Colour texture analysis: A comparative study

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Abstract

In this paper we focus on classification of colour texture images. The main objective is to determine the contribution of colour information to classification performance. Three relevant approaches to greyscale texture analysis namely Local Linear Transforms, Gabor filtering and Co-occurrence are extended to colour images. They are evaluated in a quantitative manner by means of a comparative experiment on a set of colour images. We also investigate the effect of using different colour spaces and the contribution of colour and texture features separately and collectively. The evaluation criteria is the classification accuracy with a neural network classifier based on Learning Vector Quantization

Keywords: Texture, Colour, Learning Vector Quantization, Classification.

1 Introduction

Texture and colour are widely accepted as being two key issues in image analysis. Although inherently related, texture and colour properties have been regarded separately rather than collectively. Most of the work to date in the area of texture has been limited only to grey level images. During the past decades numerous approaches for texture analysis have been developed and successfully used in various domains such as scene analysis, industrial inspection or document processing. According to many researchers [Tucerian and Jain, 1993, Haralick, 1979] the feature extraction techniques for texture description can be classified into 4 major categories: statistical, model based, signal processing and structural.

Although colour is an intrinsic attribute of an image and provides more information than a single intensity value there has been a limited number of attempts to incorporate chrominance information into textural features. A colour texture can be regarded as a pattern described by the relationship between its chromatic and structural distribution.

Two images consisting of the same colour but different texture patterns or the same texture pattern but different colours are two different colour textures. At the moment it is still unclear how to combine colour and texture into a composite model. Two alternatives to feature extraction for colour texture analysis appear to be most often used and they consist of:

- processing of each band separately by applying grey level texture analysis techniques
- deriving textural information from luminance plane along with pure chrominance features

The former approach represents a straightforward method of extending the grey level algorithms to colour images and has been used in colour texture segmentation and classification [Thai and Healy, 1998]. The latter approach allows a clear separation between texture and colour features. This is particularly useful in segmentation where grey level algorithms can be applied to luminance plane with colour information used as a cue [Paschos and Valavanis, 1999].

The aim of this work is to evaluate the colour texture features extracted using the aforementioned approaches. Three relevant techniques for texture feature extraction namely local linear transforms [Unser, 1996], Gabor filtering [Jain and Farrokhnia, 1991] and co-occurrence [Haralick, 1979] are used in a our classification experiment. The comparative study is performed on a set composed of 16 colour images from VisTex database [VisTex,] using a supervised classifier based on Learning Vector Quantization [Kohonen, 1995]. In order to obtain realistic results the training data and the test data are disjoint. The effect of using different colour spaces is also examined. Colour texture features extracted from images represented in various colour spaces are used in a comparative experiment.

The paper is organised as follows. Section 2 describes the feature extraction techniques used in the experiment. It also presents some relevant information about colour spaces. Section 3 details the classification setup and presents the experimental results. Finally, Section 4 outlines out conclusions and the directions for future work.

2 Feature extraction approaches and colour spaces

In this section we detail the feature extraction techniques used in the comparative experiments. We also discuss the relevant issues related to colour space.

2.1 Local linear transforms

Local linear transforms [Unser, 1996] characterize the texture by a set of statistical measures at the outputs of a filter bank of relatively small size. Each filter mask is tuned to capture a particular property of the local texture structure. The local linear transformation framework is presented in [Unser, 1996]. The transformation selected for this paper is Discrete Cosine Transform (DCT). The DCT has been widely used especially in image coding. It is orthogonal and separable, therefore can be computed using fast algorithms. A $N \times 1$ DCT basis column vector h_m can be computed as follows :

$$h_m(k) = \begin{cases} \frac{1}{\sqrt{N}} & \text{if } m = 0; \\ \sqrt{\frac{2}{N}} \cos \frac{(2k-1)m\pi}{2N} & \text{if } m > 0; \end{cases} \quad (1)$$

These vectors are derive to obtain the 2D DCT filters of N^2 coefficients using the outer product: $h_{mn} = h_m h_n^T$. Considering $I(x,y)$ the original image, the texture features f_{mn} are defined as the variance of the filtered $M \times M$ image I_{mn} by the h_{mn} mask using the following equations:

$$I_{mn} = I * h_{mn} \tag{2}$$

$$f_{mn} = \frac{1}{M^2} \sum_{x,y=0}^{M} I_{mn}(x,y) - \mu_{mn} \tag{3}$$

where

$$\mu_{mn} = \sum_{x,y=0}^{M} I_{mn}(x,y) \tag{4}$$

represent the average over the filtered image.

