

# EEE6081 (EEE421)

## Visual Information Engineering (VIE)

### Topic 5: Multi-Resolution Analysis (MRA)

- Wavelet transforms-based MRA.
  - On 1-D signals
  - On Images
  - Memory requirement
- Pyramid decompositions –based multi-resolution representations.
  - On 1-D signals
  - On Images
  - Memory requirement
- Applications
  - Image fusion
  - Image denoising
  - Information hiding

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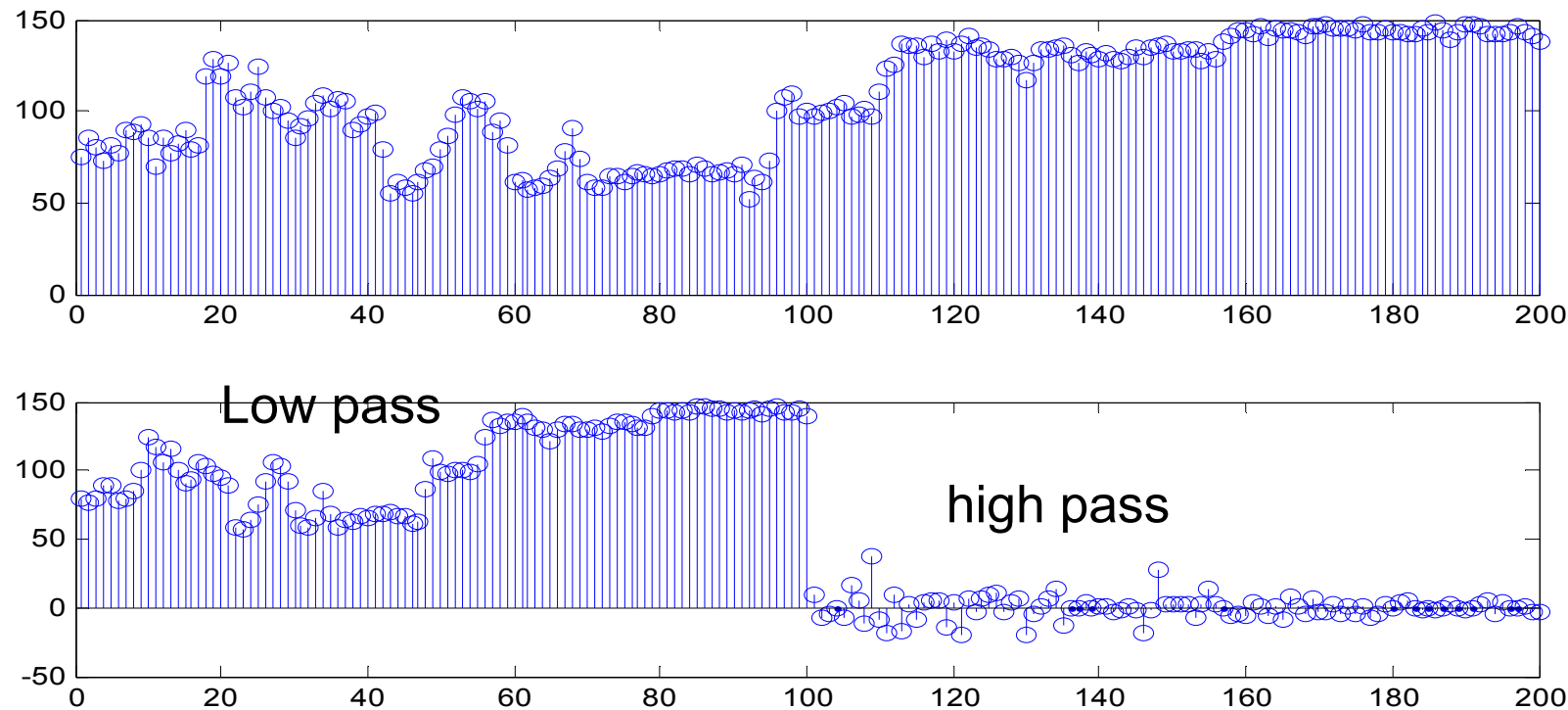
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## Multi-resolution analysis (MRA)

