

Feature Extraction from image
Wavelet texture, twice wavelet transform
(2D WT)

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Chapter 1

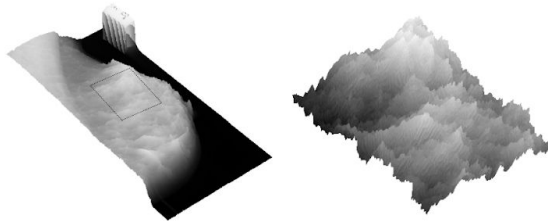
1. Introduction

1.1 What is Texture

Texture is that innate property of all surfaces that describes visual patterns, and that contain important information about the structural arrangement of the surface and its relationship to the surrounding environment. Texture consists of primitive or texture elements called texels.

Texture is a repeating pattern of local variations in image intensity

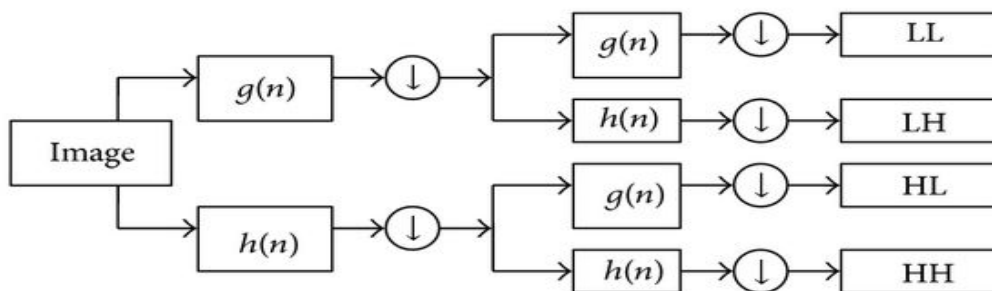
Texture cannot be defined for any particular point.



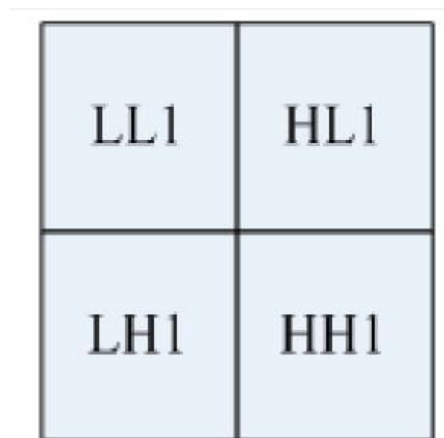
3

1.2 What is Discrete wavelet transform

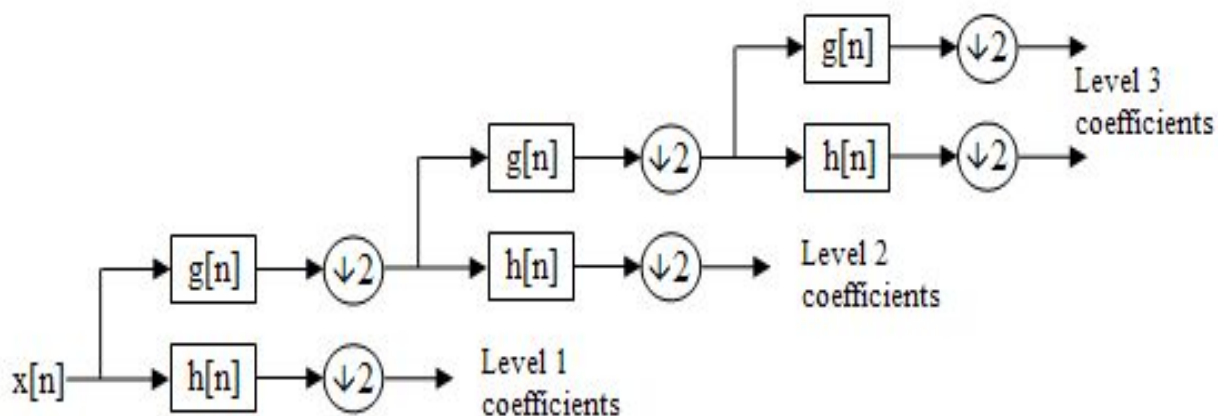
Now-a-days wavelet transforms become very popular when it comes for doing analysis, de-noise, and compression of signals and images. In this the image is actually decomposed into four sub-bands and critically sub-sampled by applying DWT as described in fig(1).

