



*small wave*

# LECTURE 06 **WAVELETS** AND MULTIRESOLUTION PROCESSING

Punnarai Siricharoen, Ph.D.

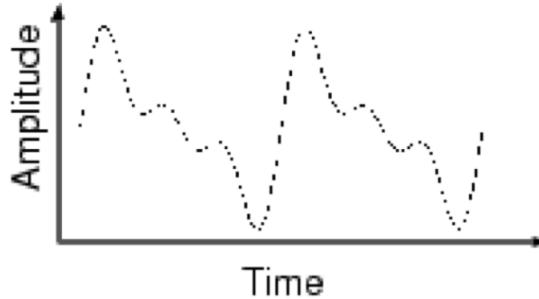
## OBJECTIVES

- To be able to understand the basic concept of wavelets (Haar wavelet)
- To be able to apply wavelets transform for multiresolution analysis

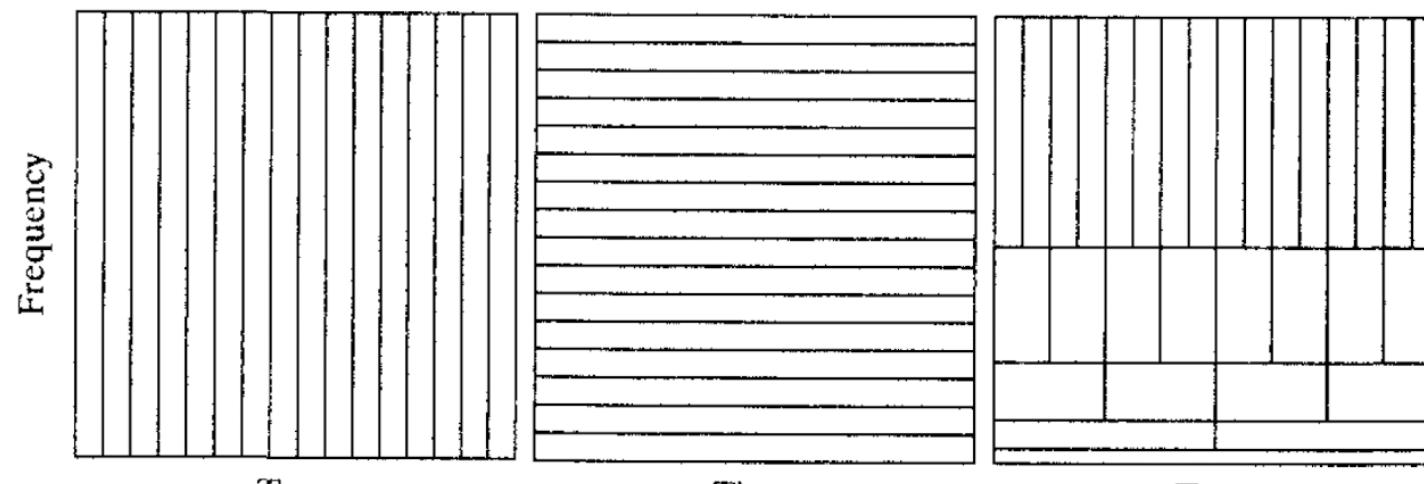
# CONTENT

- Introduction
- Image Pyramid
- Fast Wavelet Transform (1D & 2D)
- Python Exercises

# INTRODUCTION



each pixel have impact to every freq, so  
FT give a global information



a b c

**FIGURE 7.21** Time-frequency tilings for (a) sampled data, (b) FFT, and (c) FWT basis functions.

# INTRODUCTION

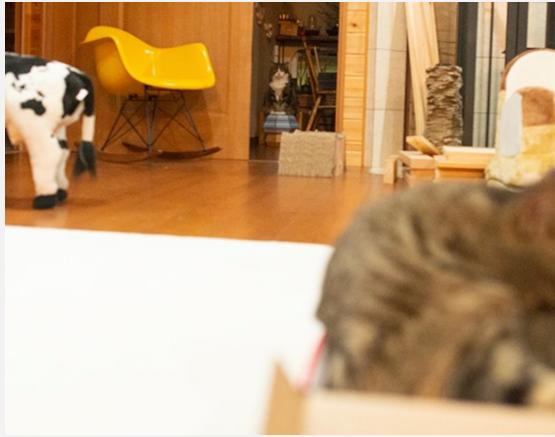
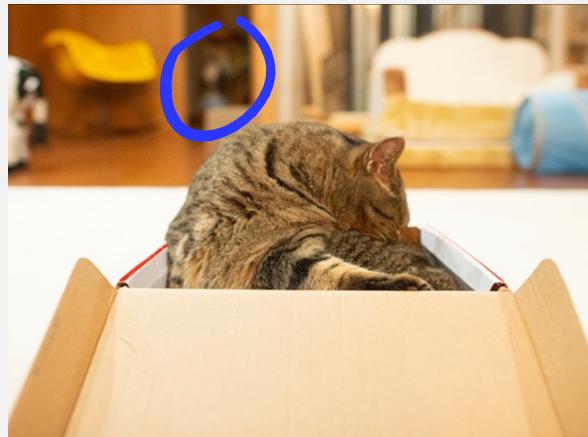
- Small object, low contrast – make it higher resolution
- Large object, high contrast – look at coarse view
- Motivation for multiresolution processing :wavelet
  - All of them together – study them in several resolutions



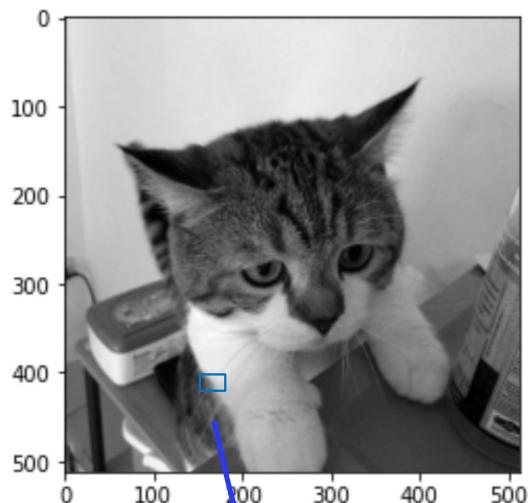
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# INTRODUCTION

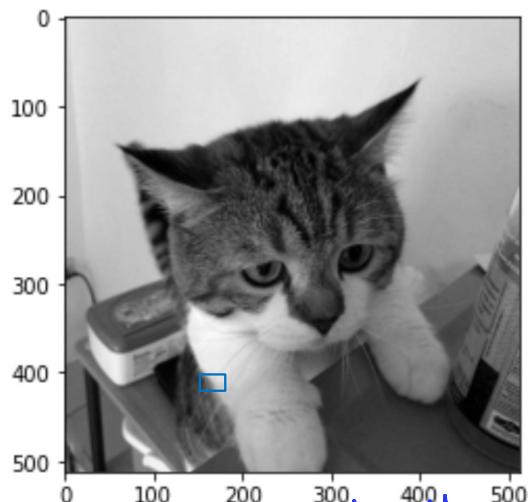
- Small object, low contrast – make it higher resolution
- Large object, high contrast – look at coarse view
- Motivation for multiresolution processing
  - All of them together – study them in several resolutions



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[[ 67 66 70 87 98 114 138 147 151 166 180 183 180 181 186 185]  
[ 56 61 75 87 96 110 127 132 138 155 174 179 178 180 184 184]  
[ 57 68 85 88 89 96 108 115 124 140 156 168 174 177 178 176]  
[ 55 65 77 77 77 84 98 111 122 132 149 163 171 176 179 179]  
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[ 43 50 57 57 65 80 89 90 98 112 118 134 149 162 171 172]]



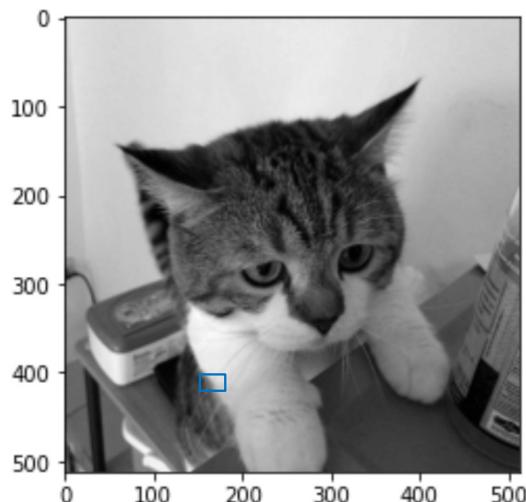
[ [ 67 66 70 87 98 114 138 147 151 166 180 183 180 181 186 185]  
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[ 57 68 85 88 89 96 108 115 124 140 156 168 174 177 178 176]  
[ 55 65 77 77 77 84 98 111 122 132 149 163 171 176 179 179]  
[ 48 53 63 63 70 83 97 106 114 122 136 149 157 165 172 175]  
[ 43 50 57 57 65 80 89 90 98 112 118 134 149 162 171 172]

average

88.5

difference

-1



```
[ [ 67  66  70  87  98 114 138 147 151 166 180 183 180 181 186 185]
[ 56  61  75  87  96 110 127 132 138 155 174 179 178 180 184 184]
[ 57  68  85  88  89  96 108 115 124 140 156 168 174 177 178 176]
[ 55  65  77  77  77  84  98 111 122 132 149 163 171 176 179 179]
[ 48  53  63  63  70  83  97 106 114 122 136 149 157 165 172 175]
[ 43  50  57  57  65  80  89  90  98 112 118 134 149 162 171 172]
```

average

88.5	102
77	91
66.5	90
61	84.5

difference

-1	-12
0	-14
-7	-14
-8	-9

88	89	96	108
77	77	84	98
63	70	83	97
57	65	80	89

average

88.5	102
77	91
66.5	90
6	84.5

Vertical

difference

-1	-12
0	-14
-7	-14
-8	-9

average

difference

82.75	96
63.75	87.25

11.5	11
5.5	5.5

88	89	96	108
77	77	84	98
63	70	83	97
57	65	80	89

average

88.5	102
77	91
66.5	90
6	84.5

difference

-1	-12
0	-14
-7	-14
-8	-9

average

82.75	96
63.75	87.25

difference

11.5	11
5.5	5.5

average of the  
vertical  
difference

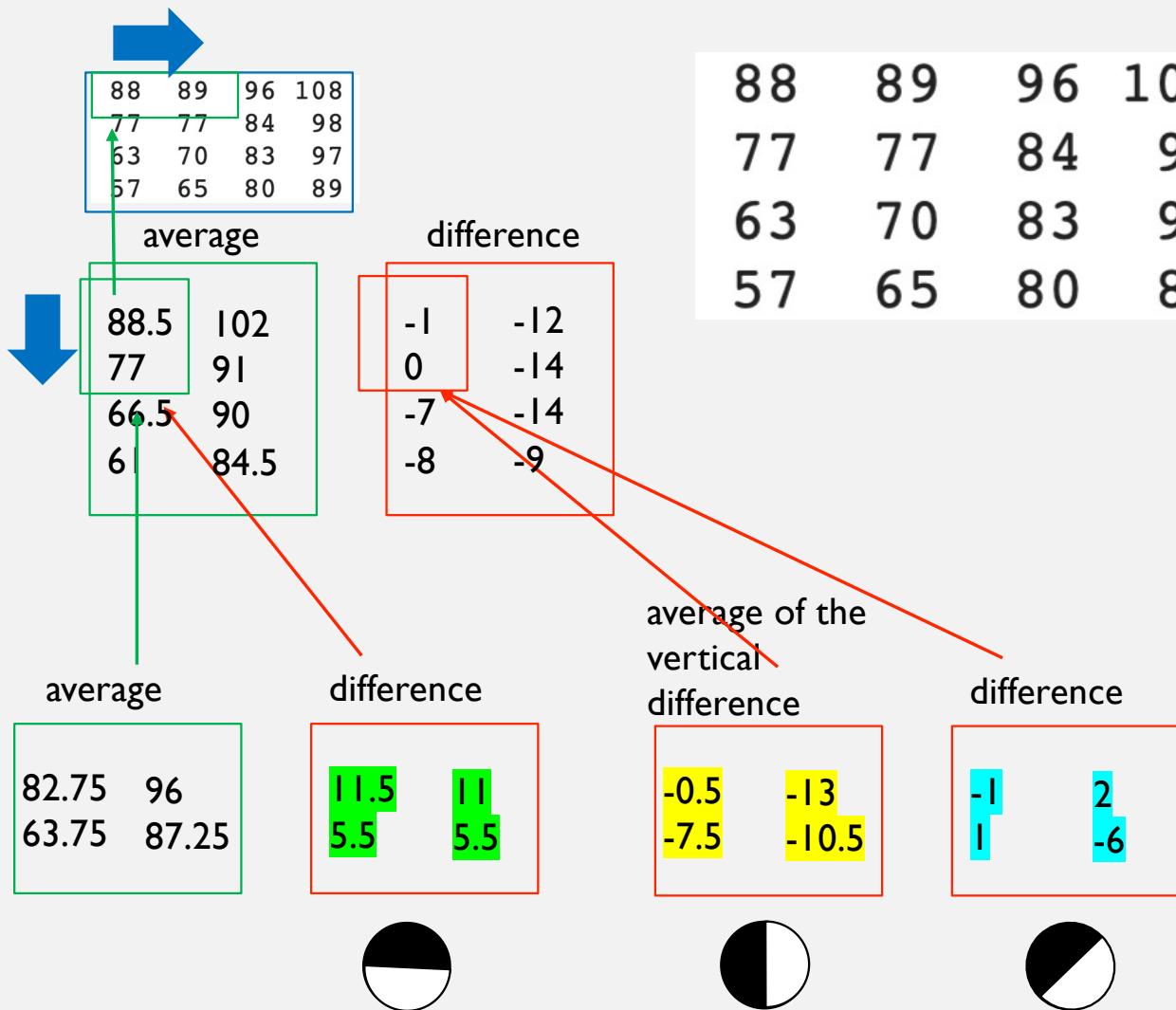
-0.5	-13
-7.5	-10.5

difference

-1	2
1	-6



Three species of differences

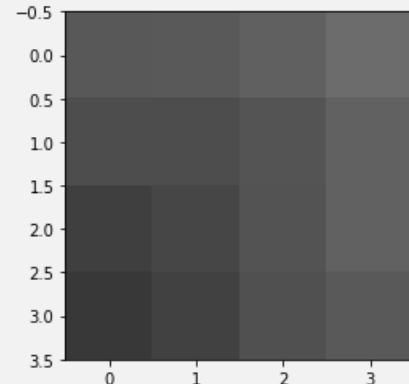


82.75	96
63.75	87.25

-0.5	-13
-7.5	-10.5

-1	2
1	-6

Three species of differences



average

88	89	96	108
77	77	84	98
63	70	83	97
57	65	80	89

difference

-1	-12
0	-14
-7	-14
-8	-9

average

88.5	102
77	91
66.5	90
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difference

