Classification Method for Colored Natural Textures Using Gabor Filtering

Leena Lepistö[1], Iivari Kunttu[1], Jorma Autio[2], and Ari Visa[1],

[1]*Tampere University of Technology*
Institute of Signal Processing
P. O. Box 553, FIN-33101 Tampere, Finland

[2]*Saanio & Riekkola Consulting Engineers*
Laulukuja 4
FIN-00420 Helsinki, Finland

Leena.Lepisto@tut.fi

Abstract

In texture analysis the common methods are based on the gray levels of the texture image. However, the use of color information improves the classification accuracy of the colored textures. In the classification of non-homogenous natural textures, human texture and color perception are important. Therefore, the color space and texture analysis method should be selected to correspond to human vision.

In this paper, we present an effective method for the classification of colored natural textures. The natural textures are often non-homogenous and directional, which makes them difficult to classify. In our method, the multiresolution Gabor filtering is applied to the color components of the texture image in HSI color space. Using this method, the colored texture images can be classified in multiple scales and orientations. The experimental results show that the use of the color information improves the classification of natural textures.

1. Introduction

The analysis of color and texture are both essential topics in image analysis and pattern recognition. Usually texture and color content of the image have been analyzed separately. Hence the conventional texture analysis methods use only the gray level information of the texture image. However, color of the texture image provides a significant amount of information about the image content. Therefore, in several recent studies, color has been taken into account in the analysis of texture images. The experimental results show that the use of the color in texture analysis has improved the texture classification results.

In most of the studies concerning color texture analysis, the commonly used texture analysis methods have been applied to the colored textures. One of the most popular texture analysis methods is based on wavelets [6]. Gabor filtering [9], [11] is a wavelet-based method that provides a multiresolution representation of texture. In the comparison of Manjunath and Ma [9], Gabor filtering method proved to be the most effective wavelet-based method in the texture classification. Gabor filtering has also been the basis of many color texture analysis methods, such as [3], [5], [10].

The choice of the color space is essential in the color texture analysis. The use of RGB color space is common in the image processing tasks. However, it does not correspond to the color differences perceived by humans [13]. In the work of Paschos [10], Gabor filtering was applied to the classification of color textures. He compared the color texture classification in RGB, L*a*b*, and HSI color spaces. The best classification result was obtained using HSI color space.

Most of the natural textures are non-homogenous. Classification of natural non-homogenous textures is significantly more difficult than classification of homogenous textures such as the commonly used texture image set presented by Brodatz [2].

In this type of texture images, there can be variations in directionality, granularity, and other textural features. Color is also an essential feature of natural texture images. Color levels may vary significantly within these images. In [7] we presented a method for the classification of colored natural non-homogenous textures. In this method, the texture image was divided into blocks and the textural and spectral features of these blocks formed a feature histogram. The classification of the texture images was based on these histograms. Many natural texture types, like rock texture [1], are directional. Directionality is also one of the most remarkable dimensions in human texture perception [12]. Therefore, directionality can be used as a classifying feature between natural textures. In [8] we presented a directionality-based method for the retrieval of non-homogenous textures. Because Gabor filtering method can be used in multiple orientations, it is a powerful tool for the analysis of the directional textures. Therefore, it is a suitable method for the classification of these kinds of textures. In addition to its ability to describe

Proceedings of the 12th International Conference on Image Analysis and Processing (ICIAP'03)
0-7695-1948-2/03 $17.00 © 2003 **IEEE**

Figure 1. An example image of non-homogenous rock texture.

the texture directionality, Gabor filtering can be used in multiple scales, which is a desirable property in the classification of non-homogenous natural textures.

In this paper, we present an effective method for the use of multiscale Gabor filtering in the classification of colored natural textures. In our method, we apply a bank of Gabor filters presented in [9]. This filter bank is used for the texture images in HSI color space. Compared to the conventionally used gray level Gabor filtering, our approach gives clearly better classification result without significantly increasing the computational cost.

In section 2, the classification of colored natural textures is discussed. In the same section, our method for color-based Gabor filtering is presented. Section 3 is the experimental part of this work. The classification experiments are made using two databases of colored rock textures. The results are discussed in section 4.

2. Classification of colored natural textures

In non-homogenous natural textures, one or more of the texture properties are not constant in the same texture sample. An example image of non-homogenous rock texture is presented in figure 1. The texture sample presented in this figure is strongly non-homogenous in terms of directionality, granularity, and color. The homogeneity of a texture sample can be measured by dividing the sample into blocks. If the texture or color properties do not vary between the blocks, the texture is homogenous. On the other hand, if these feature values have significant variance, the texture sample is non-homogenous. In our previous approach [7], this division into blocks was applied.

