

HAAR WAVELET TRANSFORM (IMAGE MULTI-RESOLUTION ANALYSIS)

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Introduction:

This work shows that the Haar transformation can be used for image compression. The results and effectiveness is determined in terms of PSNR value between original image and reconstructed image at different thresholds.

A Wavelet transformation converts data from the spatial into the frequency domain and then stores each component with a corresponding matching resolution scale

The **Haar** function:

$$\psi(t) = \begin{cases} 1 & t \in [0, 1/2) \\ -1 & t \in [1/2, 1) \\ 0 & t \notin [0, 1) \end{cases}$$

and

$$\psi_i^j(t) = \sqrt{2^j} \psi(2^j t - i), \quad j = 0, 1, \dots \text{ and } i = 0, 1, \dots, 2^j - 1.$$

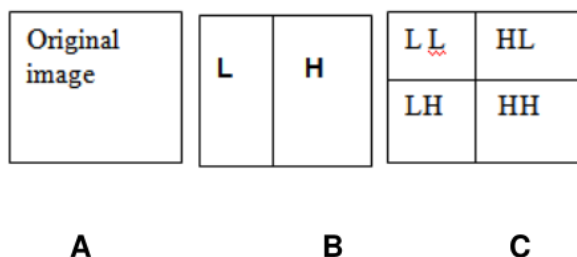
Haar Transform is nothing but averaging and differencing.

This can be explained with a simple 1D image with eight pixels [3 2 -1 -2 3 0 4 1]. Applying the Haar wavelet transform, we can represent this image in terms of a low-resolution image and a set of detail coefficients.

So the image after one Haar Wavelet Transform is:

$$\begin{array}{lcl} \text{Transformed coefficient} & = & [2.5 \ -1.5 \ 1.5 \ 2.5] \\ \text{Detail Coefficients} & = & [0.5 \ 0.5 \ 1.5 \ 1.5] \end{array}$$

The detail coefficients are used in reconstruction of the image. Recursive iterations will reduce the image by a factor of two for every cycle.



A = Original Image
B = First Run along Row
C = First Run Along Column

The image array is split into two halves containing the transformed data and the detail coefficients. The transformed data coefficients are the results of the low-pass filter while the detail coefficients are the results of the high-pass filter.

After transforming the image in the row, the image is then transformed along the column. This process repeats till three iterations

Methods:

1. Choose a gray-scale image with a maximum value (intensity) M - this value is used in the definition of the below PSNR



Grayscale image ('lena.jpg')

2. Apply the DWT (multiresolution analysis with the Haar Wavelet) on 1 level

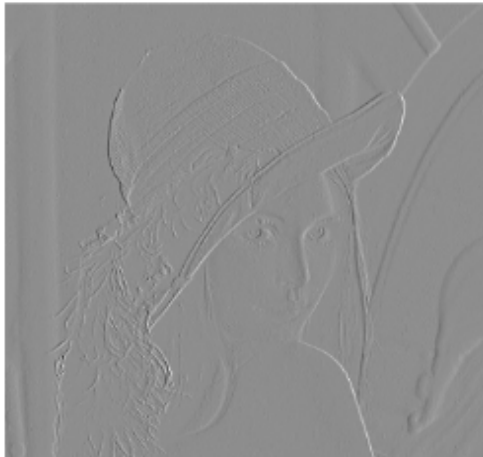
Approximation (cA)



Horizontal Detail (cH)



Vertical Detail (cV)



Diagonal Detail (cD)



3. Apply a threshold T

```
def dwt_threshold(img, threshold):  
    coeffs = pywt.dwt2(img, 'haar')  
    cA, (cH, cV, cD) = coeffs  
    cA_thresh = np.where(np.abs(cA) < threshold, 0, cA)  
    cH_thresh = np.where(np.abs(cH) < threshold, 0, cH)  
    cV_thresh = np.where(np.abs(cV) < threshold, 0, cV)  
    cD_thresh = np.where(np.abs(cD) < threshold, 0, cD)  
    coeffs_thresh = (cA_thresh, (cH_thresh, cV_thresh, cD_thresh))  
    img_thresh = pywt.idwt2(coeffs_thresh, 'haar')  
    return img_thresh, (cA, (cH, cV, cD))
```

The absolute values of cA, cH, cV, cD are compared to the given threshold value. If the absolute value is less than the threshold, it is set to 0; otherwise, it remains unchanged.

```
dwt_img, coeffs = dwt_threshold(img, M)  
cA, (cH, cV, cD) = coeffs
```

dwt_threshold value is M: maximum intensity value in the grayscale image.