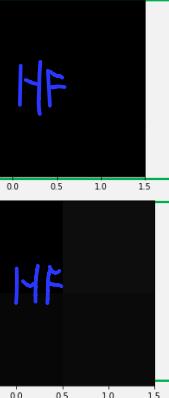
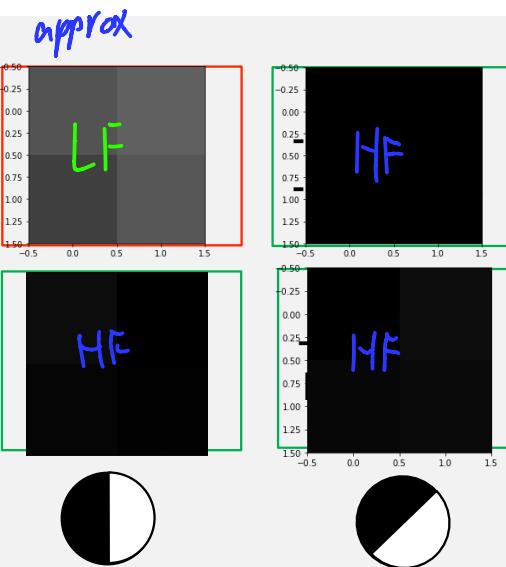
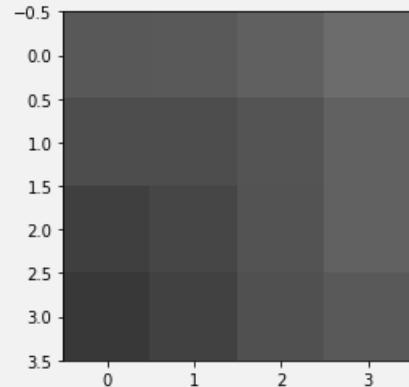
11.5	11
5.5	5.5

horizontal detailed

-0.5	-13
-7.5	-10.5

average of the vertical difference

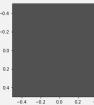
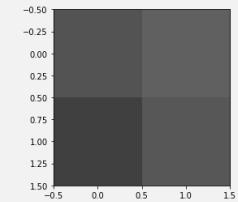
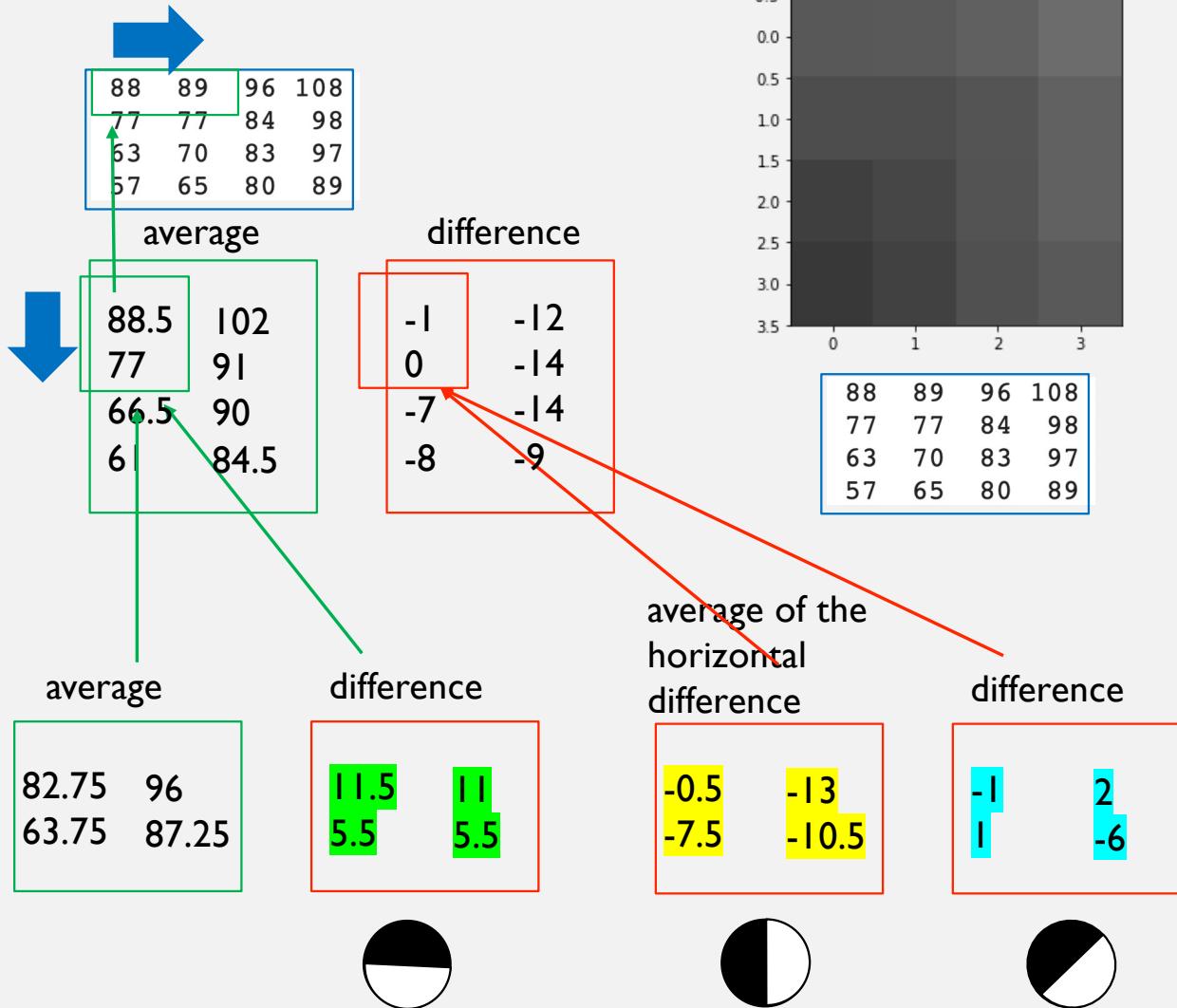
-1	2
1	-6



vertical detailed

diagonal detail

Three species of differences

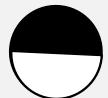


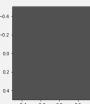
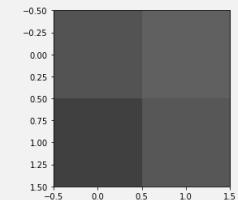
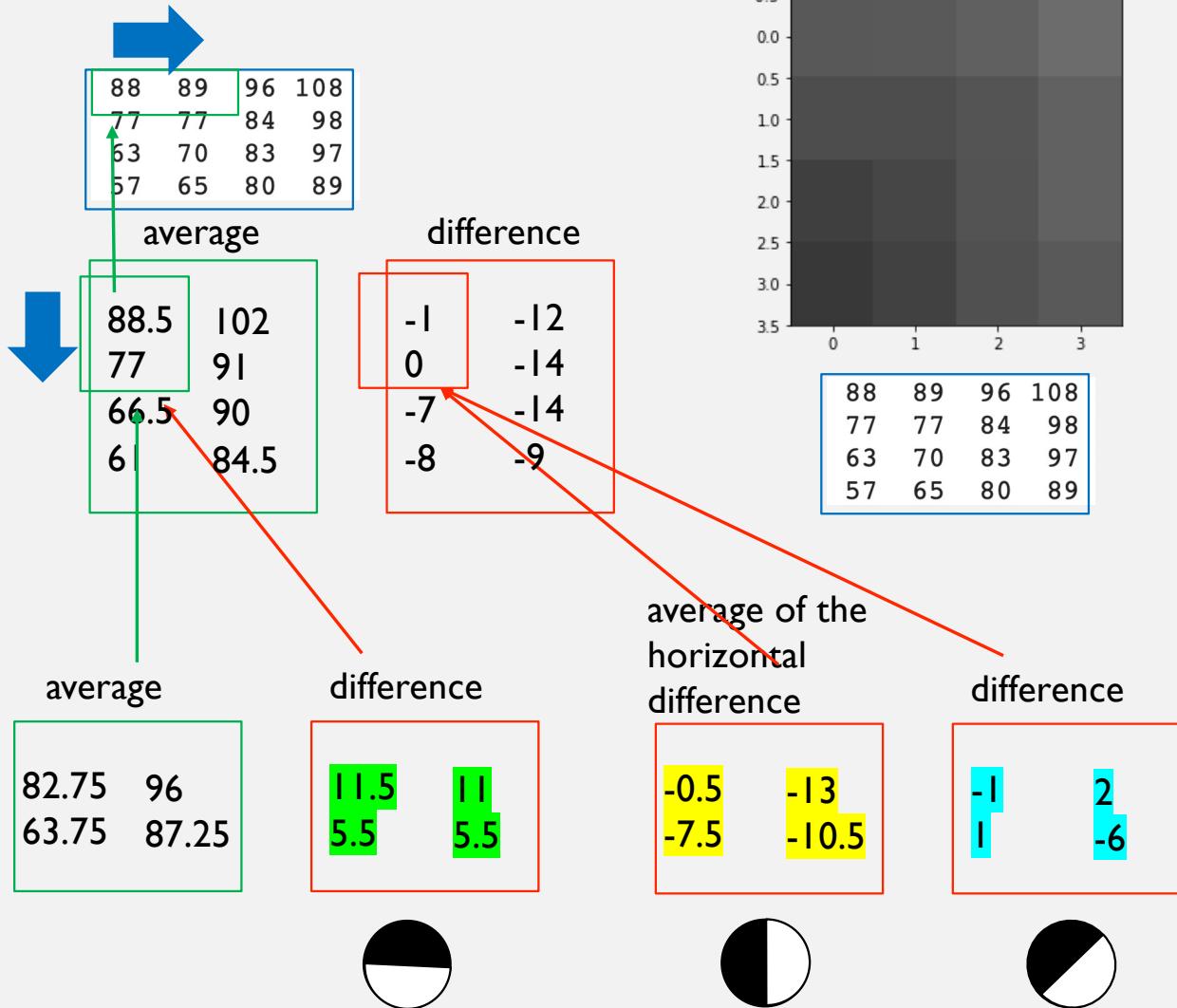
88	89	96	108
77	77	84	98
63	70	83	97
57	65	80	89

82.75	96
63.75	87.25

82.44
-------

Three species of differences





82.75 96  
63.75 87.25

82.44

-18.38

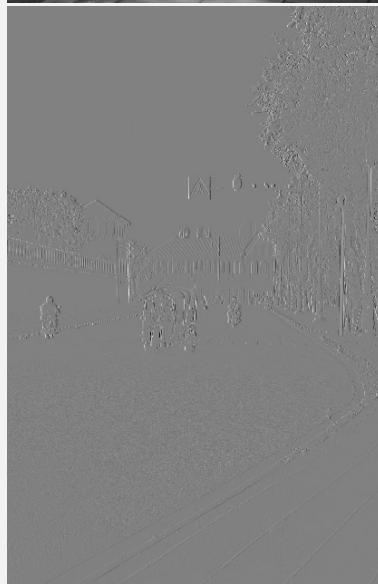
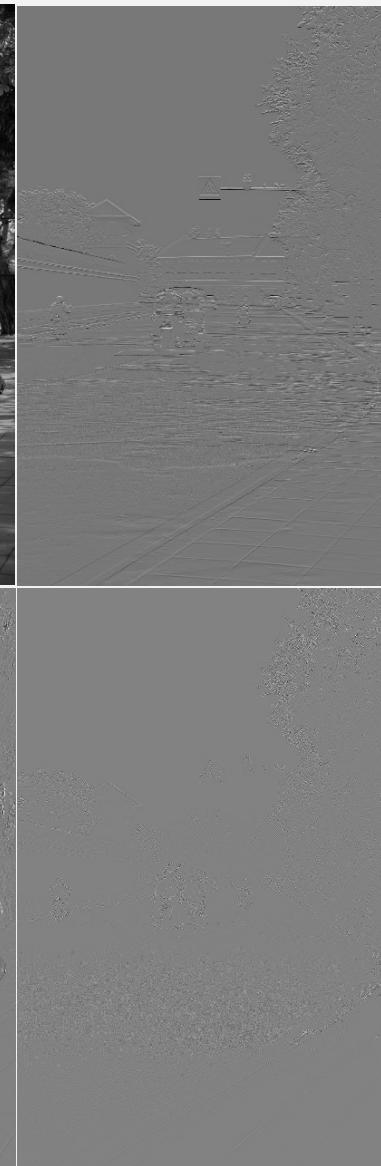
13.875

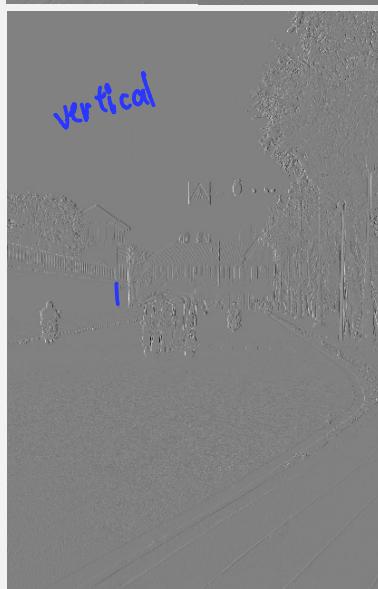
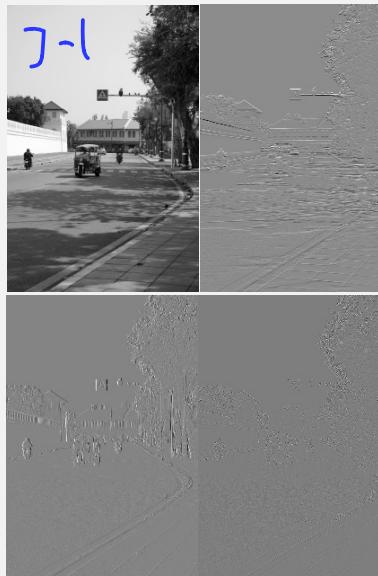
10.25