- In the Human Visual System (HVS), the amount of details we perceive depends on the angle subtended by a scene or an object on the eye.
- Various details are visible from various distances.
- In visual information engineering, this aspect of the HVS can be mimicked by employing a decomposition scheme that allows us to view the scene (or the image) at different space-frequency representations.
- That is at different spatial resolutions and at different frequency resolutions.
- Analysing signals (1-D or any multi-dimensional) in different space frequency resolutions for information engineering applications is called Multi-resolution analysis (MRA)
- The Wavelet transform-based decomposition is a good example for MRA.

## Multi-resolution analysis (MRA) - Wavelets

- A 2- channel filter bank decomposes data into two sub bands: low pass and high pass.
- Non-expanding --- i.e., number of coefficients = number of data points
- The low pass signal looks the same as the original (only smoothed)
- The filter bank can be applied repeatedly on the low pass signal. This is called Dyadic decomposition



## Multi-resolution analysis (MRA) - Wavelets

- At each level of decomposition, the low pass sub band represents a half resolution approximation of the low pass signal of the previous level.
- Draw the filter bank operation for the dyadic decomposition:
- We can represent the Multi-resolution analysis using wavelets as below.
  - Let the starting resolution as  $a_0$ . After one level of decomposition we have
 
$$\begin{array}{ccc}
 a_0 & \longrightarrow & a_{-1} \\
 & \searrow & \\
 & & d_{-1}
 \end{array}$$
 where  $a_{-1}$  is the half resolution approximation and  $d_{-1}$  the details seen at that resolution.
  - For n levels
 
$$\begin{array}{ccccccc}
 a_0 & \longrightarrow & a_{-1} & \longrightarrow & a_{-2} & \longrightarrow & a_{-3} & \longrightarrow & a_{-n} \\
 & \searrow & & \searrow & & \searrow & & \searrow & \\
 & & d_{-1} & & d_{-2} & & d_{-3} & & d_{-n}
 \end{array}$$
  - Which resolution-bands are resulted in a 2 level decomposition?
  - Specify the memory requirement (in terms of the original signal size) for a 1-D wavelet based MR representation.
  - How are the resolution bands combined to get back the original resolution data?