In this section, we present a method for the classification of natural non-homogenous textures. Because texture directionality can be used as a classifying feature between the texture samples [8], we use a bank of multiple oriented Gabor filters. The benefit of this approach is also the fact that the textures are considered in multiple scales, which makes the classification more accurate. In our approach, we apply the filter bank for the colored texture images.

In the beginning of this section, the previous work in the Gabor filtering of color textures is presented. After that, we present our approach to this purpose.

2.1 Gabor filtering of colored textures

Gabor filtering is a wavelet-based method for texture description and classification. Gabor filters extract local orientation and scale information of the texture. These features have been shown to correspond to human visual system [11]. In the classification and retrieval, the common approach is to use a bank of multiple oriented Gabor filters in multiple scales [9].

In the color texture analysis, several Gabor-based methods have been presented. In [10], the Gabor filters have been applied to different color bands of the texture images. After that, the classification is made by calculating distances between the transform coefficients. The work of Jain and Healey [5] is based on the opponent features that are motivated by color opponent mechanisms in human vision. The unichrome opponent features are used in texture image classification. Multichannel Gabor illuminant invariant texture features (MII) combine the ideas of color angle and Gabor filtering [3]. In this approach, MII is calculated as the color angles between the image color bands convolved with two different Gabor filters.

2.2 Our approach

Our approach to the classification of the colored natural textures is based on the Gabor filtering in HSI color space. This color space is selected to be the basis of our texture analysis, because it corresponds to the human visual system [13]. Also the comprehensive comparison presented in [10] proved that HSI color space gives the best result in the classification of color textures.

Manjunath and Ma [9] have introduced a method for the classification of the gray level textures. They have used a bank of Gabor filters to extract features that characterize the texture properties. The Gabor filter bank is used in multiple scales m and orientations n. The feature vector is formed using the mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transform coefficients. If the number of scales is M and the number of orientations is N, the resulting feature vector is of the form:

$$f = [\mu_{00}\sigma_{00}, \mu_{01} \ldots \mu_{MN}\sigma_{MN}] \quad (1)$$

Figure 2. Example images of the textures in the testing database I.

Figure 3. Example images of the textures in the testing database II.

This approach has proved to be effective in the classification and retrieval of different types of gray level textures [9]. Also in the case of natural non-homogenous textures, this method has given reasonably good results. However, when the color information of the texture image is added to this method, the classification results can be improved as shown in the experimental part of this paper.

In our approach, we define the feature vector f for each color channel of the texture image:

$$\begin{aligned} f_H &= \left[\mu_{00}^H \sigma_{00}^H, \mu_{01}^H \ldots \mu_{MN}^H \sigma_{MN}^H\right] \\ f_S &= \left[\mu_{00}^S \sigma_{00}^S, \mu_{01}^S \ldots \mu_{MN}^S \sigma_{MN}^S\right] \\ f_I &= \left[\mu_{00}^I \sigma_{00}^I, \mu_{01}^I \ldots \mu_{MN}^I \sigma_{MN}^I\right] \end{aligned} \tag{2}$$

Then the feature vectors can be combined to a single vector that characterizes all the color channels:

$$f_{HSI} = \left[f_H, f_S, f_I\right] \tag{3}$$

When μ_{mn} and σ_{mn} are calculated for M scales, N orientations, and C color channels, the size of the resulting feature vector is $2*M*N*C$. In classification, the feature vectors of texture samples i and j are compared using the distance measure:

$$d(i,j) = \sum_m \sum_n d_{mn}(i,j) \tag{4}$$

where

$$d_{mn}(i,j) = \left|\frac{\mu_{mn}^{(i)} - \mu_{mn}^{(j)}}{\alpha(\mu_{mn})}\right| + \left|\frac{\sigma_{mn}^{(i)} - \sigma_{mn}^{(j)}}{\alpha(\sigma_{mn})}\right| \tag{5}$$

in which $\alpha(\mu_{mn})$ and $\alpha(\sigma_{mn})$ are the standard deviations of the respective features over the whole database [9].

3. Experiments

In this section, our approach to the classification of the colored natural textures is tested. For testing purposes, we used two testing databases. These databases consisted of colored rock textures, which are typical natural textures.

3.1 Testing databases

The two testing databases used contained several types of non-homogenous rock textures. Test-set I (figure 2), consisted of 64 industrial rock images. The size of the images was 714x714 pixels and their texture was strongly directional. The texture samples were divided manually in three visually similar classes. The second testing database, test set II (figure 3), consisted of 168 rock texture samples. The size of each sample image was 500x500 pixels. The test set II represented seven different rock texture types, and there were 24 samples from each texture class. Also in this test set, most of the texture types were directional and non-homogenous.

3.2 Classification

In classification, k-nearest neighbor classification principle [4] was used. The validation of the classification experiments was made using leave one out validation method [4]. In this method, each sample is left out from the database in turn, whereas the rest of the images form the testing database. This classification is repeated for the whole image database, and the average classification rate can be defined as the mean value of these classification experiments. In the classification, the value of k was selected to be 3.