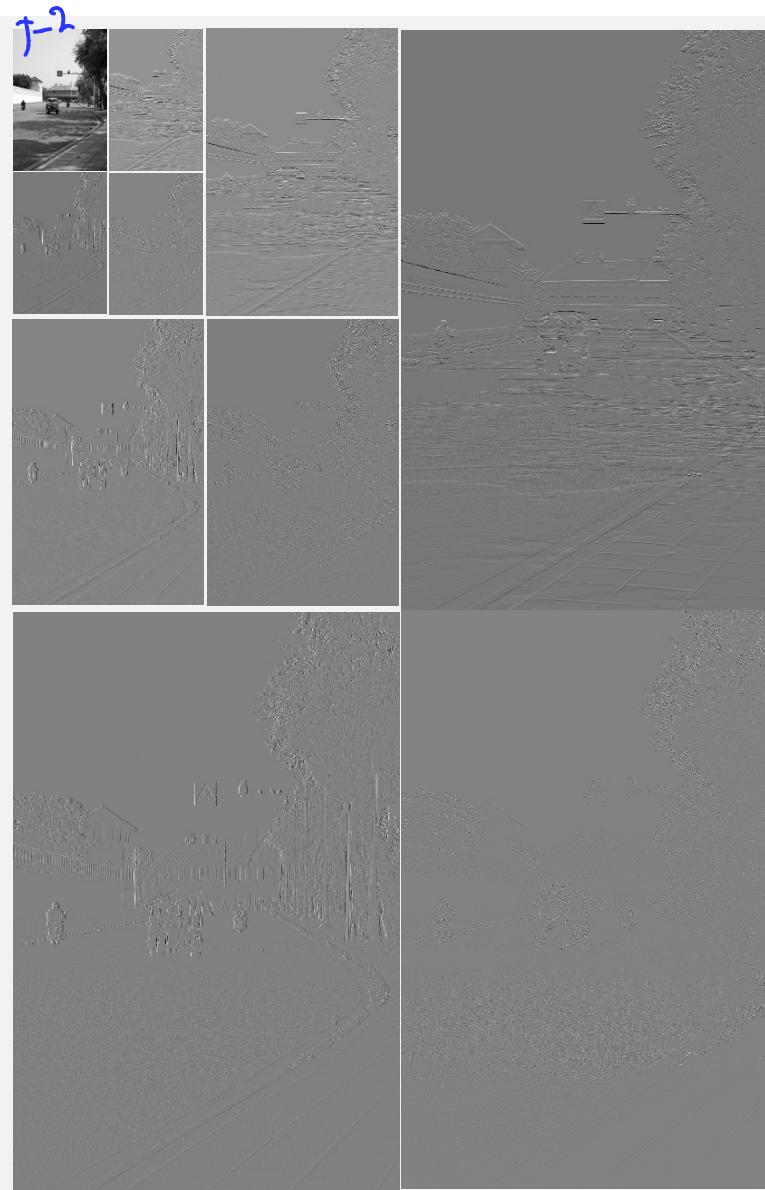
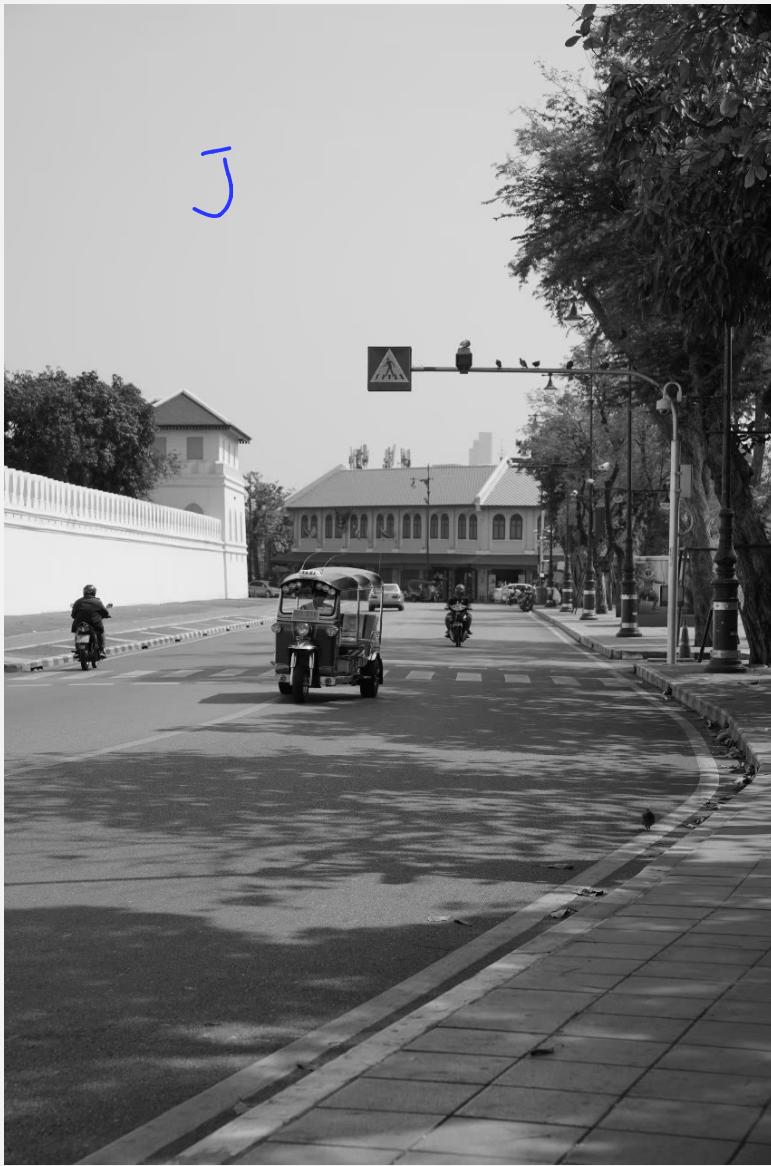
89.375 -13.25  
75.5 -23.5