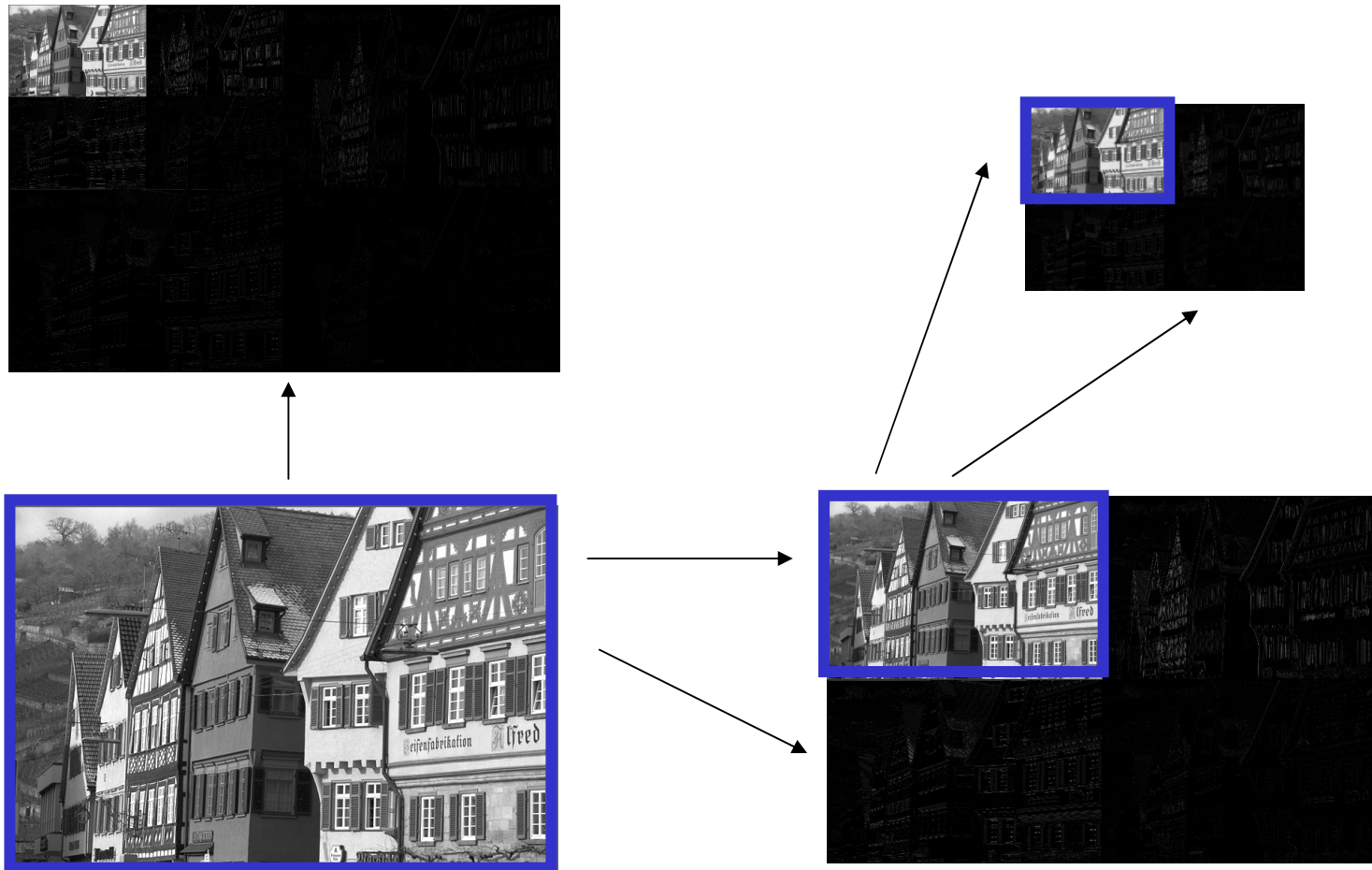


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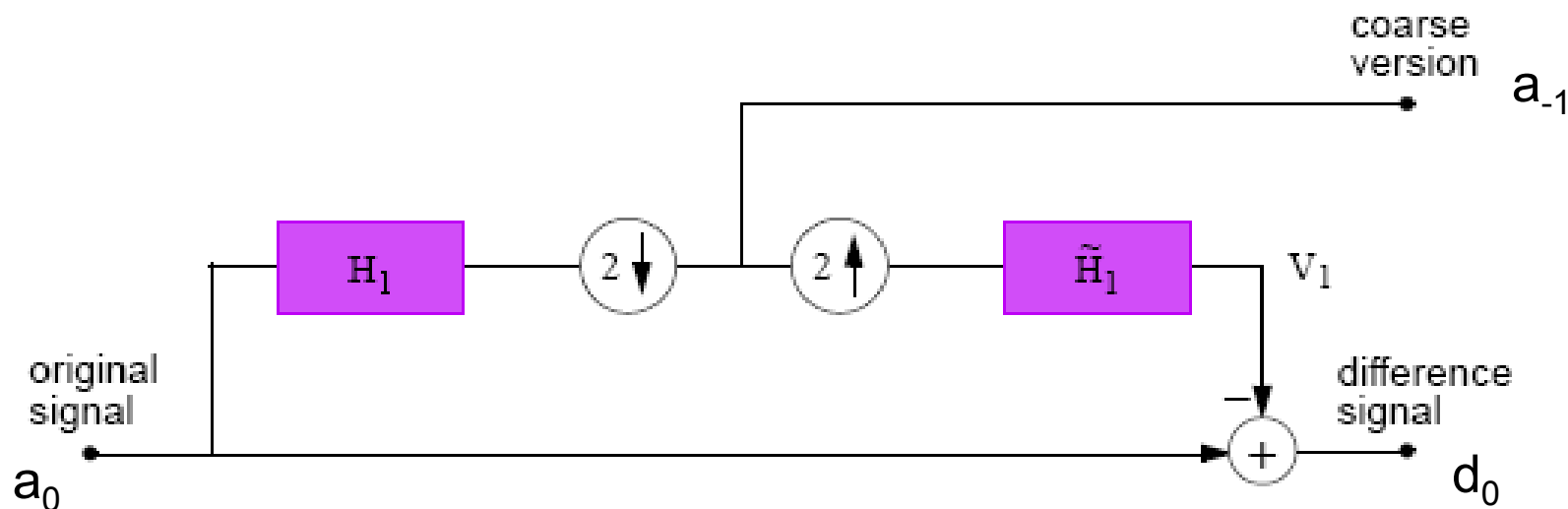
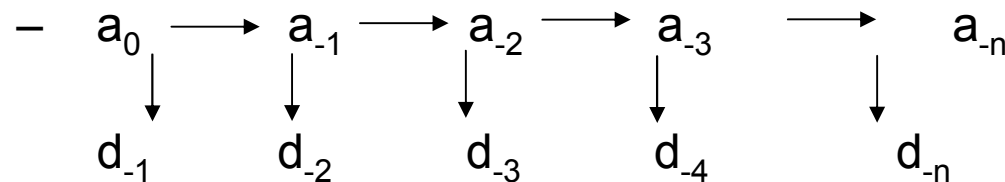
## Multi-resolution analysis (MRA) - Wavelets

- What are  $a_n$  and  $d_n$  when a 2D wavelet transform (dyadic) is used?



## Multi-resolution analysis (MRA) - Pyramids

- Using the pyramid decomposition
  - Use the same MRA concept
  - i.e., half resolution approximation + details
  - With the wavelet transform, the details are represented at half resolution too.
  - But in pyramidal transform, the details are represented at the resolution of the previous level.
  - Takes the following form:



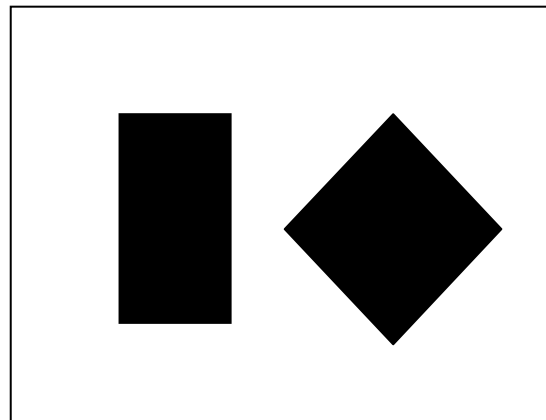
## Multi-resolution analysis (MRA) - Pyramids

- Draw the inverse transform block diagram
- Draw a block diagram for a pyramid transform for an image.



## Multi-resolution analysis (MRA) - Pyramids

- Draw the inverse transform block diagram for a pyramid transform for an image.
- For this image show the resulting sub bands for a 2 level decomposition using the pyramid transform:





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## Multi-resolution analysis (MRA) - Pyramids

- The memory requirement for a 2-level 2D pyramid decomposition:
  - If  $N$  is the original image size: Then the pyramidal decomposition based MRA requires  $N + N/4 + N/16 = N(1 + 1/4 + 1/16)$
  - The above is greater than  $N$ . Therefore, called expansive or redundant representation.
  - Derive an expression for the required space for an  $n$ -level decomposition
  
- What is the redundancy factor for a pyramidal decomposition?