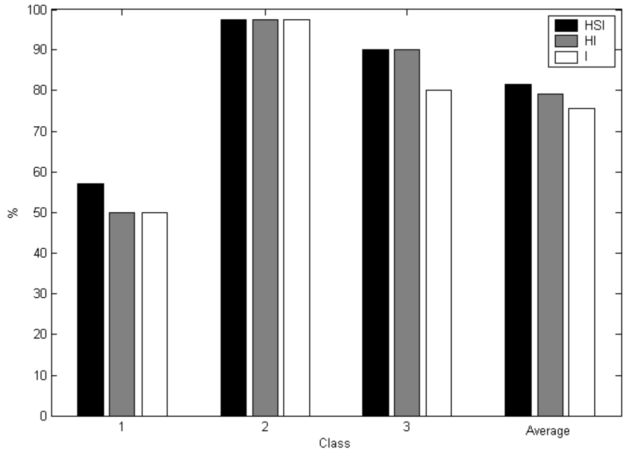

Figure 4. The mean classification results in each class of the testing database I.

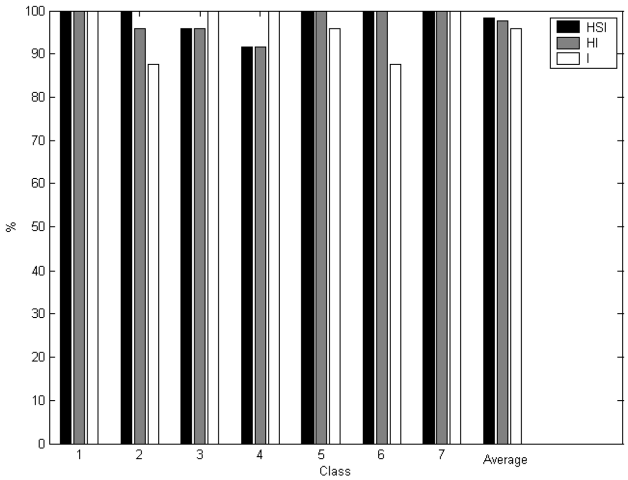

Figure 5. The mean classification results in each class of the testing database II.

The classification experiments were made for hue, saturation, and intensity channels (HSI) as well as for hue and intensity channels (HI). For comparison, classification result was calculated also for intensity channel (I), which represents the gray level of the image. In the experiments, we used four scales and six orientations, as in [9].

Table 1 presents the average classification results. These results show that the best classification rate was achieved using HSI color space, whereas hue and intensity channels (HI) gave the second best result. In both testing databases, the classification based on intensity component (gray level) gave the lowest classification result. The mean classification results in each class of both testing databases are presented in figures 4 and 5. The computational characteristics of the methods are presented in table 2. In this table, the feature vector lengths and the classification times are presented for the testing databases. The computation was made using Matlab on a PC with 804 MHz Pentium III CPU and 256 MB primary memory.

Table 1. The average classification rates.

Color space	Database I	Database II
HSI	87.5 %	98.2 %
HI	85.9 %	97.6 %
I	84.4 %	95.8 %

Table 2. The computational characteristics of the methods.

Color space	Vector length	Classification time	
	$2*M*N*C$	DB I	DB II
HSI	144	1.8 sec	9.1 sec
HI	96	1.7 sec	8.9 sec
I	48	1.4 sec	8.4 sec

4. Discussion

In this paper, we studied the color properties of the natural textures. The color information of the texture images is an essential feature in the classification of them. The results of the texture classification can be improved by combining the color information of the texture image in the classification.

Rock texture is an example of natural textures. Rock texture images are often non-homogenous. The non-homogeneity of these textures may appear as variations in directionality, granularity and color. Because Gabor filters have proved to be effective in the classification of directional textures, they were selected also to this study. Gabor filters can also be used to analyze the texture images in multiple scales, which is desirable in practical applications. This is due to the variations in the granular size of the rock textures. The multiscale texture representation is also essential, when human texture perception is considered.

The objective of this work was to include the color information of the textures to the Gabor-based texture classification. In this way, the classification results obtained from the Gabor filtering could be further improved. The color space selected to be HSI, which corresponds to human color vision. In our texture classification method, the Gabor filtering is applied to the selected color channels separately. Then the feature vectors of each channel are combined into a single vector, which is used in the classification.

Compared to the commonly used, gray level based Gabor filtering, our method provides improved classification results. These results are achievable at a reasonable computational cost. Good computational efficiency is the benefit of the presented method when compared to the other color texture analysis methods.

5. Acknowledgment

We would like to thank Saanio & Riekkola Oy and Technology Development Centre of Finland (TEKES's grant 40397/01) for financial support.

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