

Color Image Classification Using Gabor Filters

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ABSTRACT

In this paper, a texture based algorithm is developed for classifying color images. The images are filtered by a set of Gabor filters at different scales and orientations. The energy of the filtered images in each channel and between channels are computed and used for classification. The normalized RGB, xyY and HIQ color spaces are used to identify the best space for classifying the color images. The best representation of the textures are found to be using normalized RGB and HIQ space and chrominance values. A filter selection process using texture similarity is adopted. Unichannel and interchannel features are computed. A feature reduction process is applied before using a classifier. The algorithm is used to classify sets of textures from databases of color texture images and it gives good results. It is also applied to Landsat TM images. The 7 channels are used and the best channels for classification of the image are found to be R and G. The algorithm has been designed to use the appropriate Gabor filters based on texture transition characteristics within and between channels. The algorithm performs better than using only the gray scale values of the color images.

1. Introduction

Color images can be based on different systems such as RGB, xyY, HIQ and other systems capable of representing the color information for

better perception by human eye or for better processing and display depending on the application. It plays a major role in image improvement/enhancement. There are several models for color vision. In image processing color cues have been used for visual monitoring, for surveillance, for image retrieval from databases and for color device calibration. Color information based on the geometry of the sensing method such as illuminant spectral power distribution, reflectance and mapping of illuminants have been derived for various applications. Not much work has been done for developing an image classification system using color. To name one, color features have been used for texture recognition by Jain, using a Gabor based multiscale representation. Multispectral random field models have been developed to analyze color textures. Sampling methods have been used for color matching. A classification system can take advantage of the additional information available through multiple channels. Previous methods for image classification have converted color images to gray scale images and used statistical, random field, spectral and multiresolution methods on these gray scale images. In this paper the color images are directly used for classification. A background on color spaces and color perception is given in Section 2. Section 3 explains the algorithm used for classification. Section 4 presents experimental results. Section 5 gives conclusions.

2. Color Spaces

Color measures are treated by the science of colorimetry which measures color qualitatively, and luminance measures are subject of the science of photometry. Color is perceived as per its brightness, hue and saturation. Brightness is the perceived luminance. The hue refers to the amount of redness, greenness of the image. Saturation varies and is stronger as more and more white light is added to a monochromatic light. All of the three components change when either the wavelength, the intensity, the hue, or the amount of white light in a color is changed. Additive and subtractive color matching techniques are available. In colorimetry the measurements are in terms of the tristimulus values of a color. For image processing apart from knowing the relative amount of light from each primary the absolute value has to be determined which is the luminance. RGB image is based on primary relative color. An RGB color image is 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 . In this work k value is 5.

3. Classification Algorithm

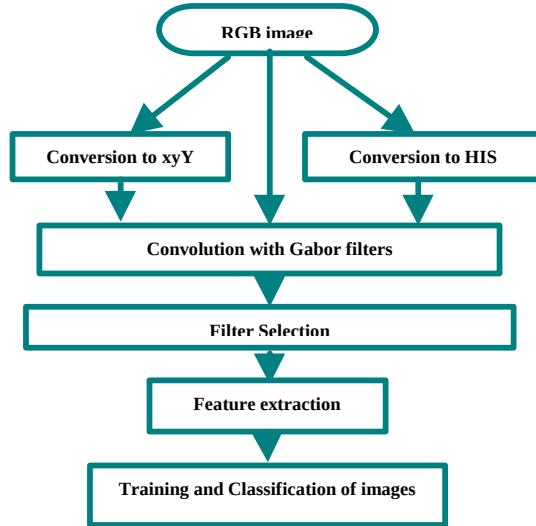


Fig. 1 Algorithm implementation

In this method the images are filtered by Gabor filters at different scales and orientations. The bank of filters in spatial domain is given by

$$f_{m,n}(x,y) = \frac{1}{2\pi\sigma_m^2} \exp\left\{-\frac{x^2+y^2}{2\sigma_m^2}\right\} \cos(2\pi(u_m x \cos q_n + u_m y \sin q_n))$$

where m is the index for scale and n index for orientation. σ is the scale parameter. If $I_i(x,y)$ is the i^{th} spectral band, the filtered image is

$$h_{imn}(x,y) = I_i(x,y) * f_{mn}(x,y)$$

3.1. Feature Extraction

A set of features are computed from the response of the image samples to the Gabor filters. They are unichannel features given by

$$e_{imn} = \sqrt{\left(\sum_{x,y} h_{imn}^2(x,y)\right)}$$

where e is the energy in the filtered image. The interchannel features between different spectral channels i and j with m and m' denoting the scales of the filters is computed as

$$c_{ijmm'n}^2 = 2 - 2 \sum_{x,y} \frac{h_{imn}(x,y)h_{jm'n}(x,y)}{e_{imn}e_{jm'n}}$$

$c_{ijmm'n}$

where $c_{ijmm'n}$ is the zero offset normalized cross-correlation between $h_{imn}(x,y)$ and $h_{jm'n}(x,y)$.

