

# Praktikum Extraction Feature (Weber Local Descriptor)

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# WLD: A Robust Local Image Descriptor

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**Abstract**—Inspired by Weber’s Law, this paper proposes a simple, yet very powerful and robust local descriptor, called the Weber Local Descriptor (WLD). It is based on the fact that human perception of a pattern depends not only on the change of a stimulus (such as sound, lighting) but also on the original intensity of the stimulus. Specifically, WLD consists of two components: differential excitation and orientation. The differential excitation component is a function of the ratio between two terms: one is the relative intensity differences of a current pixel against its neighbors; the other is the intensity of the current pixel. The orientation component is the gradient orientation of the current pixel. For a given image, we use the two components to construct a concatenated WLD histogram. Experimental results on the Brodatz and KTH-TIPS2-a texture databases show that WLD impressively outperforms the other widely used descriptors (e.g., Gabor and SIFT). In addition, experimental results on human face detection also show a promising performance comparable to the best known results on the MIT+CMU frontal face test set, the AR face dataset and the CMU profile test set.

**Index Terms**—Pattern Recognition, Weber Law, Local Descriptor, Texture, Face detection

# WLD

An input image



$$X = \{x_s\}$$

$$x_s = \begin{bmatrix} x_0 & x_1 & x_2 \\ x_3 & x_4 & x_5 \\ x_6 & x_7 & x_8 \end{bmatrix}$$

Filtering

$$f_{00} = \begin{bmatrix} +1 & +1 & +1 \\ +1 & -8 & +1 \\ +1 & +1 & +1 \end{bmatrix}$$

$$f_{01} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & +1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$f_{10} = \begin{bmatrix} & -1 & \\ & & \\ +1 & & \end{bmatrix}$$

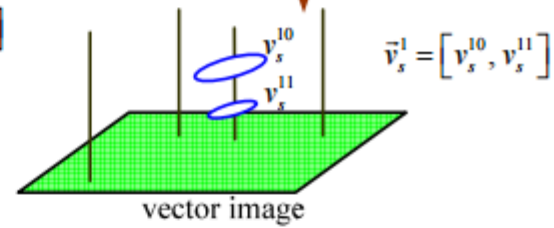
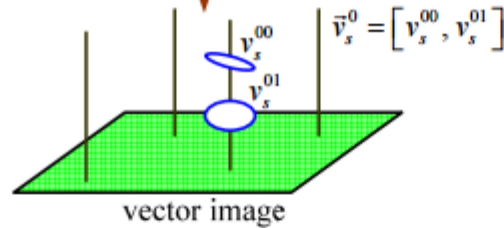
$$f_{11} = \begin{bmatrix} & & \\ +1 & & \\ & & -1 \end{bmatrix}$$

$$\downarrow v_s^{00}$$

$$\downarrow v_s^{01}$$

$$\downarrow v_s^{10}$$

$$\downarrow v_s^{11}$$



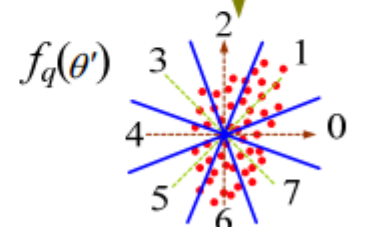
Labeling

$$\xi = \gamma_s^0 = \arctan\left(\frac{v_s^{00}}{v_s^{01}}\right)$$

$$\xi = \gamma_s^0$$

$$\theta = \gamma_s^1 = \arctan\left(\frac{v_s^{11}}{v_s^{10}}\right)$$

$$f: \theta \mapsto \theta', \quad \theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right], \text{ and } \theta' \in [0, 2\pi]$$



$$\Phi_t = f_q(\theta') = \frac{2t}{T}\pi, \quad t = \text{mod}\left(\left\lfloor \frac{\theta'}{2\pi/T} + \frac{1}{2} \right\rfloor, T\right)$$