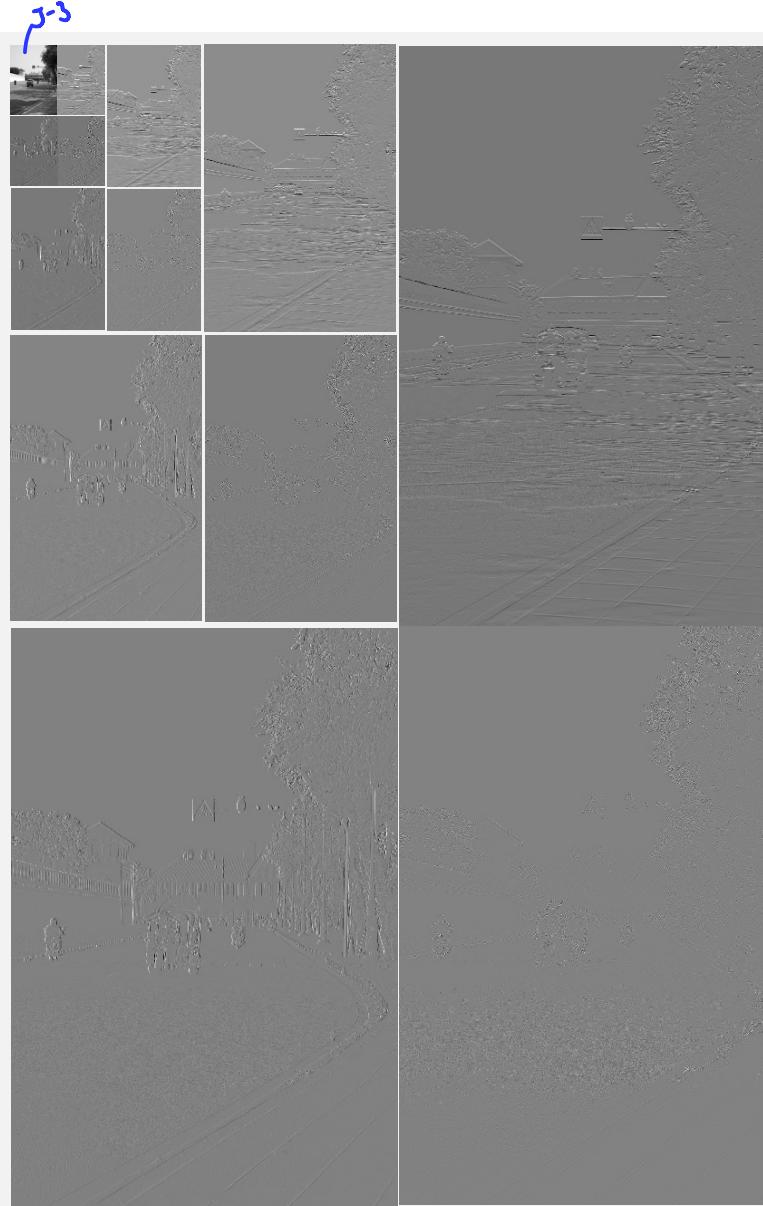


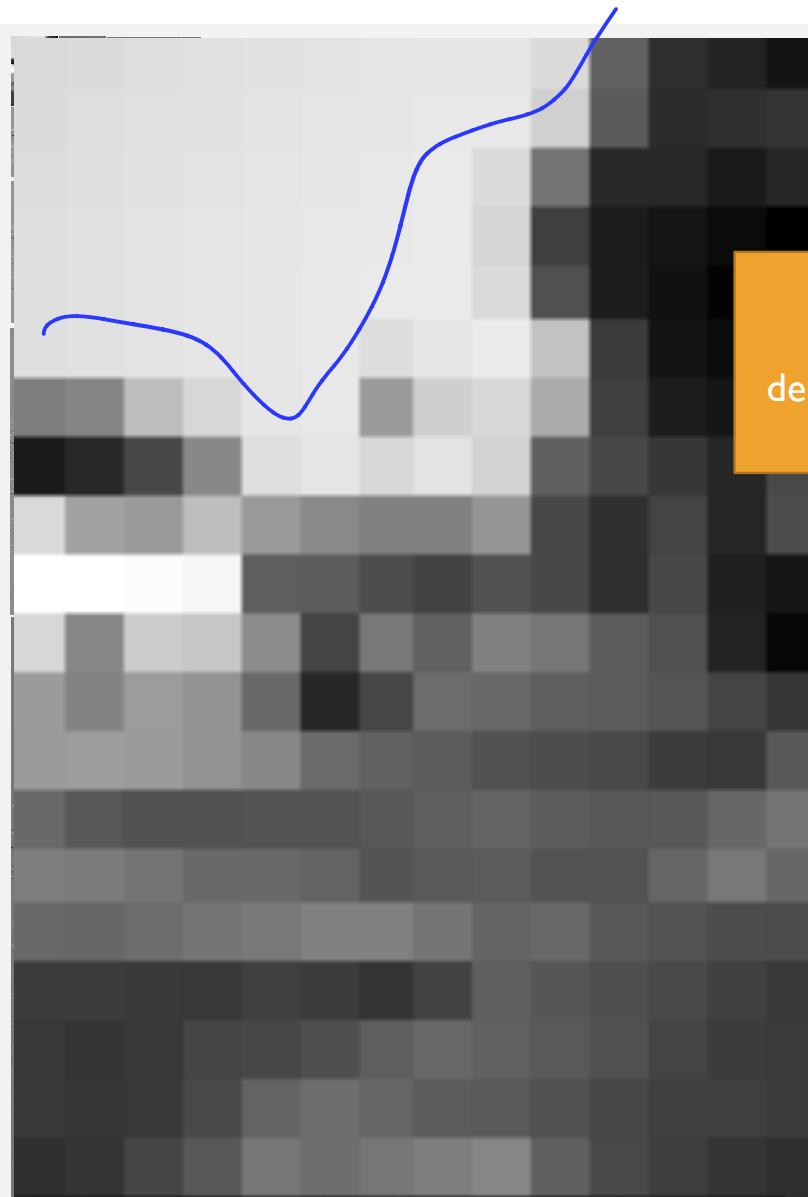
Three species of differences











J-6  
Six-scale  
decomposition

can use to reserve ROI



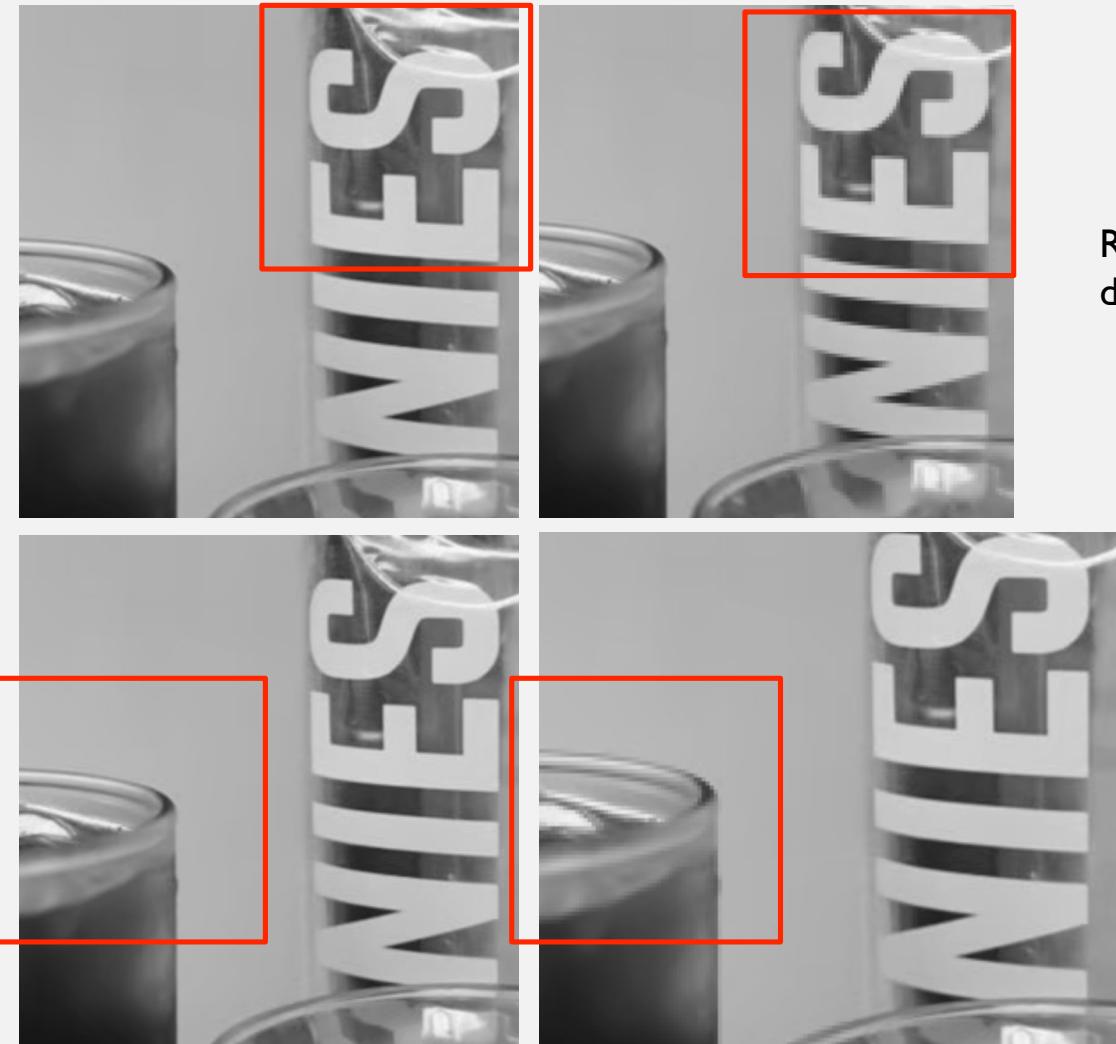
Original image

All details are removed except for Tuk-Tuk



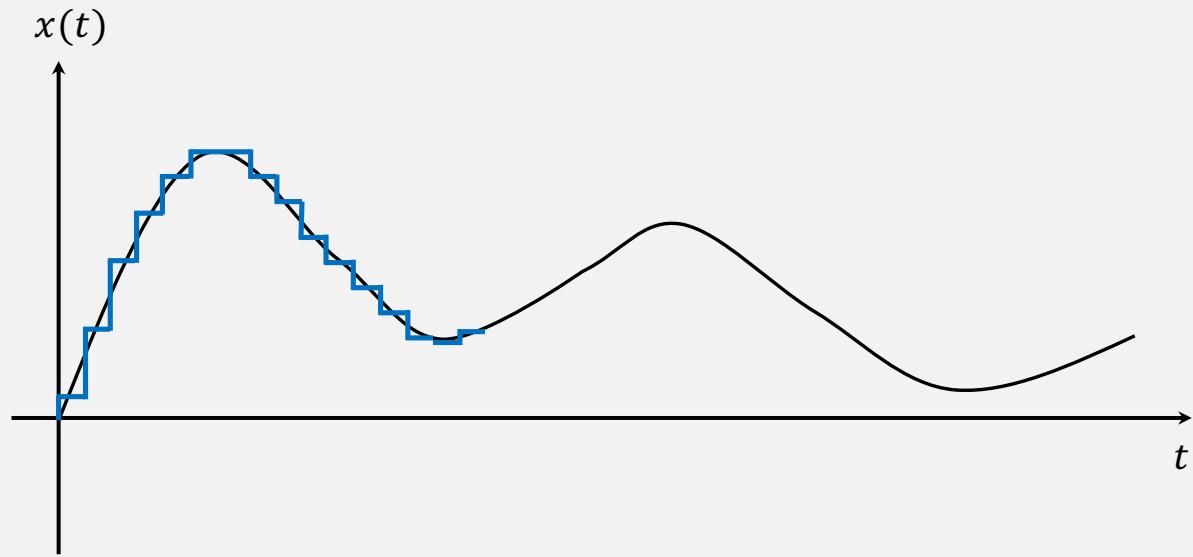
All details of Tuk-Tuk are removed

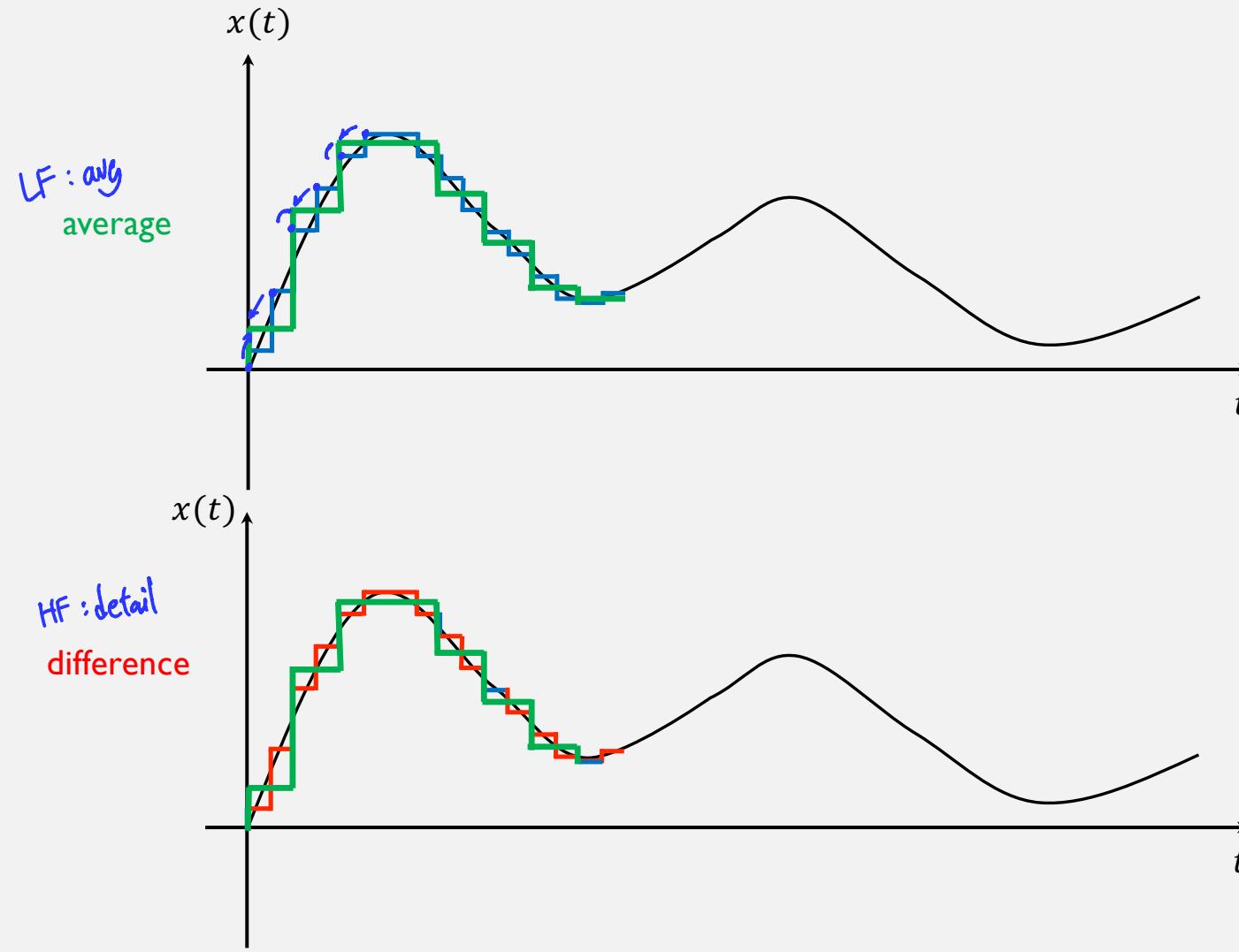


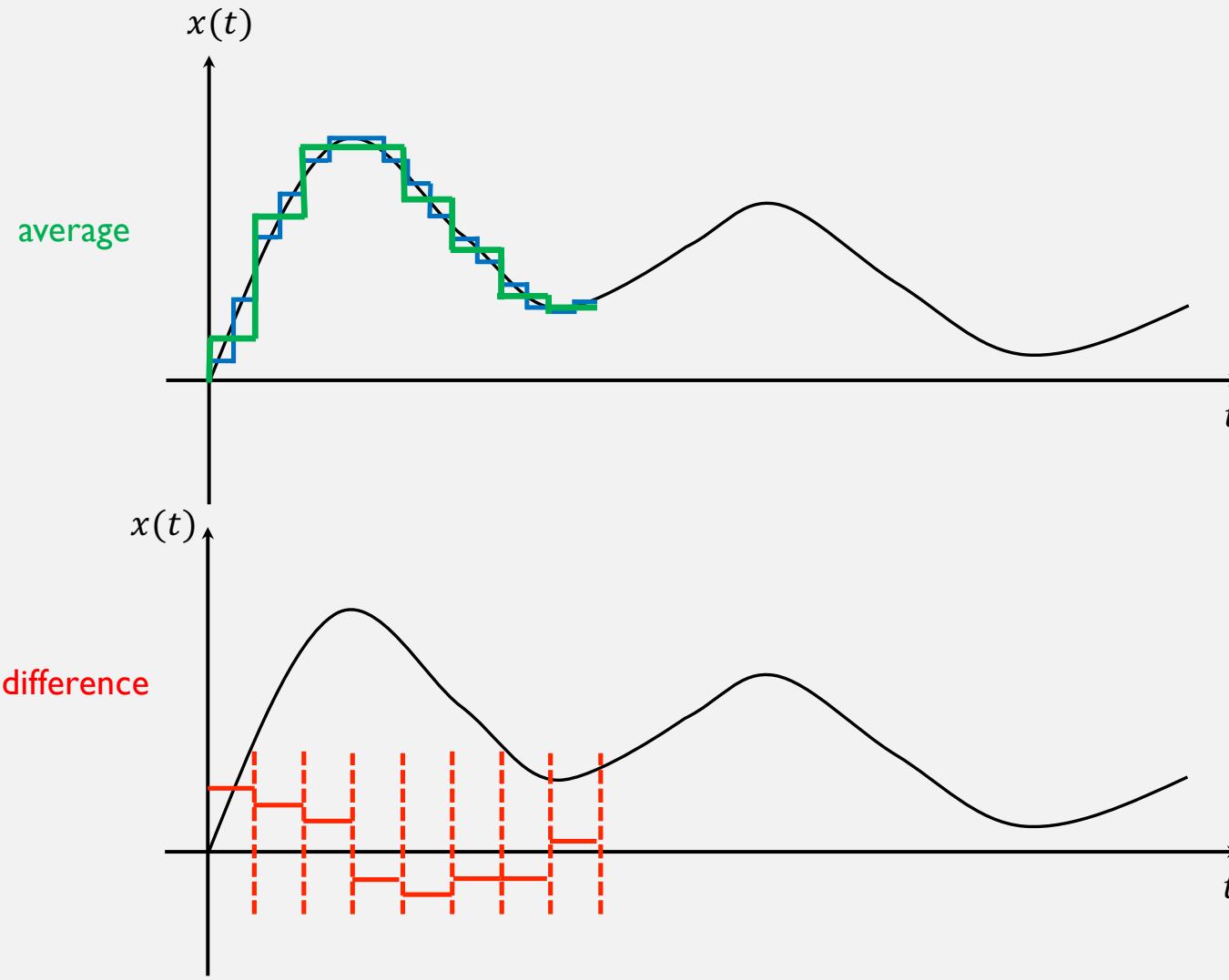


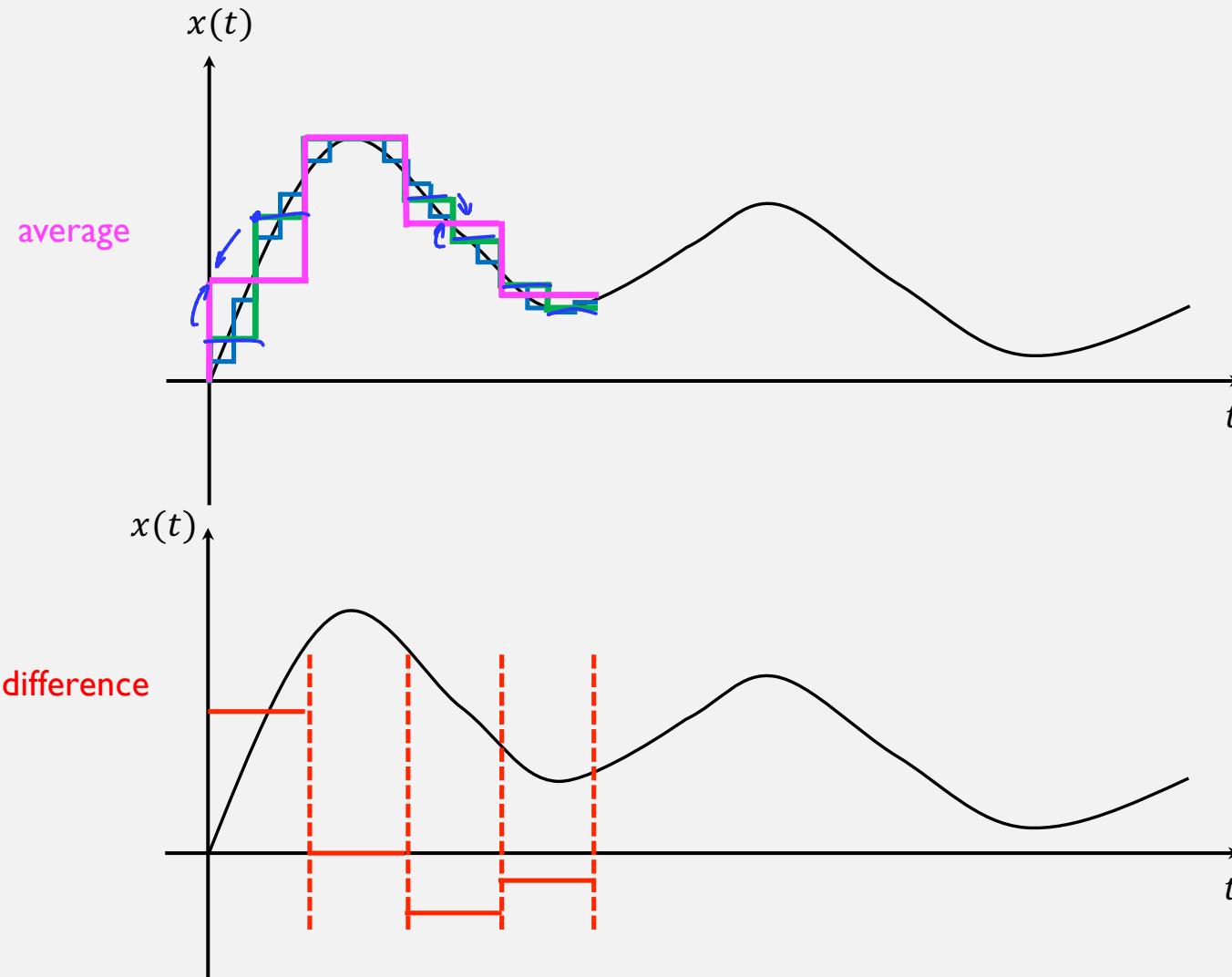
Remove "ES"  
details

Remove edge  
of the glass  
details









# IMAGE PYRAMIDS

- Representing an image more than one resolution
  - Base – high resolution
  - Apex – low resolution
  - Base level  $J$  is size  $2^J \times 2^J$  (or  $N \times N$ ) ( $J = \log_2 N$ )
  - Level  $j$  is size  $2^j \times 2^j$ , where  $0 \leq j \leq J$
  - Fully populated pyramid – from  $2^J \times 2^J$  to  $2^0 \times 2^0$  ( $1 \times 1$  too small)
  - Most pyramid truncated to  $P+1$  levels ( $j = J-P, J-P+1, \dots, J$ )