It is used as the threshold for the DWT coefficients. Thresholding compares the absolute values of the *coefficients* to the threshold (M) and sets them to 0 if they are below the threshold.

img_thresh = pywt.idwt2(coeffs_thresh, 'haar')

Performs the inverse Discrete wavelet Transform (IDWT) using the thresholded coefficients (coeffs_thresh) and the Haar wavelet. It reconstructs the denoised image.

Thresholded Image



4. Compute the PSNR (reference image = original image) of the reconstruction (DWT-1)

```
def compute_psnr(img1, img2):  
    # Resize images to match dimensions  
    img1 = cv2.resize(img1, (img2.shape[1], img2.shape[0]))  
  
    mse = np.mean((img1 - img2) ** 2)  
    max_value = np.max(img1)  
    psnr = 10 * np.log10((max_value ** 2) / mse)  
    return psnr
```

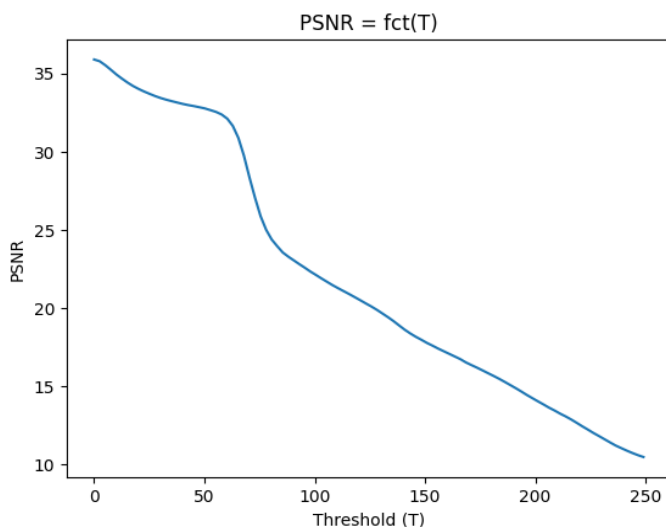
```
# Compute PSNR for reconstruction  
psnr_reconstruction = compute_psnr(img, dwt_img)  
print("PSNR for reconstruction (DWT-1):", psnr_reconstruction)
```

```
PSNR for reconstruction (DWT-1): 10.47258377947826
```

5. Plot PSNR = fct(T)

```
thresholds = np.linspace(0, M, 100)
```

So, **thresholds** array will contain 100 values starting from 0 and ending at M, with evenly spaced intervals between them.



PSNR as a function of the threshold values (T).

6. Repeat the process with the noisy image (add a Gaussian White Noise, noise level > standard deviation D)

```
# Add Gaussian white noise to the image  
std_dev = 20  
noisy_img = add_gaussian_noise(img, std_dev)
```

Gaussian white noise added



7. Find the optimal threshold T_o for denoising (PSNR). Note the reference image is the noise-free image

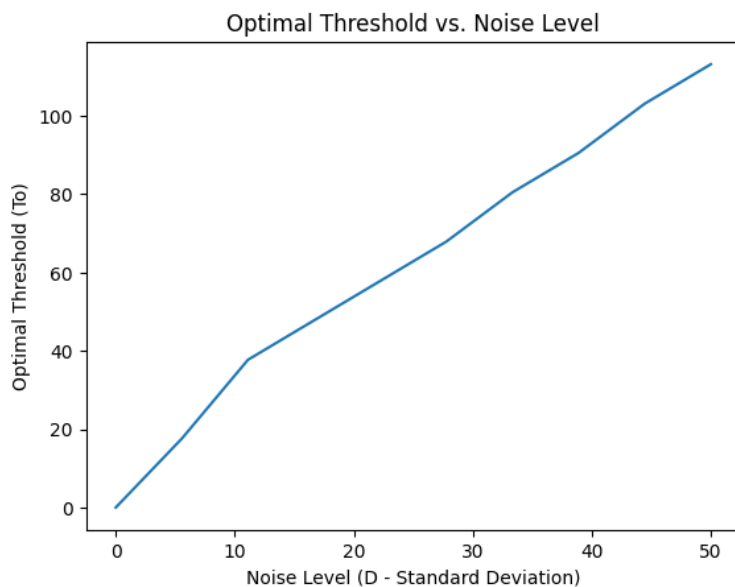
```
# Find the optimal threshold for denoising
optimal_threshold, psnr_values = optimal_threshold_denoising(noisy_img, img, M)
print("Optimal threshold for denoising (PSNR):", optimal_threshold)
```

```
Optimal threshold for denoising (PSNR): 52.81818181818182
```

