan 3: Cb1, Cb2, Cb3, Cb4

Interleaved: Y1, Y2, Y3, Y4, Cr1, Cb1, Y5, Y6, Y7, Y8, Cr2, Cb2, ...

## JPEG – quantization matrices

- Check out the matlab workspace (dctex.mat).
  - Quantization table for the luminance channel.
  - Quantization table for the chrominance channel.
  - JPEG baseline method
    - Consider the 8x8 image (matlab: array s.)
    - Level shifted ( $s-128=sd$ ).
    - 2d-DCT:  $dct2(sd)=dcts$
    - After dividing by quantization matrix qmat:  $dctshat$ .
    - Zigzag scan as in threshold coding.
- [20, 5, -3, -1, -2, -3, 1, 1, -1, -1, 0, 0, 1, 2, 3, -2, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, EOB].

## An 8x8 sub-image (s)

s = (8x8block)

```
183 160 94 153 194 163 132 165
183 153 116 176 187 166 130 169
179 168 171 182 179 170 131 167
177 177 179 177 179 165 131 167
178 178 179 176 182 164 130 171
179 180 180 179 183 164 130 171
179 179 180 182 183 170 129 173
180 179 181 179 181 170 130 169
```

sd =(level shifted)

```
55 32 -34 25 66 35 4 37
55 25 -12 48 59 38 2 41
51 40 43 54 51 42 3 39
49 49 51 49 51 37 3 39
50 50 51 48 54 36 2 43
51 52 52 51 55 36 2 43
51 51 52 54 55 42 1 45
52 51 53 51 53 42 2 41
```

## 2D DCT (dcts) and the quantization matrix (qmat)

dcts=

```
312 56 -27 17 79 -60 26 -26
-38 -28 13 45 31 -1 -24 -10
-20 -18 10 33 21 -6 -16 -9
-11 -7 9 15 10 -11 -13 1
-6 1 6 5 -4 -7 -5 5
3 3 0 -2 -7 -4 1 2
3 5 0 -4 -8 -1 2 4
3 1 -1 -2 -3 -1 4 1
```

qmat=

```
16 11 10 16 24 40 51 61
12 12 14 19 26 58 60 55
14 13 16 24 40 57 69 56
14 17 22 29 51 87 80 62
18 22 37 56 68 109 103 77
24 35 55 64 81 104 113 92
49 64 78 87 103 121 120 101
72 92 95 98 112 100 103 99
```

## Division by qmat (dctshat)=dcts/qmat

dctshat=

```
20 5 -3 1 3 -2 1 0
-3 -2 1 2 1 0 0 0
-1 -1 1 1 1 0 0 0
-1 0 0 1 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
```

dcts=

```
312 56 -27 17 79 -60 26 -26
-38 -28 13 45 31 -1 -24 -10
-20 -18 10 33 21 -6 -16 -9
-11 -7 9 15 10 -11 -13 1
-6 1 6 5 -4 -7 -5 5
3 3 0 -2 -7 -4 1 2
3 5 0 -4 -8 -1 2 4
3 1 -1 -2 -3 -1 4 1
```

## Zig-zag scan of dctshat

dctshat=

```
20 5 -3 1 3 -2 1 0
-3 -2 1 2 1 0 0 0
-1 -1 1 1 1 0 0 0
-1 0 0 1 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
```

Zigzag scan as in threshold coding.

[20, 5, -3, -1, -2, -3, 1, 1, -1, -1, 0, 0, 1, 2, 3, -2, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, EOB].