cuz apex b  $1 \times 1$  = literally No Info

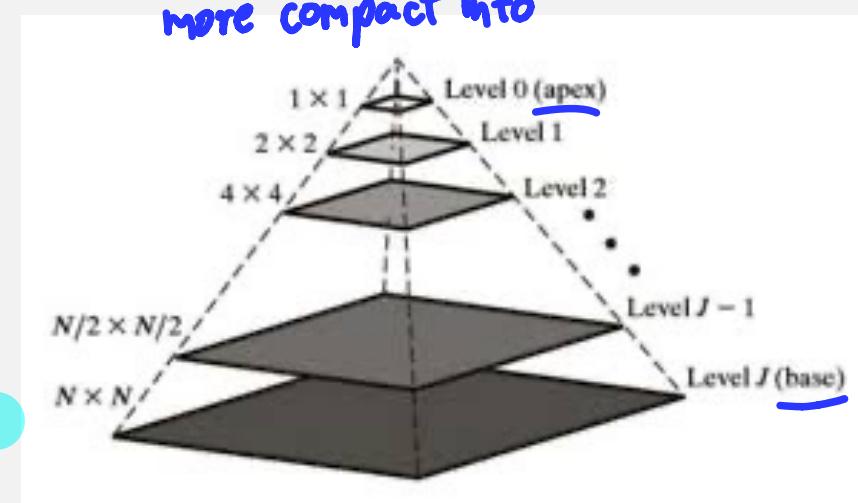


Image from Gonzalez & Woods, Digital Image Processing

# IMAGE PYRAMIDS

- System block diagram to create a pyramid

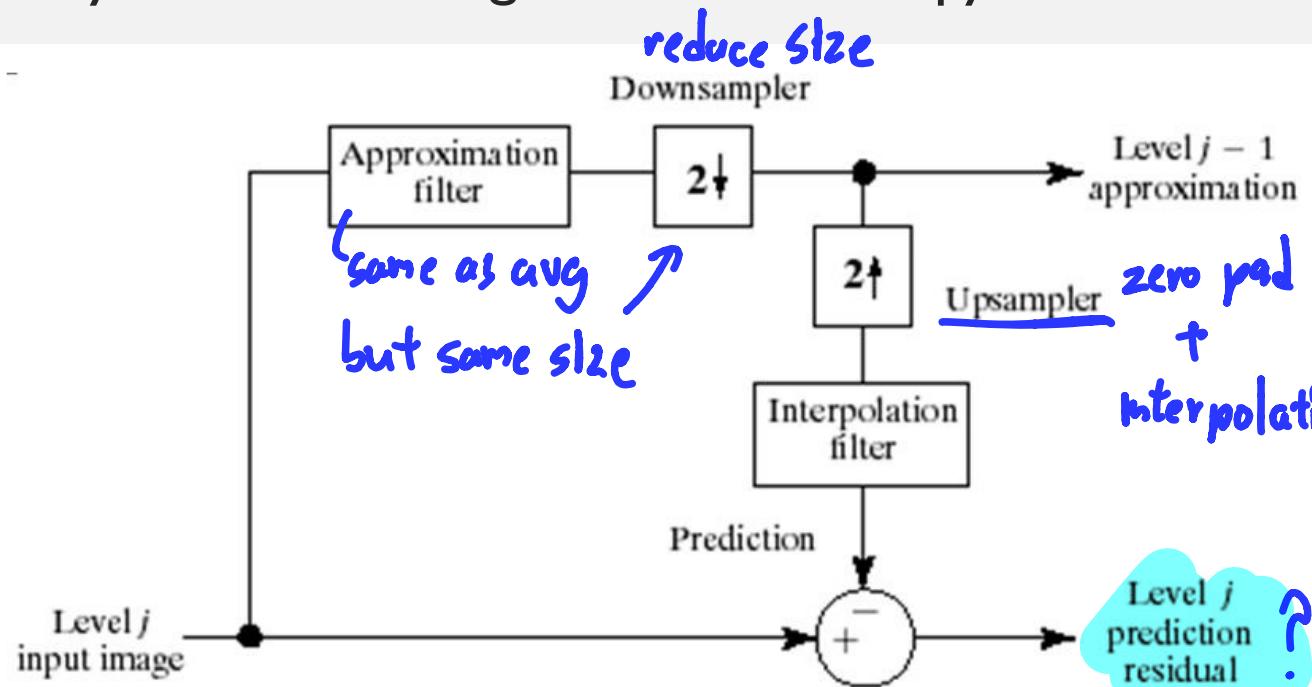
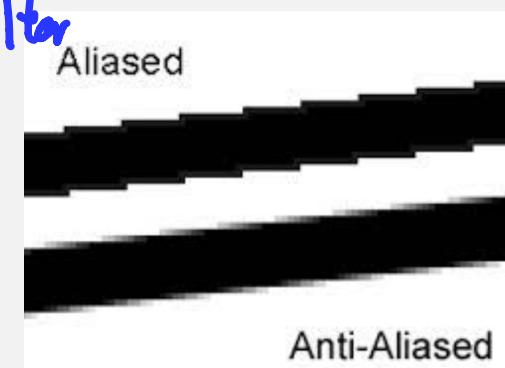


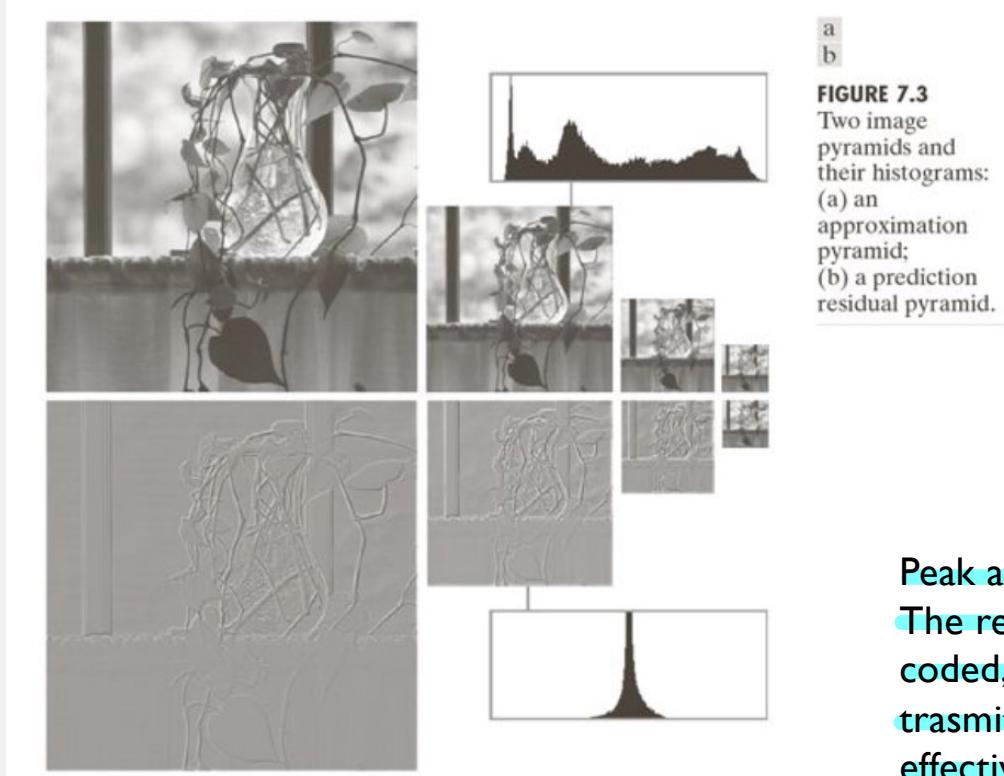
Image from Gonzalez & Woods, Digital Image Processing

## Filtering

- averaging filtering creates a mean pyramid
- lowpass Gaussian filtering creates a Gaussian pyramid  $f_o > 2f_s$
- Without filtering, aliasing can be occurred in the upper levels. (subsampling pyramid)



# IMAGE PYRAMIDS



a  
b

**FIGURE 7.3**  
Two image pyramids and their histograms:  
(a) an approximation pyramid;  
(b) a prediction residual pyramid.

Use 5x5 low pass Gaussian convolution kernel (for filtering)  
-Original image  $512 \times 512$  ( $J = 9$ )  
 $-P+1 = 4$  so  $j = 6, 7, 8, 9$

Laplacian level 6 ( $64 \times 64$ ) predicts Gaussian pyramid level 7 ( $128 \times 128$  approximation) by upsampling and filtering and add the Laplacian level 7.

Peak at around zero.  
The residuals can be coded, stored, and transmitted more effectively than approximation

Image from Gonzalez & Woods, Digital Image Processing

## BASIS FUNCTIONS

: unit , and orthogonal

- Basis functions used by the wavelet transform are all generated from one initial function called the mother wavelet. The simplest mother wavelet is the Haar wavelet. The basis functions are orthonormal wavelets.

- $h_\varphi(n)$  - scaling function coefficients

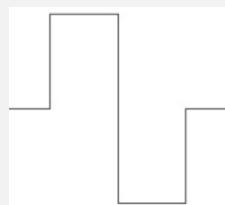
- $h_\psi(n)$  - wavelet function coefficients

$$h_\varphi(n) = \begin{cases} 1/\sqrt{2} & n = 0, 1 \\ 0 & \text{otherwise} \end{cases}$$

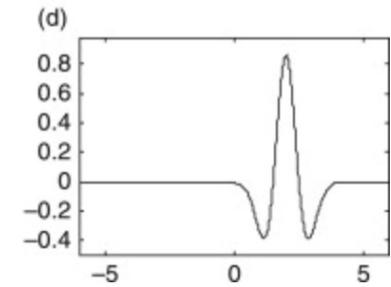
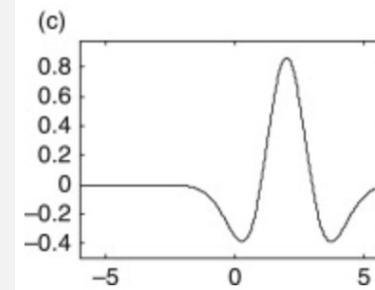
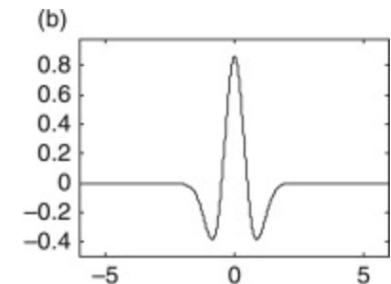
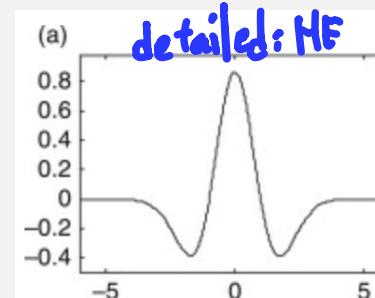


avg LF

$$h_\psi(n) = \begin{cases} 1/\sqrt{2} & n = 0 \\ -1/\sqrt{2} & n = 1 \\ 0 & \text{otherwise.} \end{cases}$$



difference HF



The Mexican Hat wavelet. (a) Mother wavelet, (b) dilation by a factor of 2, (c) translation of 4 to the right, and (d) combination of (b) and (c).

$$\psi(t) = \frac{2}{\sqrt{3}} \pi^{-\frac{1}{4}} (1 - t^2) e^{-\frac{t^2}{2}}$$

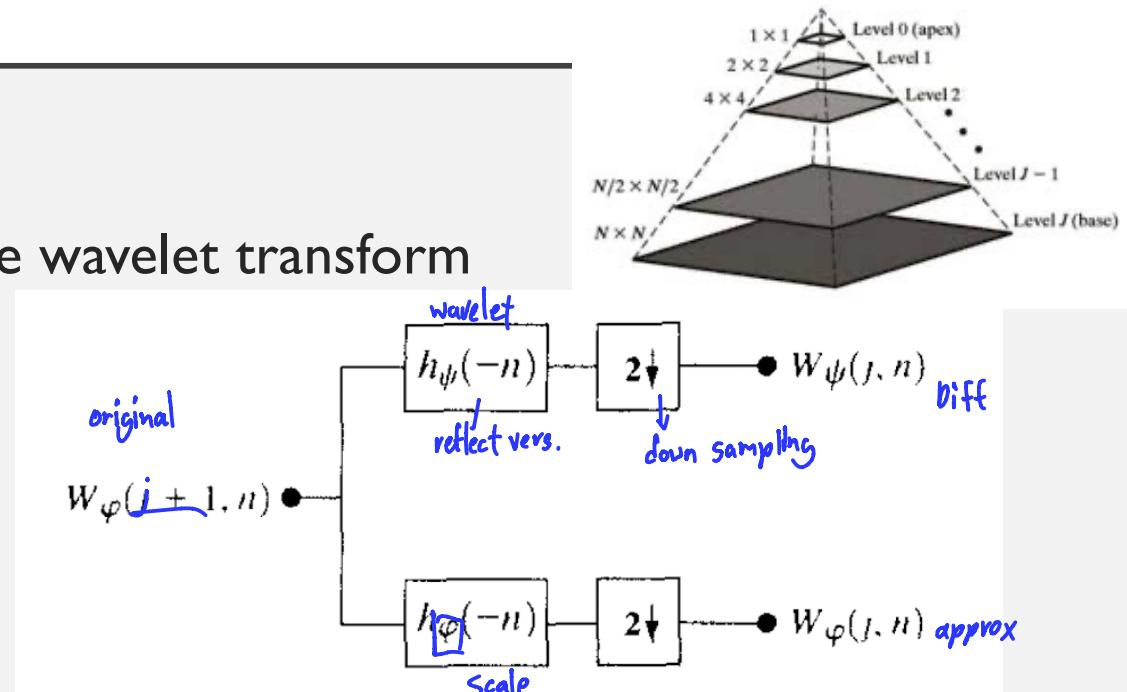
# ONE-DIMENSIONAL FAST WAVELET TRANSFORM (FWT)