### 2.2.1 Differential Excitation

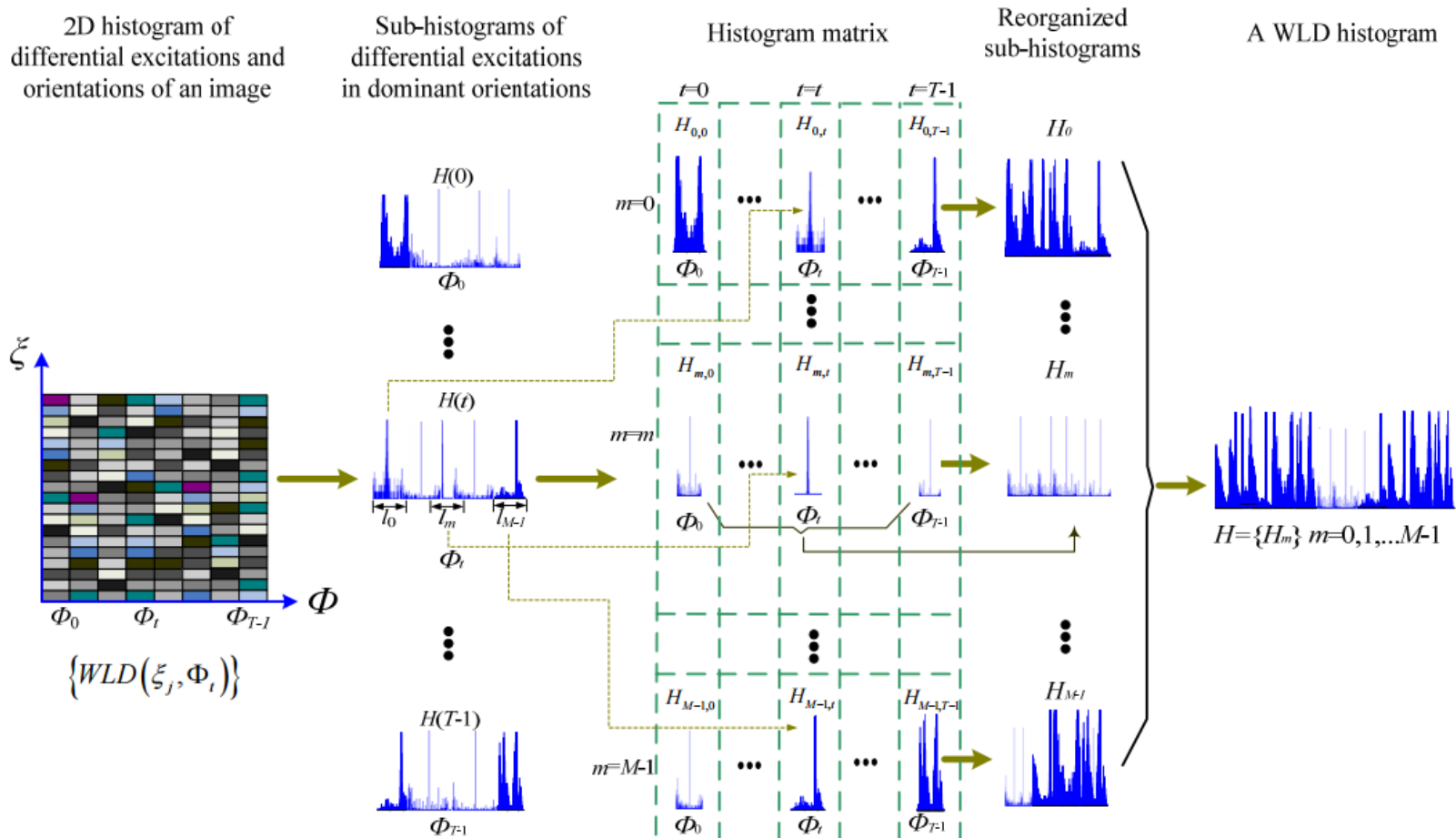
We use the intensity differences between its neighbors and a current pixel as the changes of the current pixel. By this means, we hope to find the salient variations within an image to simulate the pattern perception of human beings. Specifically, a differential excitation  $\xi(x_c)$  of a current pixel  $x_c$  is computed as illustrated in Fig. 1. We first calculate the differences between its neighbors and the center point using the filter  $f_{00}$ :

$$v_s^{00} = \sum_{i=0}^{p-1} (\Delta x_i) = \sum_{i=0}^{p-1} (x_i - x_c), \quad (2)$$

where  $x_i$  ( $i=0,1,\dots,p-1$ ) denotes the  $i$ -th neighbors of  $x_c$  and  $p$  is the number of neighbors. Following hints in Weber's Law, we then compute the ratio of the differences to the intensity of the current point by combining the outputs of the two filters  $f_{00}$  and  $f_{01}$  (whose output  $v_s^{01}$  is the original image in fact):

$$G_{ratio}(x_c) = v_s^{00} / v_s^{01}. \quad (3)$$

We then employ the arctangent function on  $G_{ratio}(\cdot)$ :