In the comparative experiments the DCT approach is evaluated for filter size of $N = 3$. In this case after normalisation, the 1D DCT filter masks defined in Equation 1 are $h_0 = \{1,1,1\}$, $h_1 = \{1,0,-1\}$, $h_2 = \{1,-2,1\}$. Using the outer product as explained above a set of 9 mutually orthogonal 2D DCT masks are generated and used to calculate texture features according to Equations (2) to (4). These act as bandpass filters and capture a particular aspect of the texture. In grey scale approaches the feature obtained using the low frequency filter h_{00} is generally excluded since it does not capture relevant textural information. But in the case of colour textures it may contain useful colour information and therefore we decided to consider it as a feature.

2.2 Gabor filters

The Gabor filtering approach has been widely used in texture analysis. This approach is biologically motivated and minimises the joint space frequency uncertainty. A 2-D Gabor filter is a Gaussian modulated by a sinusoidal plane wave and has the form of [Jain and Farrokhnia, 1991]:

$$g(x,y) = \exp\left\{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right\} \cos(2\pi u_0 x + \phi) \tag{5}$$

where parameters (σ_x, σ_y characterise the spatial extent and the bandwidth of the filter, u_0 is the radial frequency and ϕ is the phase of the filter. In order the compute the texture features the image is first convolved with a bank of Gabor filters of different parameters. This is called multichannel filtering and has proven a fruitful approach. The parameters can be tuned to capture the underlying texture structure. The texture features are defined as the energy of the filtered images according to the formula:

$$f_m = \frac{1}{M^2} \sum_{x=0}^{M} \sum_{y=0}^{M} |I * g_m| \tag{6}$$

where g_m is a particular Gabor filter defined by the equation 5. The main issue in Gabor filtering approach is the appropriate selection of the filters. Since the outputs of the filter bank are not mutually orthogonal the texture features might be significantly correlated.

Inspired by psychophysical research [Pollen and Ronner, 1986] on the human visual system in our study we use an octave spaced frequency set of 2, 4, 8 cycles per image size for 4 angular orientations 0, 45, 90, 135 resulting in a set of 12 features. The spread parameters σ_x, σ_y are both set to 1. Since we are concerned only with the discriminatory power of Gabor features we use the energy from a raw Gabor filtered images. Although better performances could be obtained using a non-linear transformation of filtered images [Jain and Farrokhnia, 1991], this is lacking of a formal method for determining the parameters of the transformation.

2.3 Co-occurrence

The co-occurrence approach is concerned with the grey tone spatial dependence. It is based on the estimation of the second order joint conditional probability density function $f(i,j|d,\theta)$. Each $f(i,j|d,\theta)$ is computed by counting all pairs of pixels separated by distance d having grey levels i and j , in the given direction θ. The angular displacement θ usually takes on the range of values: $\theta = \left\{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}\right\}$. The co-occurrence matrix captures a significant amount of textural information. For a coarse texture these matrices tend to have high values near the main diagonal whereas for a fine texture the values are scattered. To obtain rotation-invariant features the co-occurrence matrices obtained from the different directions are accumulated. This approach has been extensively used and has become the benchmark in texture analysis. Haralick [Haralick, 1979] extracted a set of 14 features from these matrices but only 5 of them appear to be often used. These features are as follows:

- Energy
$$E = \sum_i \sum_j [f(i,j|d,\theta)]^2 \tag{7}$$

- Entropy
$$H = \sum_i \sum_j [f(i,j|d,\theta) \cdot \log f(i,j|d,\theta)] \tag{8}$$

- Inertia
$$I = \sum_i \sum_j [(i-j)^2 f(i,j|d,\theta)] \tag{9}$$

- Local Homogeneity
$$LH = \sum_i \sum_j [(i,j|d,\theta)/(1+(i+j)^2)] \tag{10}$$

- Correlation
$$COR = \sum_i \sum_j [(i-\mu_x)(j-\mu_y) \cdot f(i,j|d,\theta)/\sigma_x \sigma_y] \tag{11}$$

  where μ_x and σ_x are the horizontal mean and variance and μ_y and σ_y are the vertical statistics

This approach captures the second order grey levels statistics which are related with the human perception and discrimination of textures [Julesz and Bergen, 1987]. The weakness of this approach is that it does not describe the shape aspects of the texture. A problem associated with the co-occurrence approach consists of choosing the level of quantization (the number of bins per image). Thus, if the number of bins is too low, some textural information may be lost. Alternatively, a large number of bins may lead to non-relevant textural features. For the experiments illustrated in section 3.3, the level of quantization was set to 8 bins per image.