- FWT Analysis bank
- Efficient implementation of discrete wavelet transform

$$W_\psi(j, k) = h_\psi(-n) * W_\varphi(j + 1, n) \Big|_{n=2k, k \geq 0}$$

down sampling by half

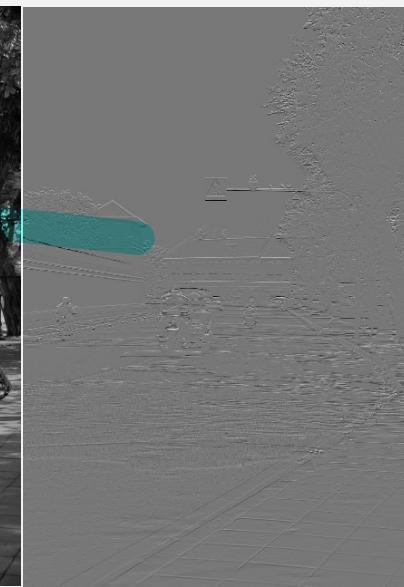
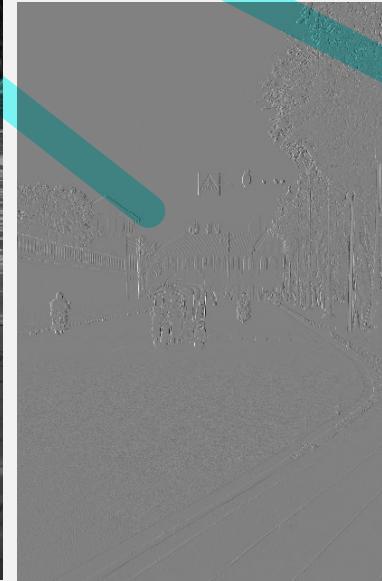
$$W_\varphi(j, k) = h_\varphi(-n) * W_\varphi(j + 1, n) \Big|_{n=2k, k \geq 0}$$



$W_\varphi(j, k)$  - approximation coefficients with scale level  $j$ , translating it by  $k$ .  $W_\psi(j, k)$  - details coefficients. The image in level  $j + 1$  is subsampled from level  $j$  so  $2k = n$ .

$$W_{\psi}(j, k) = h_{\psi}(-n) * W_{\varphi}(j + 1, n) \Big|_{n=2k, k \geq 0}$$

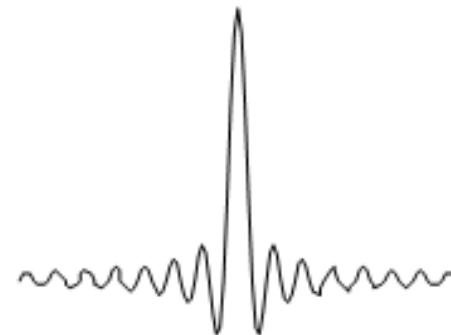
$$W_{\varphi}(j, k) = h_{\varphi}(-n) * W_{\varphi}(j + 1, n) \Big|_{n=2k, k \geq 0}$$



## OTHER WAVELETS



Haar



Shannon or Sinc



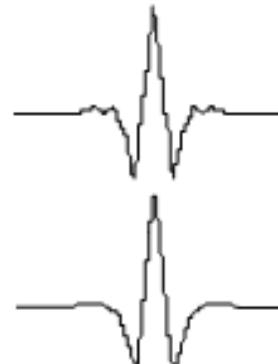
Daubechies 4



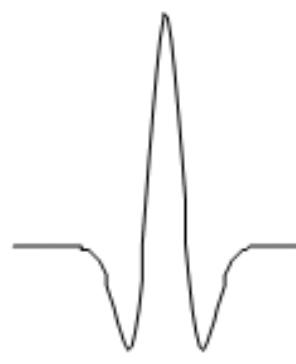
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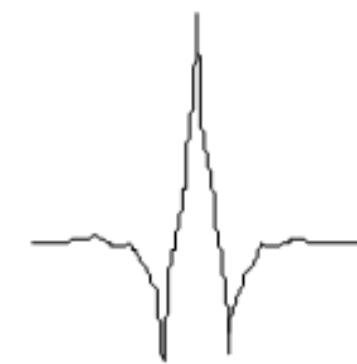
Gaussian or Spline



Biorthogonal



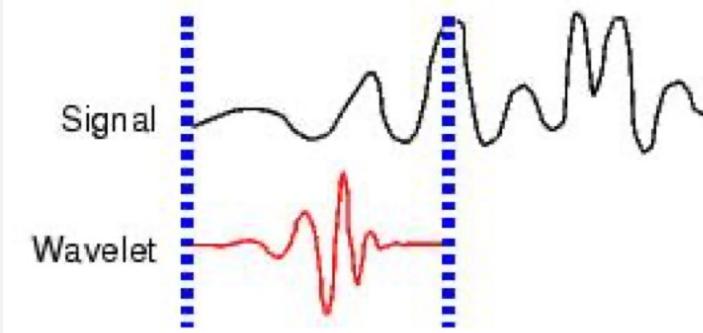
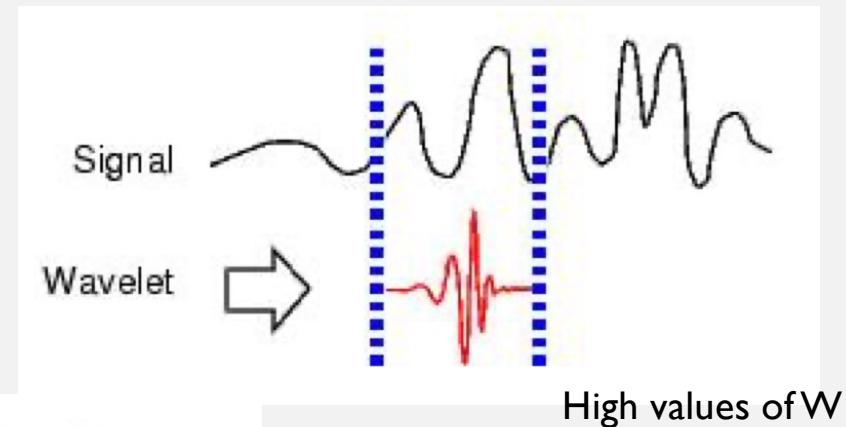
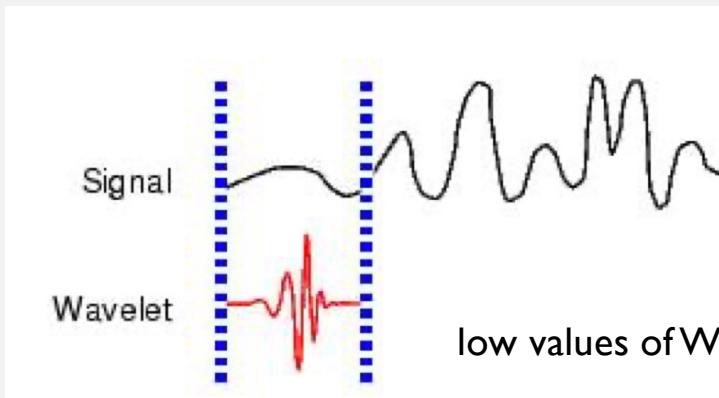
Mexican Hat



Coiflet

# WAVELET TRANSFORM IN ONE DIMENSION

- **Continuous wavelet transform**



Reference: Colorado school of Mines

# ONE-DIMENSIONAL FAST WAVELET TRANSFORM (FWT)

## Fast wavelet Transform

- FWT Analysis bank

- $f(n) = \{1, 4, -3, 0\}$  find DWT corresponding scaling and wavelet vectors (Haar)

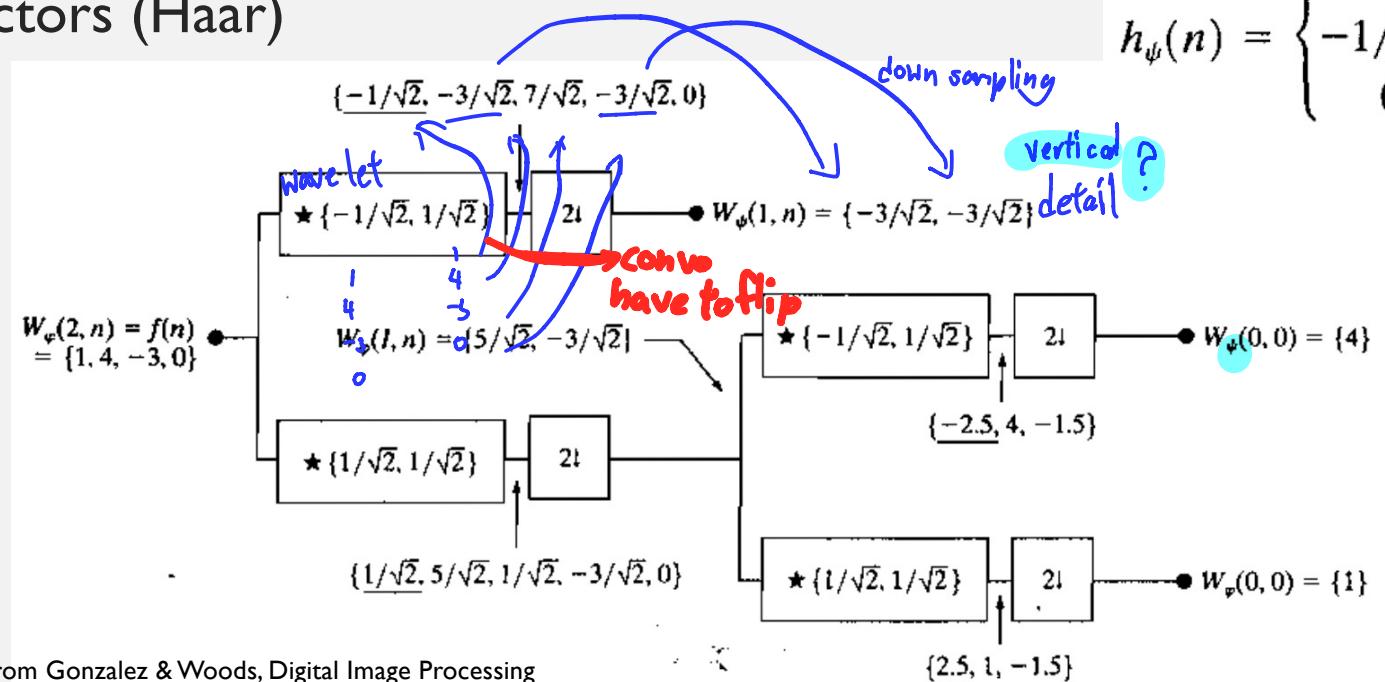


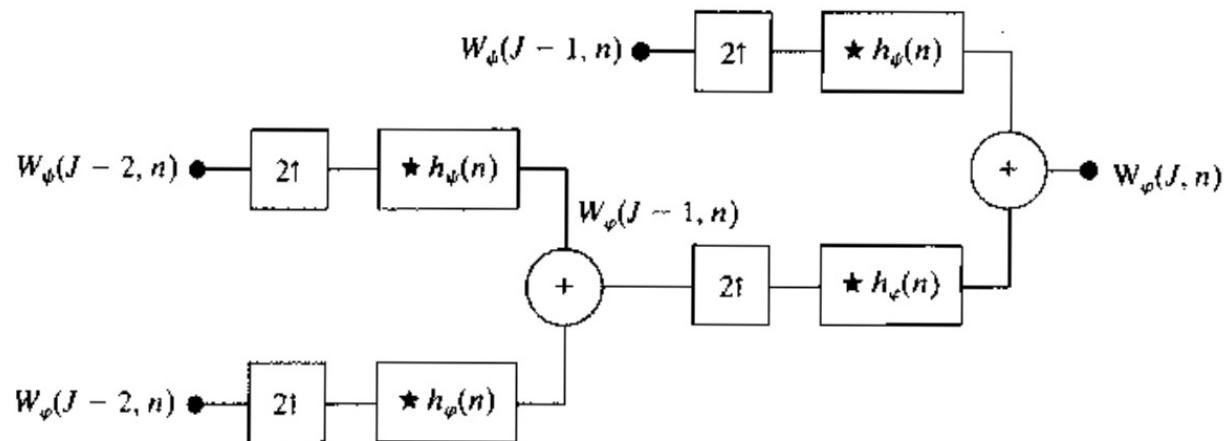
Image from Gonzalez & Woods, Digital Image Processing

$$h_\varphi(n) = \begin{cases} 1/\sqrt{2} & n = 0, 1 \\ 0 & \text{otherwise} \end{cases}$$

$$h_\psi(n) = \begin{cases} 1/\sqrt{2} & n = 0 \\ -1/\sqrt{2} & n = 1 \\ 0 & \text{otherwise.} \end{cases}$$