- (1) Detail (high pass) sub bands contain information regarding to signal singularities and high frequency components.
  - How can we exploit this to de-noise an image?
  - How can we exploit this for edge detection?
  - How can we exploit this for image compression?
- (2) Approximation (low pass) sub bands contain a smoothed low resolution version of the original image
  - How can we exploit this to reduce complexity of some image operations?

# MRA Applications: De-noising

- Original Image:  $a$
- Distorted image:  $b$  (add noise to  $a$ )
  - For example,  $b = a + v * \text{randn}(\text{size}(a));$
  - $v$  is the noise variance
  - “randn” generates noise with normal distribution of zero mean and unit variance.
  - $v=10$  results in around 28dB noise on a gray scale image.
  - Compute the PSNR of  $b$  compared to  $a$
- How to de-noise?
  - Do the forward wavelet transform (FWT) for image  $a$  (2 or 3 levels)
  - Do the forward wavelet transform (FWT) for image  $b$  (2 or 3 levels)
  - Find out the difference. Which sub bands are affected due to noise?
  - Now think of a methodology to de-noise  $b$  and perform it
  - What is the PSNR of the de-noised image compared to  $a$ ?

# MRA Applications: De-noising

- PSNR Computation
  - Peak Signal to Noise Ratio
  - $10 \log_{10} (\text{Peak signal power} / \text{Mean noise power})$

- Mean noise power  $MSE = \frac{1}{N} \sum_i \sum_j (a_{i,j} - b_{i,j})^2$

N=total number of pixels

a=original image

b=noisy image

- Peak signal power for a 8-bit gray scale image  $255^2$

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

# MRA Applications: De-noising

- De-noising methodology
  - Perform FWT on b
  - HL1, LH1, HH1 are the first level high frequency bands
  - HL2, LH2, HH2 are the second level high frequency bands
  - Noise is high frequency
  - and low amplitude
  - Important high frequency components (like edges) in images contain high amplitude compared to noise.
  - To de-noise set all wavelet domain coefficient magnitudes (c) less than a threshold (T) to zero.
  - $C_{i,j} = (|C_{i,j}| < T) ? 0 : C_{i,j}$
  - The threshold T can be global or can be chosen locally to each sub band
  - Now perform the inverse wavelet transform (IWT)

LL2	HL2	HL1
LH2	HH2	
LH1		HH1

# MRA Applications: Edge Detection

LL2	HL2	HL1
LH2	HH2	
LH1		HH1

- Edge detection methodology
  - Perform FWT on  $b$
  - HL1 and LH2 contain vertical edges
  - LH1 and LH2 contain horizontal edges
  - HH1 and HH2 contain non-horizontal and non-vertical edges
  - Important high frequency components (like edges) in images contain high amplitude compared to noise.
  - To find an edge map mark all wavelet domain coefficient magnitudes ( $c$ ) higher than a threshold ( $T$ ) to 1 and all the rest to 0.
  - $\text{Edge\_Map}_{i,j} = (|C_{i,j}| > T) ? 1 : 0$
  - The threshold  $T$  is usually chosen locally to each sub band or each wavelet decomposition level (e.g.,  $T_1$  for HL1, LH1, HH1 and  $T_2$  for HL2, LH2, HH2)



## MRA Applications: Image Compression

- Image compression methodology
  - LL sub band ---- more information  
large amplitudes
  - HL, LH, HH sub bands ---- less information (mainly edges)  
low amplitudes close to zero  
large amplitudes for edges
  - Therefore quantise high frequency sub bands heavily (use fewer bits)
  - LL sub band – low quantisation (use more bits)
  - Encoder
    - Image  $\rightarrow$  (FWT)  $\rightarrow$  (Quantisation)  $\rightarrow$  (Entropy coder)  $\rightarrow$  bit stream
  - Decoder
    - bit stream  $\rightarrow$  (Entropy decoder)  $\rightarrow$  (De-Quantisation)  $\rightarrow$  (IWT)  $\rightarrow$  Image
  - More details in Topic 7