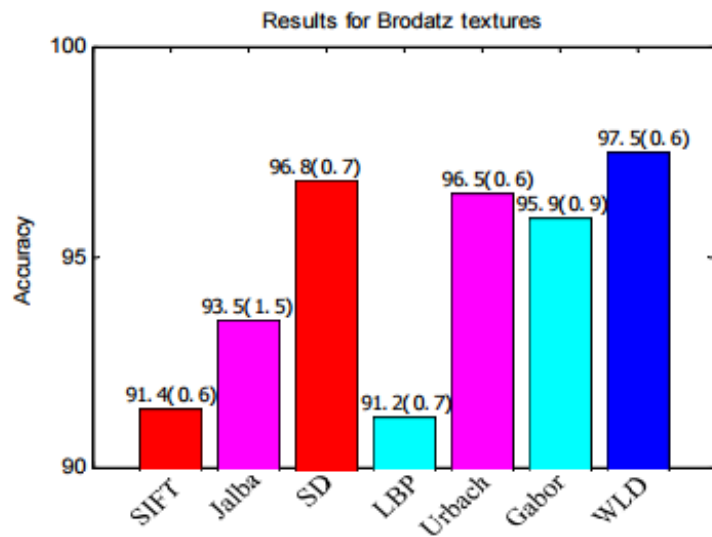
(a)

$H_{m,t}$

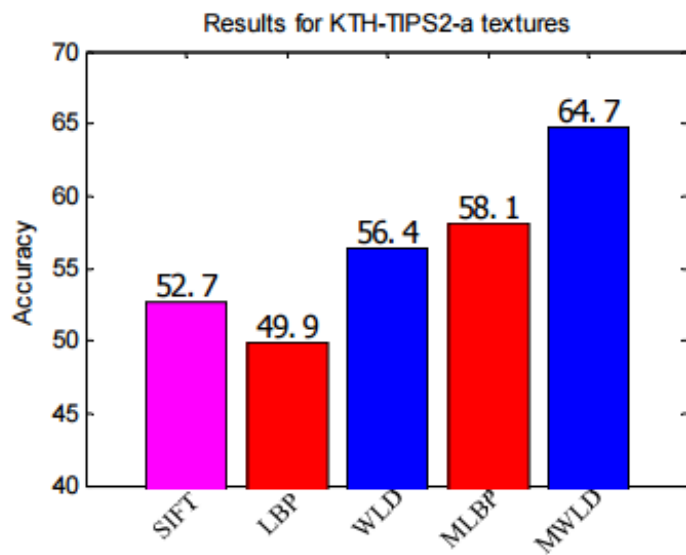
$\eta_{m,l}$   $\Phi_t$   $\eta_{m,u}$

$$h_{m,t,s} = \sum_j \delta(S_j == s)$$

$$\left( \xi_j \in l_m, \Phi_t = f_q(\theta'_j), S_j = \left\lfloor \frac{\xi_j - \eta_{m,l}}{(\eta_{m,u} - \eta_{m,l})/S} + \frac{1}{2} \right\rfloor \right)$$

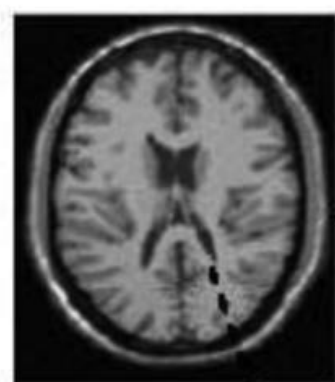


(a)

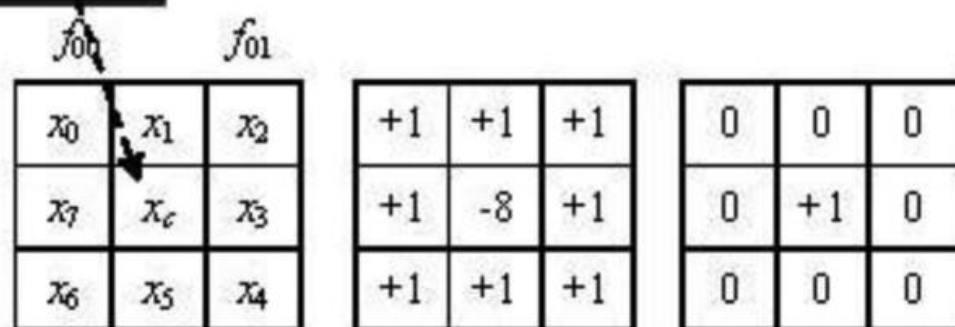
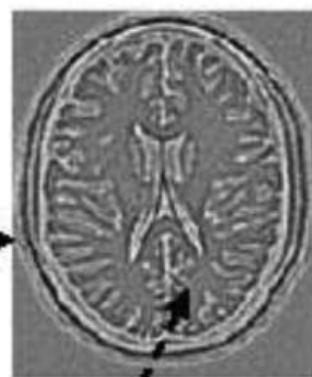