# ONE-DIMENSIONAL FAST WAVELET TRANSFORM (FWT)

iFWT



- FWT Synthesis bank

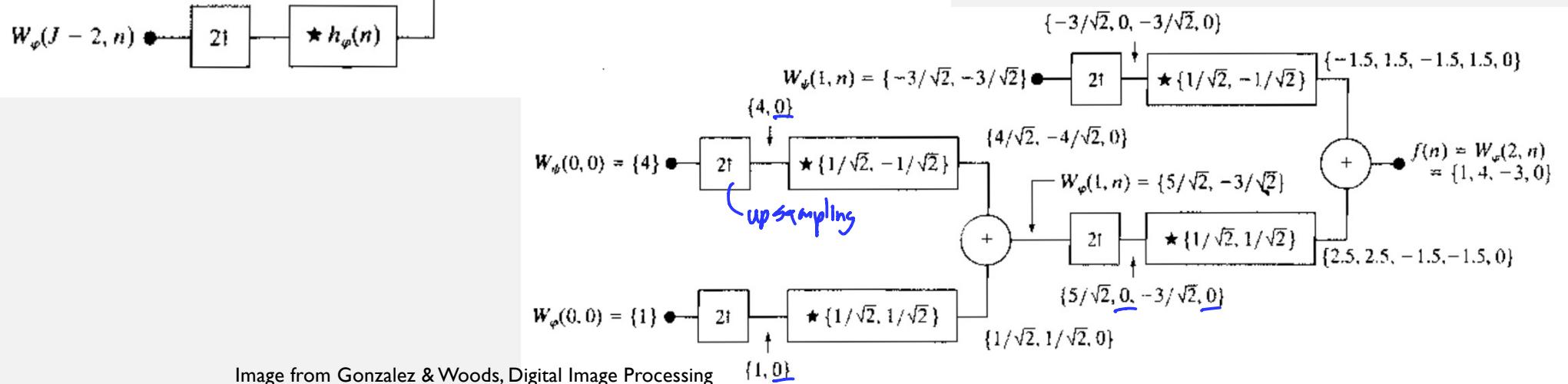


Image from Gonzalez & Woods, Digital Image Processing

## TWO-DIMENSIONAL FAST WAVELET TRANSFORM (FWT)

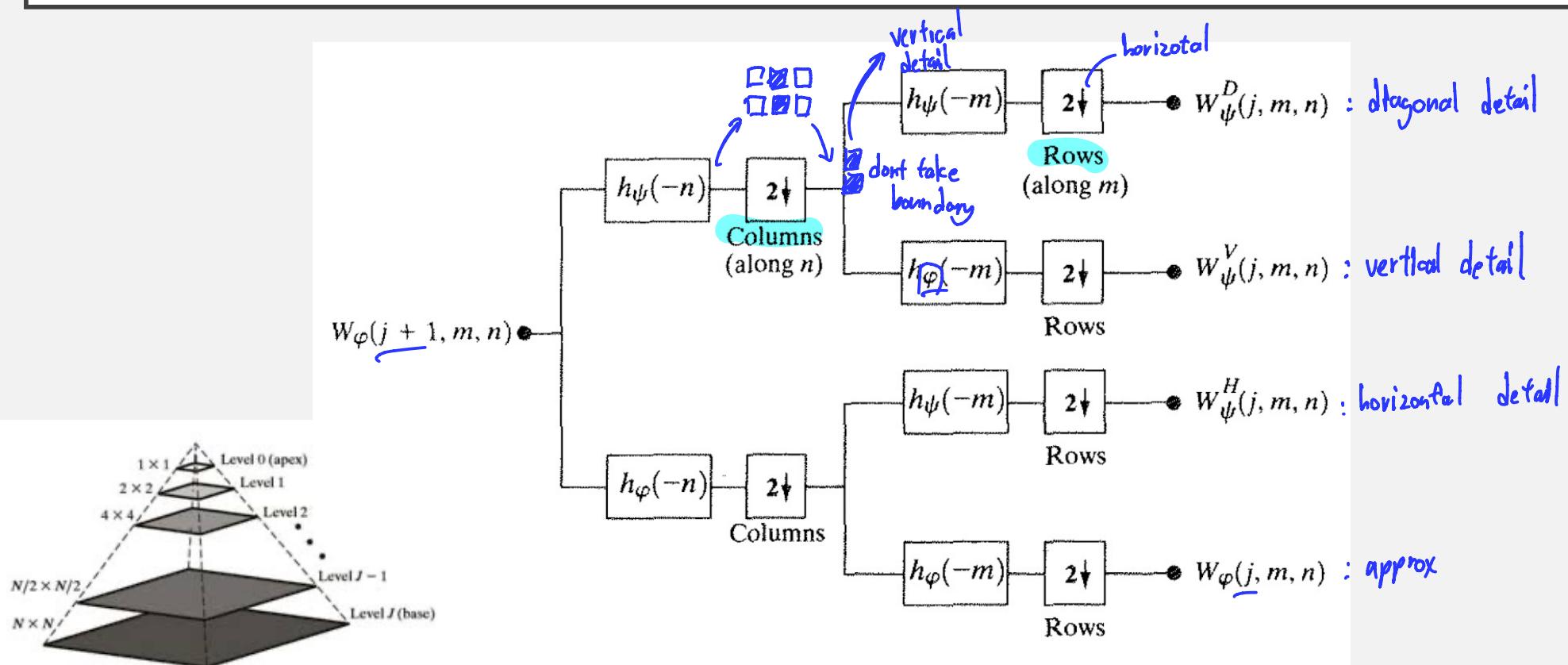
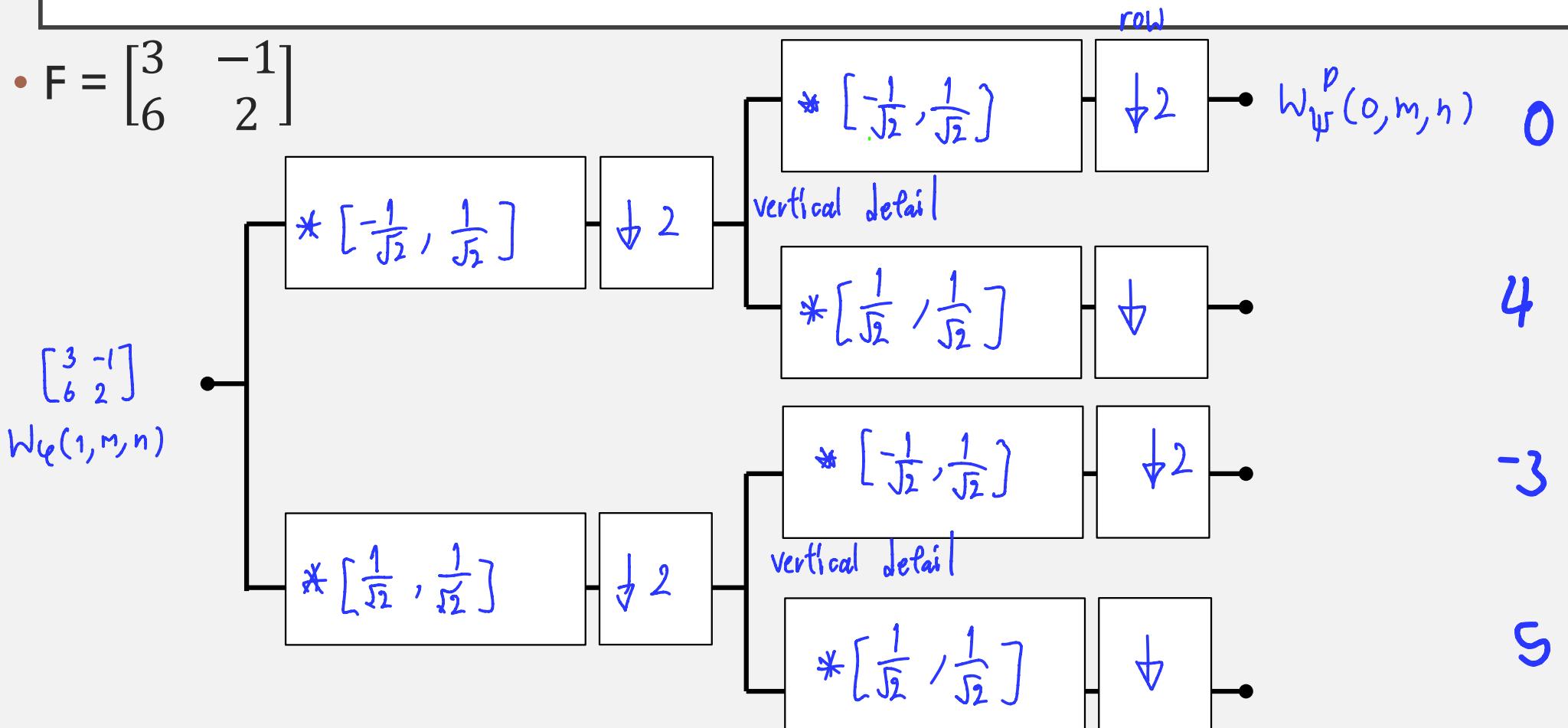


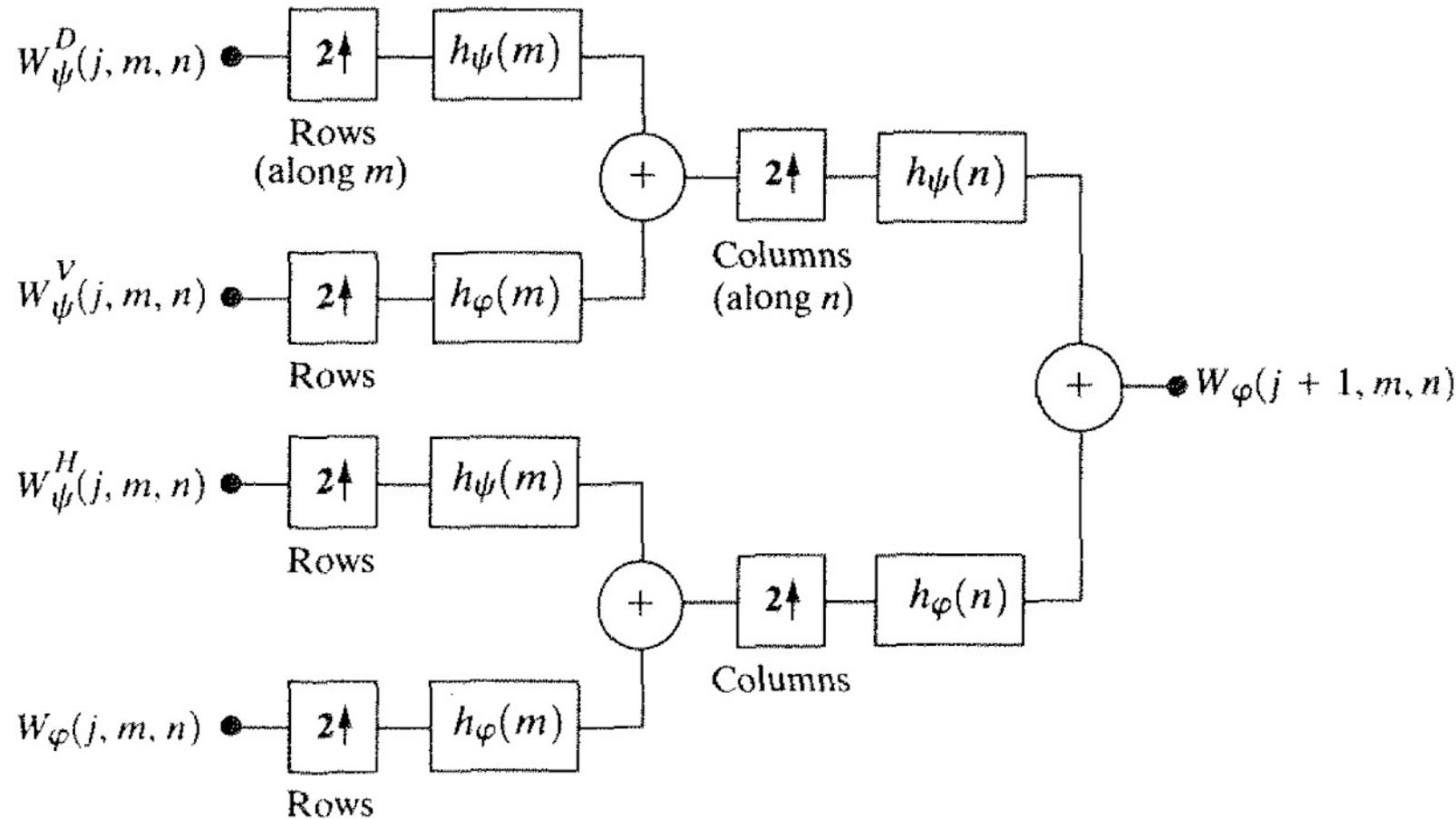
Image from Gonzalez & Woods, Digital Image Processing

## TWO-DIMENSIONAL FAST WAVELET TRANSFORM (FWT)

- Practice: a small image 2x2  $F = \begin{bmatrix} 3 & -1 \\ 6 & 2 \end{bmatrix}$
- Compute 2D Wavelet transform with respect to Haar wavelets of this image. Draw the required filter bank and label all inputs and outputs with proper arrays.

## TWO-DIMENSIONAL FAST WAVELET TRANSFORM (FWT)

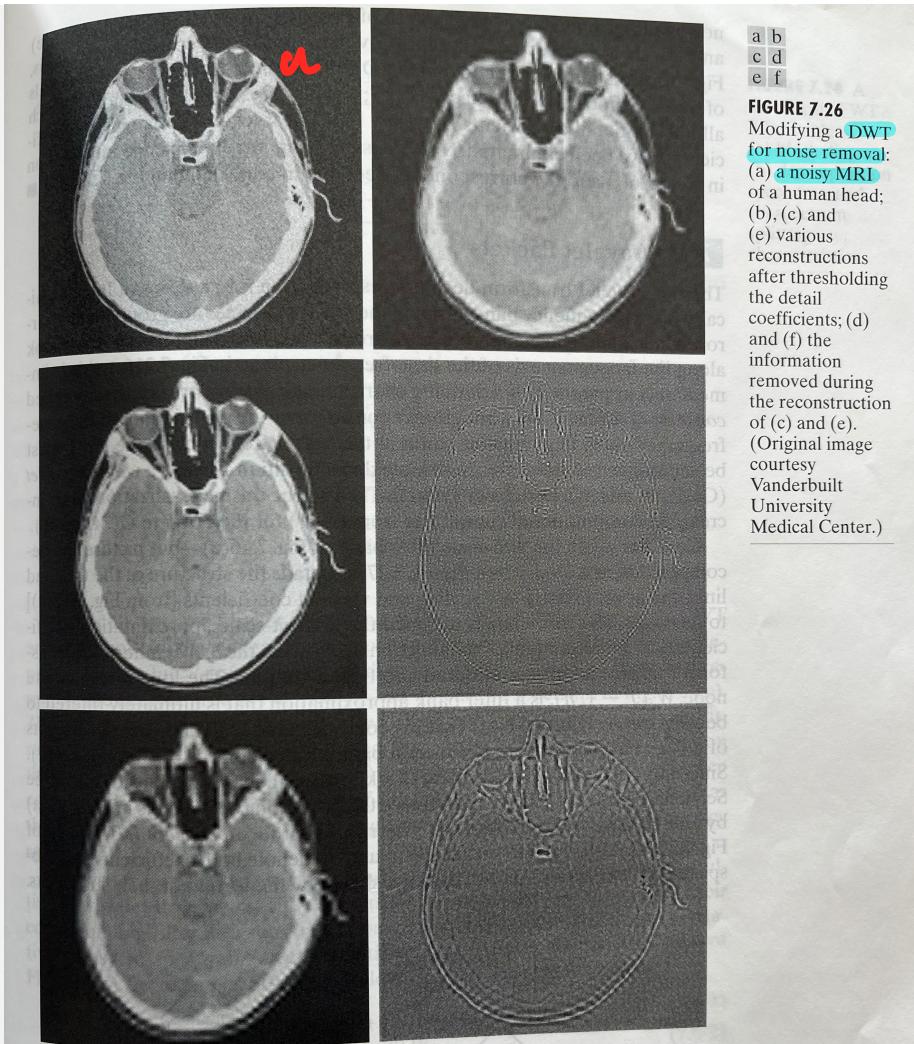




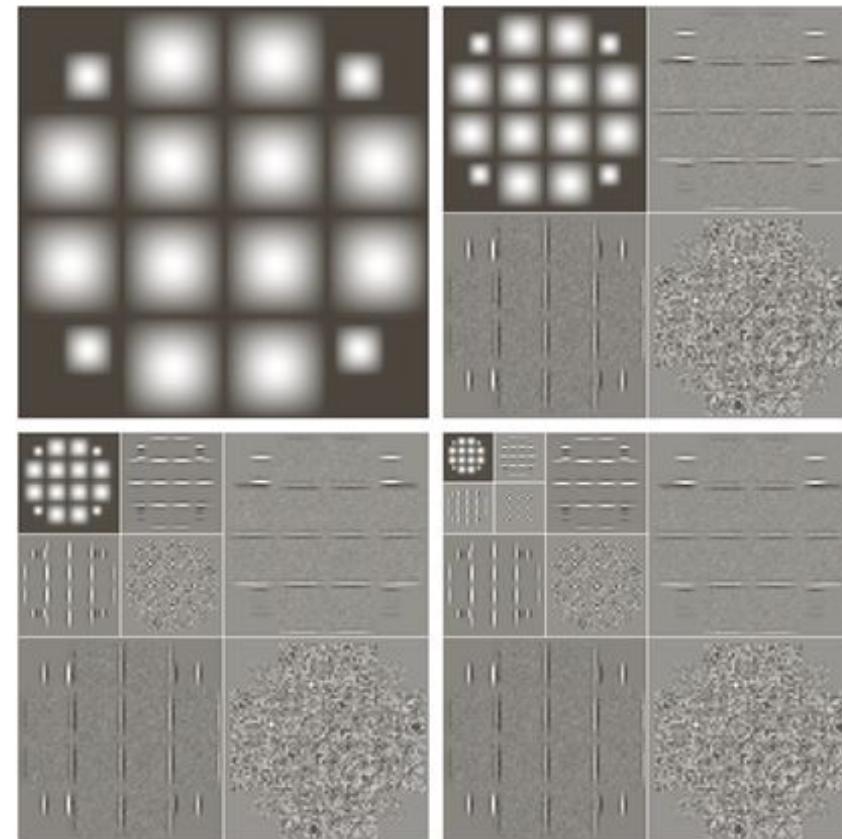
**FIGURE 7.22** The two-dimensional fast wavelet transform: (a) the analysis filter bank; (b) the resulting decomposition; and (c) the synthesis filter bank.