LL2	HL2	HL1
LH2	HH2	
LH1		HH1

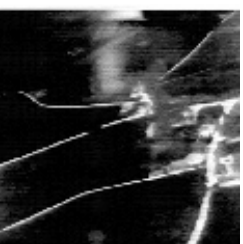
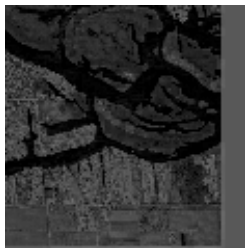
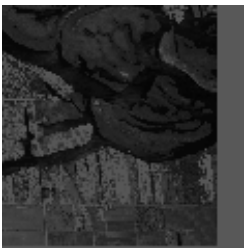
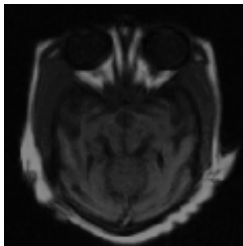
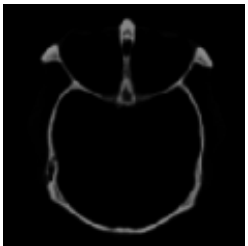
# MRA Applications: Image Fusion

Fusion applications:

A

B

Fused



1. To get a composite image from images with different camera focus on different objects. (Multi-focus fusion)
2. To get a composite image from different imaging sources (such as MRI (image 2.A) and CT (image 2.B)) in medical imaging. (Multi-modal fusion)
3. To get a composite image from different spectral bands from hyper-spectral images in remote sensing. (multi-spectral fusion)
4. To get a composite image from different imaging sources (such as normal and IR cameras) in surveillance imaging (Multi-modal fusion)

# MRA Applications: Image Fusion

- Image fusion can be
  - Multiview fusion (taken from the same camera under different conditions)
  - Multimodal fusion (taken from different sensors)
  - Multi-temporal fusion (images taken at different times)
  - Multi-spectral fusion (same image but different spectral bands)
  - Multi-focus fusion (different regions are in focus or out of focus)

LL2	HL2	HL1
LH2	HH2	
LH1		HH1

- Image pixel domain technologies:
  - A simple strategy: Compare each pixel from two images A and B to get the fused image (F).

$$F_{i,j} = (A_{i,j} > B_{i,j}) ? A_{i,j} : B_{i,j}$$

$$\text{Or } F_{i,j} = a A_{i,j} + b B_{i,j} ; \text{ with } a+b=1$$

- Any drawbacks?

- MRA-based approach

- $A \rightarrow (\text{FWT}) \rightarrow C^A$
- $B \rightarrow (\text{FWT}) \rightarrow C^B$
- Now fusion rule  $C^F_{i,j} = (|C^A_{i,j}| > |C^B_{i,j}|) ? C^A_{i,j} : C^B_{i,j}$  (For high pass bands)
- $C^F_{i,j} = a C^A_{i,j} + b C^B_{i,j}$  with  $a+b=1$  (For the low pass band)
- $C^F \rightarrow (\text{IWT}) \rightarrow F$

## MRA Applications: Data Hiding (watermarking)

- Watermarking strategy
  - Our Requirements
    - Imperceptible
    - Robust
  - Data hiding requires modification of pixel values
  - That means distortion
  - **Imperceptibility** – The human eye is more susceptible to distortion in low frequency areas than high frequency areas like edges. Therefore choose pixels in high frequency areas to hide data.
  - We can find these pixels in wavelet transform domain.
  - i.e., the high frequency sub bands.
  - **Robustness** – Should be robust to compression. In compression low amplitude high frequency data is quantized (removed). So watermarked information can be lost). Therefore the choice of pixels should consider this too.
  - Methodology
    - Image → (FWT) → (Sub band and coefficient selection) → (Coefficient modification) → (IWT) → watermarked image

LL2	HL2	HL1
LH2	HH2	
LH1		HH1