2.4 Colour spaces

Many colour spaces are used in image processing. Basically, the concept of colour space refers to a cartesian space in which the visual sensation of colour can be uniquely defined by a set of numbers representing chromatic features. This three-dimensional representation provides a simple manipulation of colour information and is a natural way of visualising the spatial relationship between the colours.

RGB space is perhaps the most common format for digital images and it is compatible with computer display and colour video camera. In the RGB space, each colour is represented as a triple (R, G, B) where R, G and B represent the Red, Green and Blue outputs from a colour camera. Colour texture features can be extracted from these colour planes separately or from cross-correlation between the RG, RB, BG planes. The RGB representation is device dependent and excludes some visible colours. For a better colour processing the RGB space is frequently converted into another colour spaces using of a non-linear transform. Along with RGB space other colour spaces investigated in this paper are: HSI, CIE-XYZ, YIQ and CIE-LAB. For a more detailed description of these transforms and their use in colour analysis, the reader is directed to [Whelan and Molloy, 2000].

3 Classification set-up and experiments

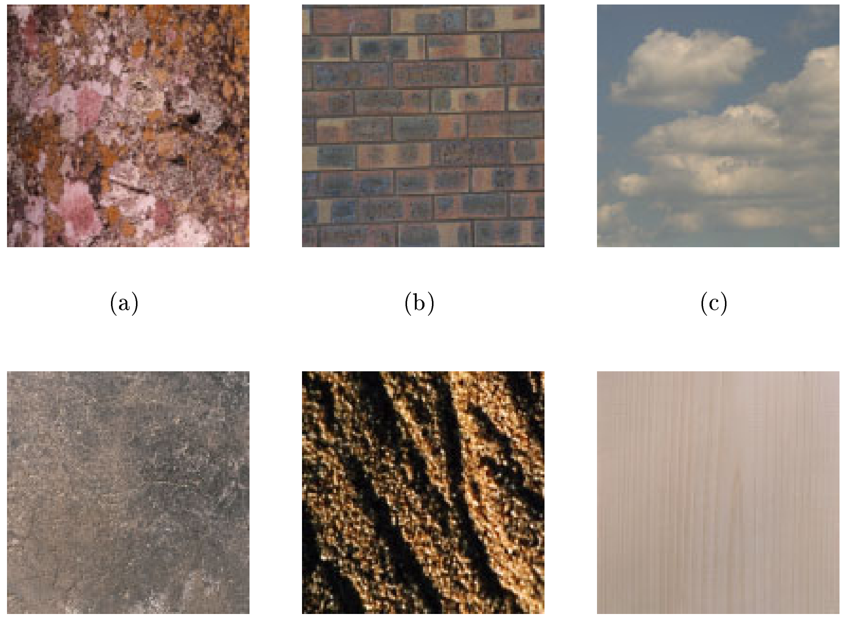
This section outlines the experimental set-up used in our classification experiments.

3.1 Classification method

In the preceding section we have presented the problem of feature extraction. At that stage a $M \times M$ texture image is transformed into a n dimension feature vector whose components collectively preserve enough textural information contained in the image. The next step is to evaluate the discriminatory power of the features using by means of a classifier. There are many classification approaches available in pattern recognition literature. For the experiments presented in this paper we have adopted the Learning Vector Quantization (LVQ) [Kohonen, 1995] supervised technique. It is beyond the scope of this paper to present detailed information about LVQ. Basically, the underlying principle of LVQ is to approximate the optimal Bayesian decision borders between different classes with a set of labeled codebook vectors. There are 3 versions of LVQ algorithms [Kohonen, 1995] each of them employing a different learning technique. The results reported in this paper are obtained using LVQ1 algorithm.