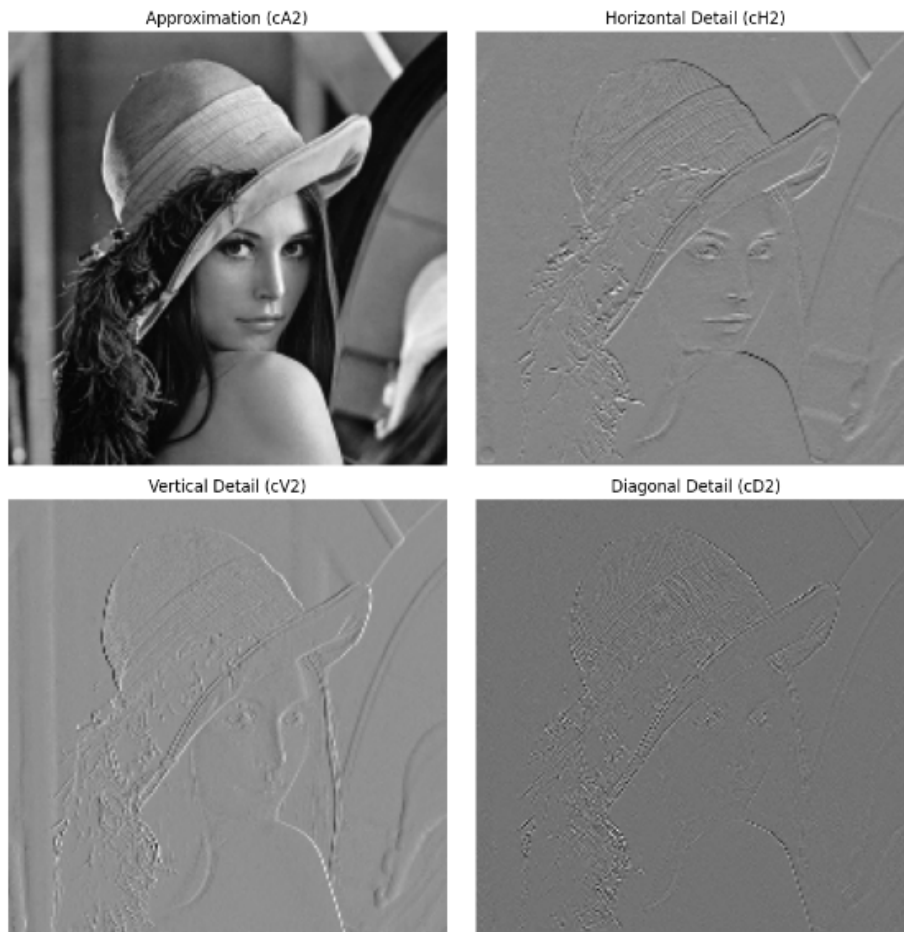
8. Study the evolution of optimal threshold T_o in respect of the noise level (D)

```
# Study the evolution of  $T_o$  in respect of the noise level (D)
std_dev_values = np.linspace(0, 50, 10)
optimal_thresholds = []
for std_dev in std_dev_values:
    noisy_img = add_gaussian_noise(img, std_dev)
    optimal_threshold, _ = optimal_threshold_denoising(noisy_img, img, M)
    optimal_thresholds.append(optimal_threshold)
```

Iterates over a range of standard deviation values (0, 50, 10), adds Gaussian noise to the image, and then finds the optimal threshold using the `optimal_threshold_denoising` function. The optimal thresholds are collected in the `optimal_thresholds` list for visualization.



9. Repeat all the process with two levels (L1 and L2) in the multiresolution analysis. Find the optimal thresholds T_1 and T_2 . What is the relation between these T_1 and T_2 ?



DWT-2 Coefficients

Conclusion

For optimal thresholds T_1 and T_2 , I apply the DWT with two levels, perform thresholding on the coefficients at each level, and then evaluate the denoising performance using PSNR.

The relation between T_1 and T_2 depends on the specific characteristics of the image and the noise such as the noise level, image content, and the desired balance between denoising and preserving image details.

From PSNR, T_2 yields the highest denoising quality because the higher-level coefficients capture finer details and noise, so a higher threshold is needed to remove the noise without excessively distorting the image.