(b)

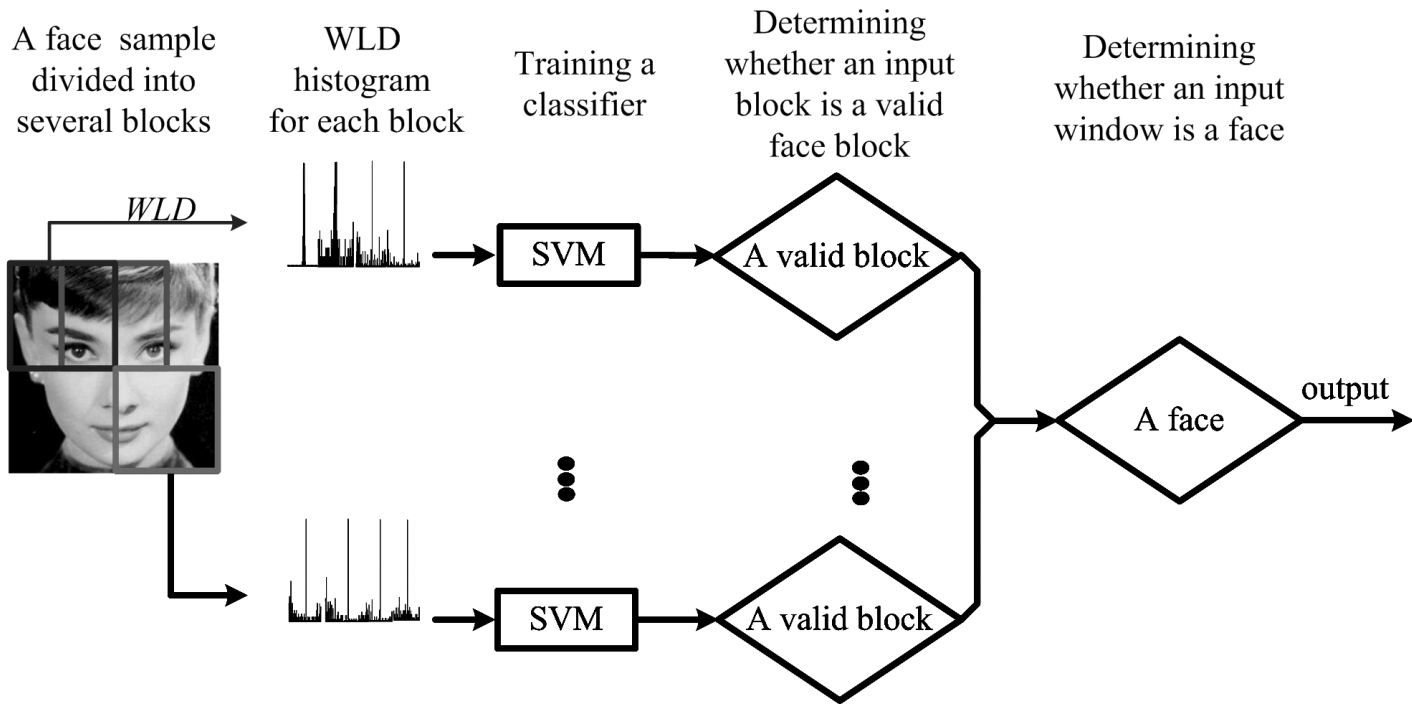
Fig. 8. Results comparison with state-of-the-art methods on Brodatz and KTH-TIPS2-a textures, where the values above the bars are the accuracy and corresponding standard deviations.