3.2 Test images

For the classification experiments we used a set of 16 RGB colour images of size 128×128 from VisTex database [VisTex,] namely Bark.0001, Brick.0000, Clouds.0000, Fabric.0001, Leaves.0010, Flowers.0000, Food.0000, Grass.0001, Metal.0000, Misc.0002, Sand.0004, Stone.0005, Tile.0007, Water.0000, Wood.0002 and WheresWaldo.0001. Each image was divided in a set of 540 overlapped 32×32 subimages resulting in total number of 8640 colour image regions. At the time of performing preliminary experiments, this approach offered a reasonable compromise between representativity and computational time. As suggested in [Randen and Husoy, 1999], 5% of the data set (i.e about 30 feature vectors per class) was used to train the classifier and the remaining data was utilized in the classification stage.



(a) (b) (c) (d) (e) (f)

Figure 1: A group of VisTex images used in the experiments (a) Bark.0001. (b) Brick.0000. (c) Clouds.0000. (d) Stone.0005. (e) Sand.0004. (f) Wood.0002.

Method	**Intensity**	**RGB Colour**
DCT	81.2%	90.6%
Gabor Filter	72.8%	82.1%
Co-occurrence	68.7%	72.5%

Table 1: Classification results for grey level and colour images

3.3 Experiments and Results

The first experiment evaluates the performance of the greyscale and colour texture features. Initially we examined the intensity component of the test images. Results were also generated from each R, G, B plane. In agreement to the equations 1-11, this lead to 9 DCT, 12 Gabor, 5 co-occurrence grey level features and correspondingly 27 DCT, 36 Gabor and 15 co-occurrence colour features. Table 1 outlines the classification results.

Table 1 indicates that the incorporation of colour information into texture features increases the accuracy of the classification. At this point, we can compare only the results obtained for grey scale images. There are no comparative studies available for colour texture features. The DCT features produced the best results followed by Gabor filter and Co-occurrence. This is the same order as in [Randen and Husoy, 1999] but we obtained a greater accuracy. This is probably due to the fact that we used uniform texture images rather than composite ones although the classification set-up was almost identical. Concerning the processing time, the DCT proved to be the fastest method due to its separability and fast algorithm. The computational burden associated with the other feature

Colour space	Three band features	Texture and pure colour features
RGB	90.6%	NA
HSI	87.2%	85.4%
CIE XYZ	91.1%	82%
CIE LAB	89.5%	91%
YIQ	92.3%	90.7 %

Table 2: Classification results for the second experiment

extraction techniques was higher since the Gabor filters have relatively large kernels and the calculation of the Co-occurrence matrices is intensive.

The next comparative experiment has two purposes. The first is to investigate the effect of using different colour spaces for feature extraction. The second consist of evaluating the texture features computed using the following approaches:

- texture features extracted from each colour band separately
- texture features extracted from intensity plane along with pure colour features extracted from colour components

The original RGB images are first converted into HSI, CIE XYZ , YIQ and CIE Lab. The first set of texture features are computed from each colour band using DCT method exactly as performed in the first experiment leading to a total number of 27 colour texture features. The second set comprises number of 9 grey level DCT texture features extracted from luminance information(when available) together with 2 colour features computed as the variance of the two chrominance planes.

Analysing the results displayed in table 2, one can draw the conclusion that none of the colour spaces investigated proved sufficiently superior. This is in concordance with the findings in [Skarbek and Koschan, 1994]. The high classification accuracy was obtained using YIQ colour space may be attributable to the fact that this transform is nearly orthogonal.

The two approaches for colour texture feature extraction performed with similar results. This suggests that the colour has an important contribution to the discriminative power of the features. Another possible explanation is the fact that computing features from each colour band determines a relatively large number of features which might lead to the saturation of the classifier. This can be avoided by employing a feature section technique in order of retain only features with relevant information but this was not used in our experiments.

The classification percentages obtained in this study are rather of minor importance. The important finding is that the colour does increase the classification results without complicating significantly the feature extraction algorithms. Taking into consideration the classification accuracy and the computational load the DCT approach appears to the most appropriate solution especially for industrial tasks.

4 Conclusions

The aim of this preliminary research was to examine to contribution of colour to texture features by means of a comparative study. Although the colour is a primary source of information in computer vision very little attempt has been made towards a joint colour-texture approach to image analysis. As shown in our experiments, the use of colour increases the performances of the standard grey level texture analysis techniques. Further work will investigate the use of correlation between different colour bands as well as a more formal framework for colour texture analysis.

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