Wavelet Features for Color Image Classification

Michael Diaz
Advisors: Vidya Manian and Ramón Vásquez

Laboratory for Applied Remote Sensing and Image Processing
Electrical and Computer Engineering Department
University of Puerto Rico, Mayagüez, P.R. 00681-5000
md_1930@hotmail.com

Abstract

In this paper, we compare the performance of three different wavelet methods for color texture classification. Wavelet transforms are useful for extracting texture features of images. These features are used for texture recognition, and constitute energy, entropy values of sub-images computed using Pyramid structure Wavelet Transform (PWT) or tree structured Wavelet Transform (TWT). As color images have 3 channels compared to 1 channel in gray scale images, they can be exploited for the additional information they can provide.

The algorithm consist of transforming the RGB color space to xyY color space and the features are computed in this space. The reason for using this space is that they provide chrominance and luminance information of the color images. The sub-band filtering is performed in particular channels depending on the histogram of the chrominance values. This reduces the computational cost, since only a few sub-bands need to be decomposed at each stage. Results of classification using photographic color textures are presented and discussed in this paper.

1. Introduction

There are different kinds of images, but what is a color image? A color image is a representation of what can capture a human eye. Color images can be of different types such as RGB, multichannel, or raster images. But, how can we apply wavelet analysis to a color image?

Fourier transforms are very useful for signal decomposition. This method uses finite complex sinusoid functions, which are sine and cosines, these represent the signal. The wavelet method is similar to the Fourier domain except that the decomposition is done in both time and frequency and give localized information of the signal. In a hierarchical wavelet transform we use a family of functions (scaling functions) that decomposes the signal in what we call bands. This process is applied in a recursive way to the lower frequency sub-bands.

2. Wavelet Methods

The wavelet method implements several variation of the wavelet filter based algorithms. These are the tree structured, pyramid structured wavelet transforms and wavelet extrema features. In the tree structured method, a wavelet and a scaling filter are used to decompose a texture image into four sub-images. Each of these sub-images are the approximate, horizontal, vertical and diagonal detail images. The sub-images can be further subdivided to form the tree structure.

The sub-image feature energy values are calculated using regional masks. In the pyramid structure only the approximate sub-image is decomposed each time with the wavelet and scaling filters. The number of levels can be chosen from 2 to 6. The wavelet extrema feature method first computes an over-complete expansion of the texture image with the wavelet filters. These expansion does not involve down-sampling at each level, hence results in sub-images which are of the same size as the original image. These expansions are also translation invariant. As sub-sampling is not performed their computational cost is higher than other wavelet transform methods. The extrema features are computed for each subimage using a moving window centered around a pixel. A general wavelet decomposition process is shown in Fig. 1. In the extrema method the down sampling shown in Fig. 1 has to be deleted.

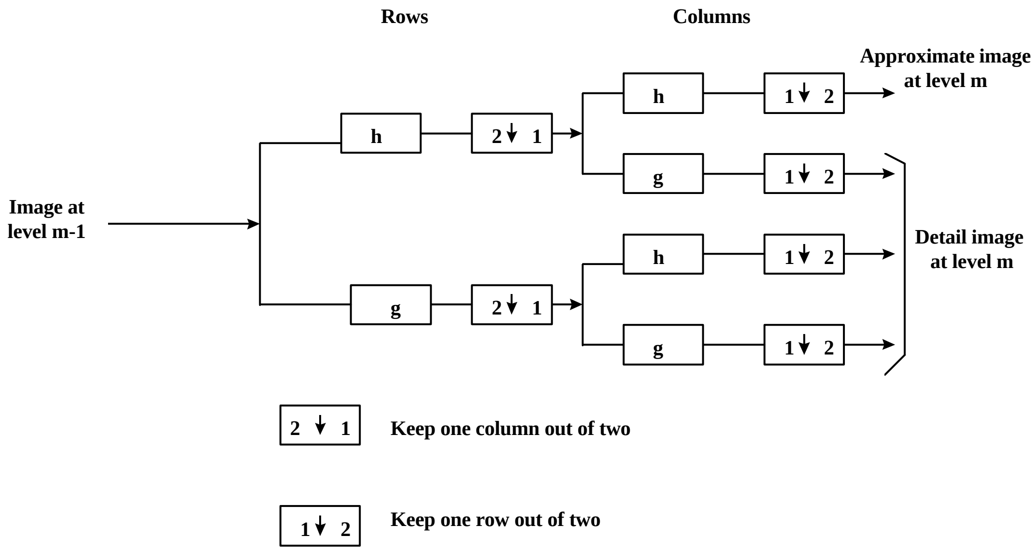

Fig. 1 Wavelet Decomposition of an Image

3. Algorithm Implementation

In this work we have implemented the three types of wavelet transforms mentioned in Section 2. An RGB color image is taken and transformed in to the xyY colorspace. The Y values are the luminances and xy values xy components have to be changed to a one dimensional chrominance value (cv). The xy values are between 0 and 1. The interval of the xy values (from 0 to 1) is divided in k intervals. The xy values are assigned to an equivalent value within 0 and k. Using the new equivalent value for each x and y the new one dimensional chrominance value is given by the following formula:

$$cv = y + k * x \tag{1}$$

In this paper we used the luminance values of each color images as input to the three wavelet transform method. In the PWT (Pyramid Wavelet Transform) method the texture features are :
energy, deviation and residual energy feature computed as below.