Synthesis filter banks

Image from Gonzalez & Woods, Digital Image Processing



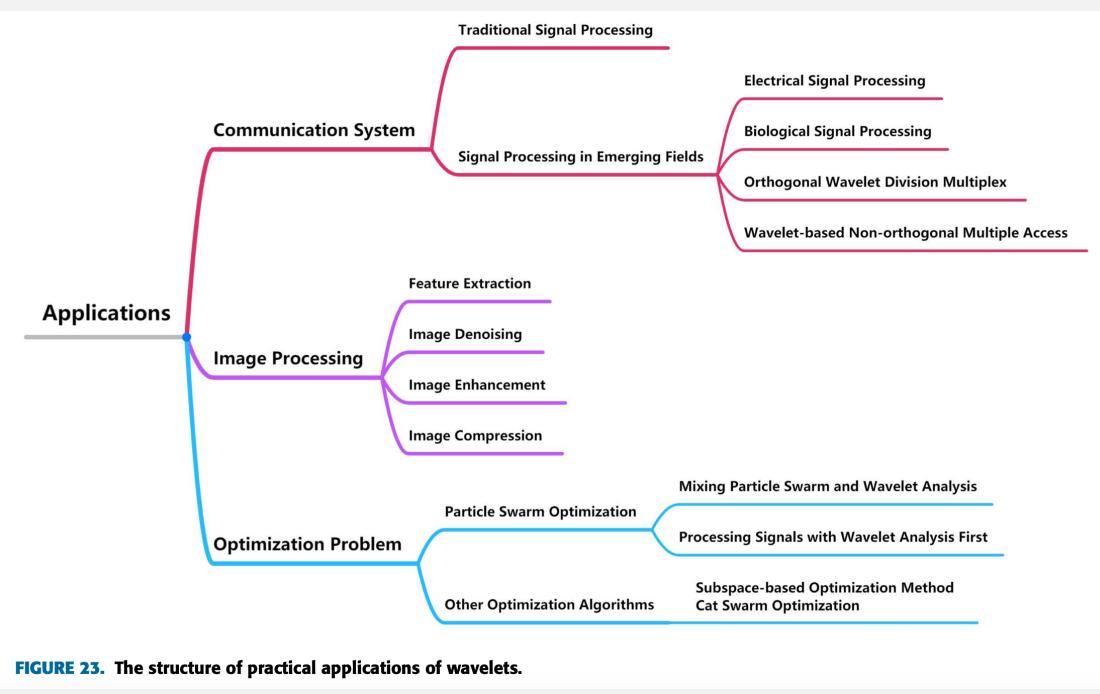
**FIGURE 7.26**  
Modifying a DWT for noise removal:  
(a) a noisy MRI of a human head;  
(b), (c) and (e) various reconstructions after thresholding the detail coefficients; (d) and (f) the information removed during the reconstruction of (c) and (e).  
(Original image courtesy Vanderbilt University Medical Center.)



**FIGURE 7.25**  
Computing a 2-D three-scale FWT:  
(a) the original image; (b) a one-scale FWT; (c) a two-scale FWT; and (d) a three-scale FWT.

tails) and reconstructing the image. Here, almost all of the background noise has been eliminated and the edges are only slightly disturbed. Figure 7.26(d) shows the information that is lost in the process. This result was generated by computing the inverse FWT of the decomposed image with all but the highest-resolution detail coefficients zeroed. As can be seen, it contains most of the

# APPLICATIONS OF WAVELETS

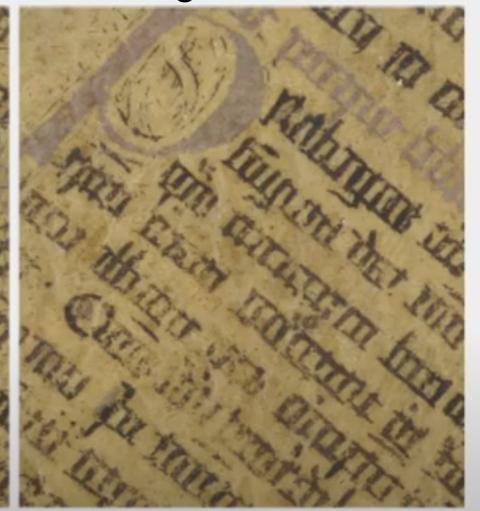


## Wavelets for image processing

- Optimally extract features in different sizes
  - Palm- print images after two-level wavelet decomposition & maintaining the uniqueness of each palmprint image and can be used for palmprint image classification
- Denoising, enhancement and compression in the image processing area
- Extracting structure and noise information through wavelet transform and generating high-quality images through GAN
- Wavelet kernel-based neural network
  - Initialization
  - Used as the activation function

T. Guo, T. Zhang, E. Lim, M. López-Benítez, F. Ma and L. Yu, "A Review of Wavelet Analysis and Its Applications: Challenges and Opportunities," in *IEEE Access*, vol. 10, pp. 58869-58903, 2022, doi: 10.1109/ACCESS.2022.3179517.

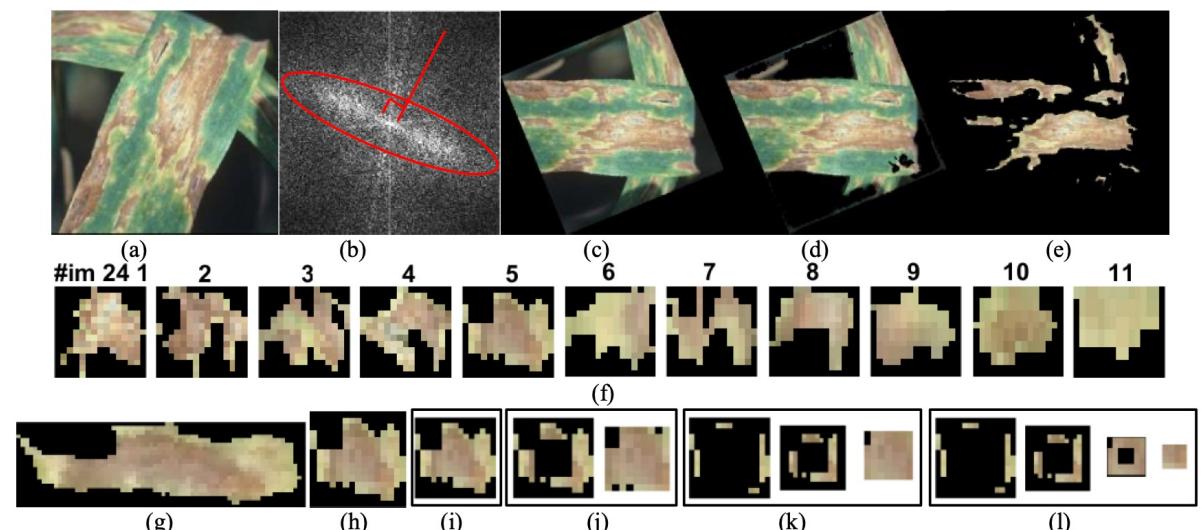
# WAVELETS FOR ART



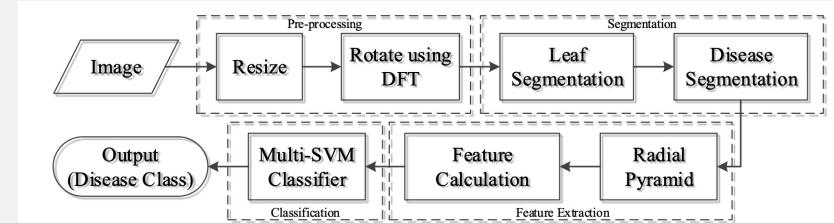
Ghent Altarpiece

Ref. <https://www.youtube.com/watch?v=jrF1SGPyF4g>  
Using Math to Understand Art | Ingrid Daubechies | TEDxDuke

# WAVELETS FOR AI



**Fig. 4.** Uncontrolled image processing in the system (a) original image, (b) DFT on Canny edge, (c) rotated image, (d) partially segmented image, (e) segmented disease, (f) constructed disease patches, (g) original disease blob (#5), (h) normalised disease patch (i) 1-level (j) 2-level (k) 3-level (l) 4-level radial pyramid patches



**Fig. 1.** Our proposed system for wheat disease classification

## 3.2 Leaf segmentation using multi-resolution discrete Wavelet transform

A single-level two-dimensional Wavelet transform (DWT) is exploited to decompose an image into coefficients of four different components, an approximation component ( $cA$ ), horizontal, vertical, and diagonal details ( $cH$ ,  $cV$ , and  $cD$ ). We combined horizontal, vertical and diagonal detail information based on Daubechies wavelets and then thresholded the low coefficient values out to remove part of the background from consideration in the subsequent stages of our process (see Fig. 4 (d)).

Punnarai Siricharoen, Bryan W. Scotney, Philip J. Morrow, Gerard P. Parr:  
 Automated Wheat Disease Classification Under Controlled and Uncontrolled Image Acquisition. ICIAR 2015: 456-464

## EXERCISE #1 USE PYWAVELETS FOR IMAGE SPACE-FREQUENCY ANALYSIS

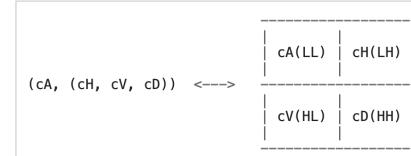
- Reference: <https://pywavelets.readthedocs.io/en/latest/>

```
import pywt
import cv2

original = cv2.imread("kitty.png", 0)
LL, (LH, HL, HH) = pywt.dwt2(original, 'haar')
```

```
# display
fig = plt.figure(figsize=(12, 3))
for i, a in enumerate([LL, LH, HL, HH]):
    ax = fig.add_subplot(1, 4, i + 1)
    ax.imshow(a, interpolation="nearest",
              cmap=plt.cm.gray)
    ax.set_title(titles[i], fontsize=10)
    ax.set_xticks([])
    ax.set_yticks([])
    fig.tight_layout()
plt.show()
```

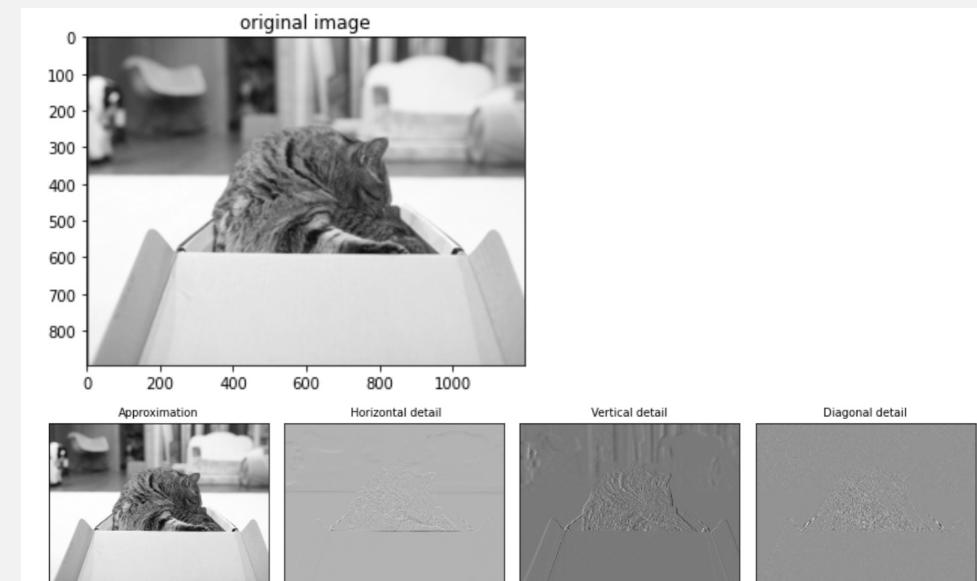
The relation to the other common data layout where all the approximation and details coefficients are stored in one big 2D array is as follows:



PyWavelets does not follow this pattern because of pure practical reasons of simple access to particular type of the output coefficients.

## **EXERCISE #1 USE PYWAVELETS FOR IMAGE SPACE-FREQUENCY ANALYSIS**

- Investigate the size of the original image, approximation, horizontal, vertical and diagonal details.
- Investigate the min/max values in the approximation, horizontal, vertical and diagonal details.



Reference:

<https://pywavelets.readthedocs.io/en/latest/>

## **EXERCISE #2 CAN YOU SEGMENT THE CAT?**

- 1) apply wavelet transform into "kitty.jpg" image
- 2) Again, investigate the min/max values in the approximation, horizontal, vertical and diagonal details.
- 3) Can you use a threshold to separate the high details from the low and segment the cat out?