WLD

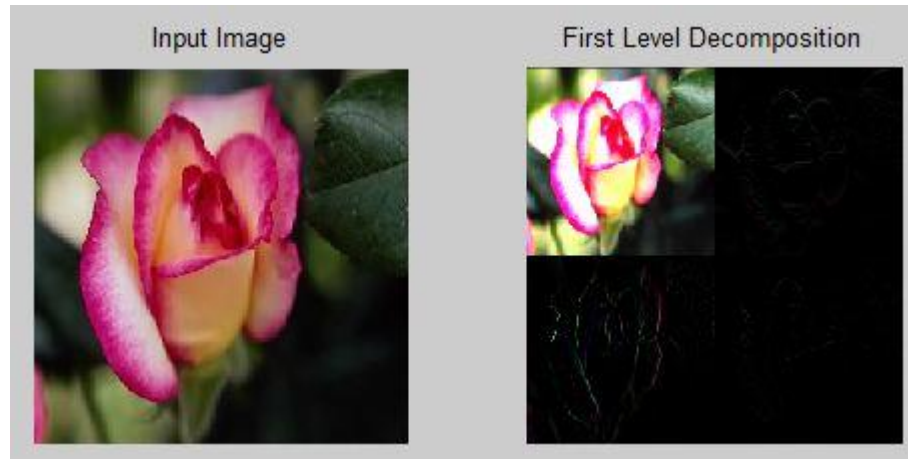


$$\xi(x_c) = \arctan \left[ \frac{v_s^{00}}{v_s^{01}} \right]$$

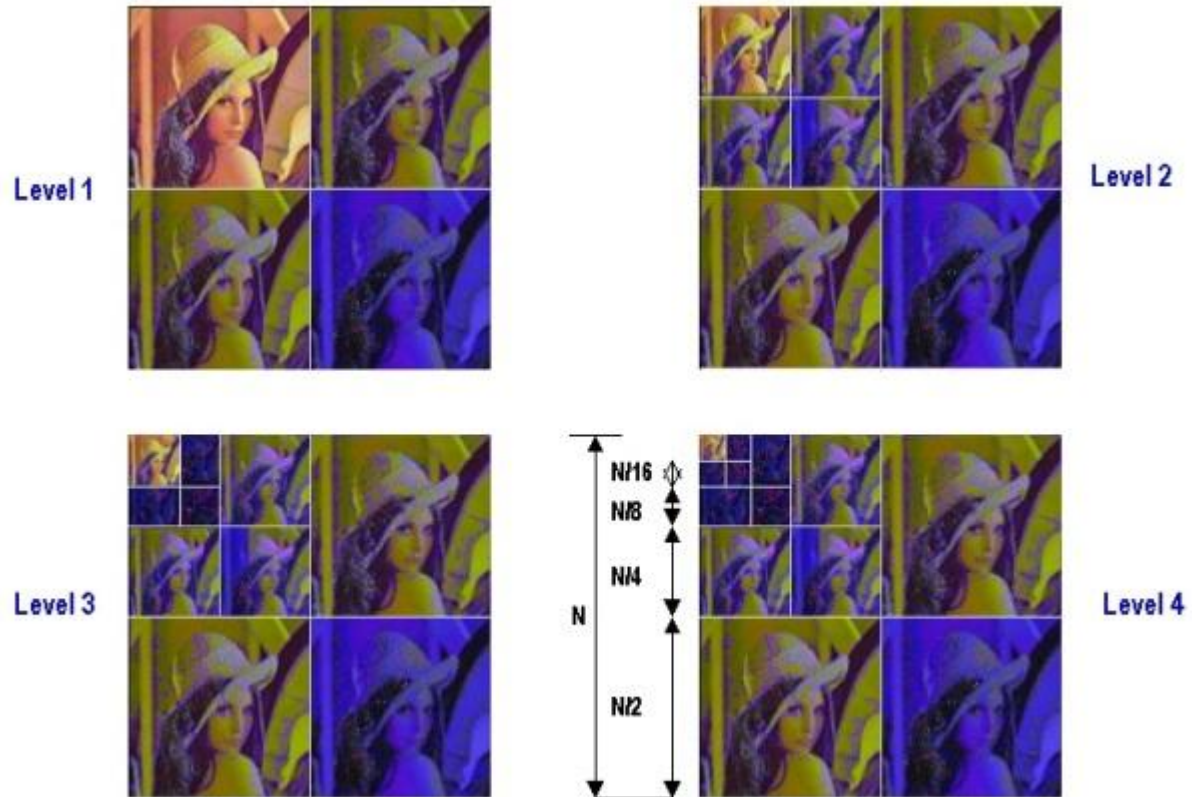




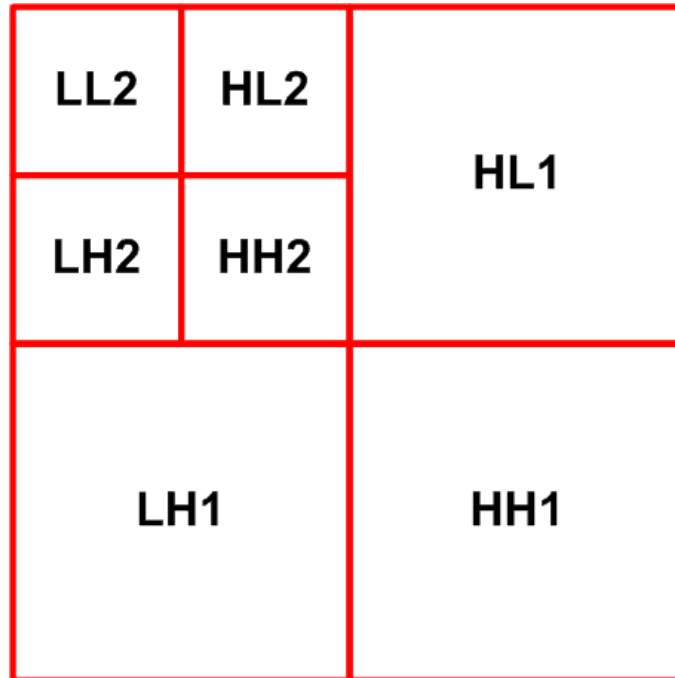