3.2. Image Classification

Gabor filters of different orientations and scales are convolved with image samples to derive feature set. A best subset of features are selected using two criterions: one is the distance between means and the other is a measure of standard deviation. The features are used to train a classifier. The classifier is then used to recognize unknown samples from the color images. Mahalanobis distance classifier is used in the experiments and is given by:

Mahalanobis distance (D1):

$$d_j(x) = \{(x - m_j)^T C_j^{-1} (x - m_j)\}$$

where x is the unknown feature vector to be classified in one of the j texture classes. m is the sample mean of each class j . C_j is the covariance matrix. The experimental setup and results are presented in the next section.

4. Experimental Results

In this Section, results are presented with different color spaces. First, the xyY color space

is used, followed by HIQ and RGB spaces. Three sets of six textures are used in the basic experiments for estimating color space representation. The textures used in this experiment are shown in Figure 2. Another two experiments were done only using HIQ and RGB. Finally a Landsat Image of San Juan was classified in 4 classes by the algorithm

4.1. Using xyY Color Space

The color images are converted from RGB color space to xyY space. The classifier used is D1 which is trained with 64 samples from each color image. 128 testing samples are then classified. The samples are selected by a random sampling method and the samples do not repeat themselves. Table 1 shows the Percentage of Correct Classification (PCC) for using the chrominance values and two Gabor filters one at frequency 0.50 and σ of 0.1, and orientation of 45° and another at frequency 0.25, orientation of 45° and σ of 0.05. In addition to these two filters two more filters at above frequencies and orientations but with σ values of 0.2 and 0.025 are also used. The features used are the unichrome features of the filtered responses. The sample size is 64×64 . The filter sizes are 32×32 . The results are much better with application of 4 filter.



Fig. 2. Texture database for six class experiments

Chrominance (cv)	Average Percentage of Correct Classification (PCC)	
	Two Filters	Four Filters
Set 1	69.48	97.79
Set 2	97.79	94.01
Set 3	98.57	86.34
Average	86.11	92.71

Table 1. Classification results using chrominance

	Average PCC Using Four Filters		
	Luminance (Y)	HIS (H ₂ , I)	RGB
Set 1	82.95	98.70	99.87
Set 2	96.49	99.61	98.31
Set 3	94.53	92.34	99.87
Average	91.32	96.88	99.35

Table 2.

4.2. Using HIQ Color Space

The other color space considered in this work is the HIS, whose primaries are Hue (H), Intensity (I), Saturation (S) which is a human vision based system. The I and H₂ which represent the luminance and chromaticity values are used. The I image for the textures are similar to the luminance and the H₂ are the quantized pixel values.

The results for classifying the 3 texture sets are given in Table 2, the average PCC is 96.88 which is a little better than the PCC obtained by using xyY color space. An experiment with 12 textures is conducted. Here, only 32 samples are used for training. Both H₂ and I values are used for classification. A best feature set with 9 features is found and used for training and classification. 100% PCC is obtained with 128 testing samples from each textured image. The sample sizes are 64×64 .

4.3. Using RGB Color Space

The RGB channels are normalized. First the experiment with the 12 textures is repeated with RGB channels. 9 best features are selected for classification which include unichannel features from channels R, G and B and interchannel features from channels R and G. 100% PCC is obtained for all the 128 samples from each texture class.

An experiment with 32 textures is conducted. 64 training samples were used and 128 testing samples from each texture of size 64×64 are classified. 14 features are used in this experiment. Filters of size 32×32 and 64×64 are used. Interchannel features were computed only with filters of size 32×32 . The number of interchannel features are 5 and rest are unichannel features. The average PCC for this experiment is 98.02%.

4.4. Classification of LANDSAT image

This is an image of San Juan city in Puerto Rico taken by the Landsat TM satellite. The original image is shown in Fig. 3 and his 4 main classes: ocean, water body, construction and hilly land. The segmented image is shown in Fig. 4. A sliding window of size 16x16 with an overlap of 17 pixels is used and is assigned a class number after classification. The best filters selected are of size 8 x 8, at 45° 90° orientation and σ values are .05, 0.1 and 0.2. The best features are found to be unichannel features from R and G channels.



Fig. 4 Landsat Image of San Juan

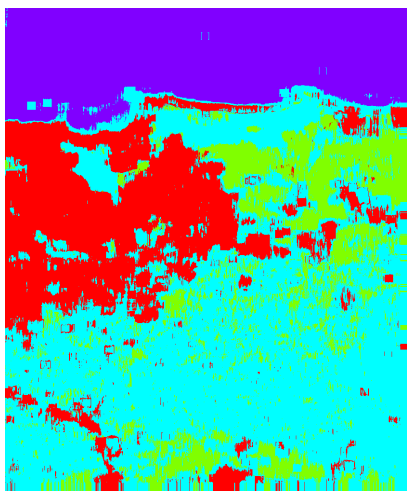


Fig. 4 Classified Image

5. Conclusions and Future Work

In this paper an algorithm based on Gabor filtering is presented for color texture classification. Suitable filters are selected by applying a similarity measure that detects the best filter that maximizes the energy of the filtered response. A set of features that compute the energy values on individual channels and between channels is used. Different color spaces have been considered in the paper. The color space conversions should not be computationally intensive and also they provide a good representation for the texture. Using gray scale values along with color channels improves classification results. Experiments conducted on real world textures and synthetic textures show that normalized RGB, HIQ spaces and chrominance values yield good classification results. The algorithm has also been tested with a remote sensing Landsat TM 7 channel image. The method should be applied to other color spaces and evaluated.

6. References

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