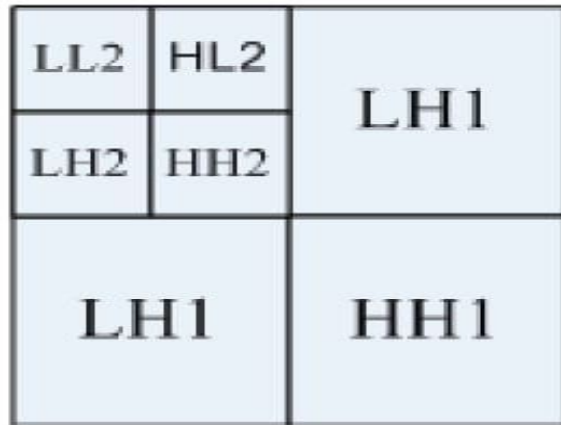


These sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients i.e., detail images while the sub-band LL1 corresponds to coarse level coefficients i.e., approximation image.



To obtain the next coarse level of wavelet coefficients, the sub-band LL1 alone is further decomposed and critically sampled. This results in a two-level wavelet decomposition as shown below. Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached.





The values or transformed coefficients in approximation and detail images (sub-band images) are the essential features, which are shown here as useful for texture analysis and discrimination. As micro-textures or macro-textures have non-uniform gray level variations, they are statistically characterized by the features in approximation and detail images. In other words, the values in the sub-band images or their combinations or the derived features from these bands uniquely characterize a texture. The features obtained from these wavelet transformed images are shown to be used for texture analysis

2. Mathematical Formulation

The basic idea of wavelet transform is to represent any arbitrary function f as a superposition of wavelets. Any such superposition decomposes f into different scale levels, where each level is then further decomposed with a resolution adapted to the level. One way to achieve such a decomposition writes f as an integral over a and b with appropriate weighting coefficients.

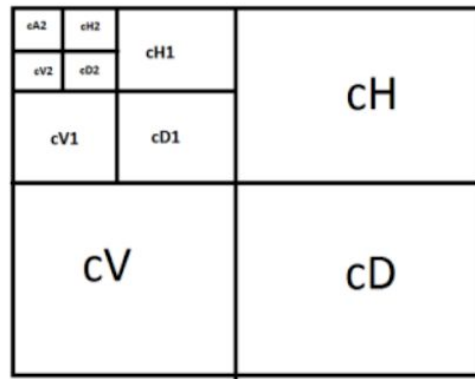
The wavelet transform extracts directional details that capture horizontal (cH), vertical (cV) and the diagonal (cD) activity.

$$\psi^{(a,b)} * t = \text{mod}(a)^{-0.5} * \psi \frac{(t-b)}{a}$$

where,

a=scale (1/frequency)

b=time shift.



3. Algorithm

In this section, we give an overview of the Single level discrete wavelet transform algorithm and Multilevel decomposition :-

Single level discrete wavelet transform

Input: Image

Output: Here we get decomposed image in which we get four images which are horizontal, vertical, and diagonals image

`pywt.dwt(data, wavelet, mode='symmetric', axis=-1)`

Single level Discrete Wavelet Transform.

Parameters

data [array_like] Input signal

wavelet [Wavelet object or name] Wavelet to use

mode [str, optional] Signal extension mode, see Modes.

axis: int, optional Axis over which to compute the DWT. If not given, the last axis is used.

Returns

(cA, cD) [tuple] Approximation and detail coefficients

Notes

Length of coefficients arrays depends on the selected mode. For all modes except periodization:

$$\text{len}(cA) == \text{len}(cD) == \text{floor}((\text{len}(\text{data}) + \text{wavelet.dec_len} - 1) / 2)$$

For periodization mode ("per"):

$$\text{len}(cA) == \text{len}(cD) == \text{ceil}(\text{len}(\text{data}) / 2)$$

Multilevel decomposition using wavedec

Input: Image

Output: Here we get decomposed image in which we get four images which are horizontal, vertical, and diagonals image and in LL we get one more decomposed image which also contain four images.

`pywt.wavedec(data, wavelet, mode='symmetric', level=None, axis=-1)`

Multilevel 1D Discrete Wavelet Transform of data.

Parameters

data: array_like Input data

wavelet [Wavelet object or name string] Wavelet to use

mode [str, optional] Signal extension mode, see Modes.

level [int, optional] Decomposition level (must be ≥ 0). If level is None (default) then it will be calculated using the `dwt_max_level` function

axis: int, optional Axis over which to compute the DWT. If not given, the last axis is used.

Returns

[cA_n, cD_n, cD_n-1, . . . , cD2, cD1] [list] Ordered list of coefficients arrays where n denotes the level of decomposition. The first element (`cA_n`) of the result is approximation coefficients array and the following elements (`cD_n - cD_1`) are details coefficients arrays.

4. Documentation of API

4.1 Package organization

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[1] Wavelet tutorial by Robi Polikar .

[2]