# Wavelett



# Wavelett



# Wavelett



# Wavelett

## Literature Review (cont..)

- 2-D DWT for Image

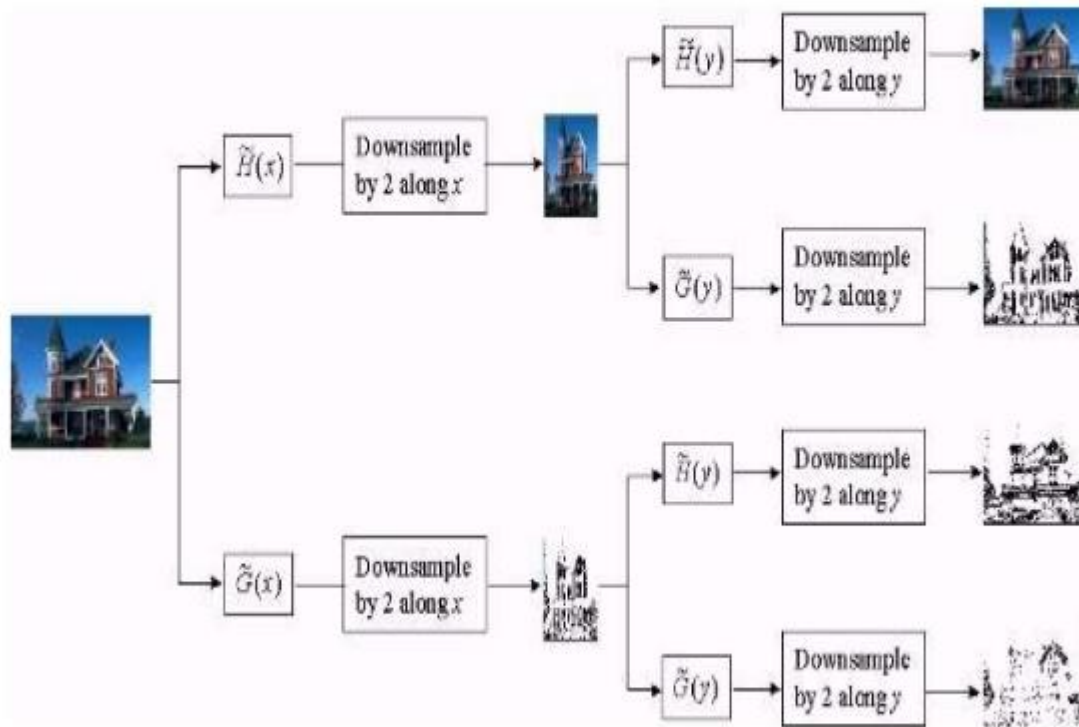


Figure 3 Image compression and decoded image