Energy: $$E_{ij} = \sum_{i=1}^{M} \sum_{j=1}^{N} | x_{ij} | . \tag{2}$$

Standard deviation:

$$S_{ij} = [\ 1/N^2 \sum_i \sum_j \ (x_{ij} - n_{ij})^2\ ]^{1/2} . \tag{3}$$

Residual energy:

$$a_{ij} = \sum_i \sum_j \ | x_{ij} - n_{ij} | , \tag{4}$$

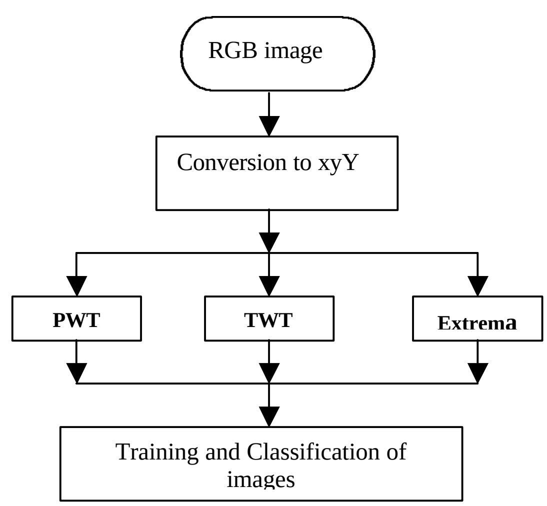

Fig. 2 Algorithm Implementation

where x_{ij} are coefficient values of the transformation, and n_{ij} is the mean value. The features computed in the TWT (Tree structured Wavelet Transform) are the energy values of the channel that satisfy

$$E < C\,E\max \qquad (5)$$

Where C is a constant chosen to be 0.15.

The operators of the extrema features are Max_row and Min_row which denote a local row maximum and minimum. Max_col and Min_col denote a column maximum and minimum, respectively, for a 2D sub-image. The Max_row and Min_row are defined for an image response x as
Max_row_x :

{(r,c)|x(r+1,c)<=x(r,c),x(r-1,c)<=x(r,c), (6)

Min_row_x:

{(r,c)|x(r+1,c)>=x(r,c), x(r-1,c)>=x(r,c)}. (7)

The wave_extrema is given by:

w_ex_x={Max_row_x∩Max_col_x,
Max_row_x ∩ Min_col_x,
Min__row_x ∩ Max_col_x, Min_row_x ∩
Min_col_x} (8)

where ∩ stands for intersection. For a particular window the number of normalized w_ex_f is given by

N_ex_f = #w_ex_x/S

Where S is the size of a square window which is chosen as 33x33, 15x15 or 7x7 depending on the texture size. The N_ex_f will form the set of features that are computed over a moving window. These values can be averaged to form a smaller feature vector. The features are used to train a classifier. The classifier is then used to recognize unknown samples from the color images. The two types of classifiers used are:

Minimum Euclidean distance:

$$D_j(x) = \sum_{q=1}^{Q} (x_q - m_{i,q})^2 \;, \qquad (9)$$

Mahalanobis Distance:

$$d_j(x)=\{(x-m)^{\tau} C_j^{-1}(x-m_j)\}\;. \qquad (10)$$

The experimental setup and results are presented in the next section.

4. Experiment Results

The color images are converted from RGB color space to xyY space. 6 color images listed in Table 1 are used. The original Food image and the chrominance and luminance images are shown in Fig. 3. Each wavelet transform method is applied to the images separately. 64 training samples are extracted from each color images. First, the PWT method is applied and training features are calculated. The Mahalanobis classifier given in Eqn. (8) is trained with these features. 32 testing samples are then extracted from the 6 color images and the classifier recognizes the unknown samples. The samples are selected by a random sampling method. The number of features used in the classification are 5, 2 and 4 for PWT, TWT and extrema methods, respectively.The Percentage of Correct Classification (PCC) is given in Table 1 for each method.

As seen from the results in the Table, the PWT method performs best compared to the TWT and extrema method. In the TWT method 64 test samples have been classified in each texture class. It can be considered to perform close to PWT.

Table 1. Classification Results

Texture	**PCC (22%)**		
	PWT	**TWT**	**Extrema**
Flower	**90.625**	**81.25**	**40.625**
Brick	**93.75**	**96.875**	**87.5**
Water	**50**	**3.125**	**46.875**
Sand	**100**	**100**	**68.75**
Grass	**50**	**75**	**62.5**
Food	**93.75**	**59.375**	**46.875**
Average	**79.6875**	**69.27**	**58.8542**

Fig. 3 (a) Original Color Image

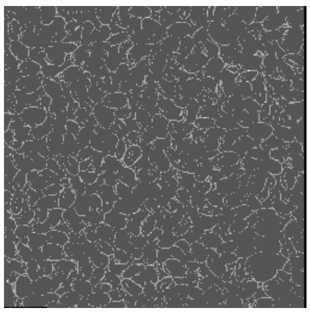

Fig. 3 (b) Chrominance Image

Fig. 3 (c) Luminance Image

5. Conclusions and Future Work

In this paper application of wavelet algorithms for recognizing color textures is presented. The best performing method is found to be PWT. Although the PCC is not high, we should remember that only luminance values have been used in the transformations. For future work, we will use chrominance values also. The performance of the extrema method will be improved. Also, the PWT may have performed better as we used 5 features from this method for classification while the other methods employed only 2 and 4. More features will be computed to improve the performances.

6. References

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