Experiments in colour texture analysis

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In this paper we focus on the classification of colour texture images. The main objective is to determine the contribution of colour information to the overall classification performance. Three relevant approaches to grey scale texture analysis, namely *local linear transforms*, *Gabor filtering* and the *co-occurrence* approach 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 using a neural network classifier based on Learning Vector Quantization. Experimental results indicate that the incorporation of colour information enhances the performance of the texture analysis techniques examined.

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. Numerous approaches for texture analysis have been developed and successfully used in various domains such as scene analysis, industrial inspection or document processing, although most of this work has been limited to grey level image analysis. Feature extraction techniques for texture description can be classified into four major categories: statistical, model based, signal processing and structural (Tucerian and Jain, 1993; Haralick, 1979).

Although colour is an intrinsic attribute of an image and provides more information than a single intensity value there has been few attempts to incorporate chrominance information into textural features (the recent works of Paschos (2000); Mirmehdi and Petrou (2000) and Setchell and Campbell (1999) are notable exceptions). 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 best 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 each colour 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, 1986), Gabor filtering (Jain

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and Farrokhnia, 1991) and the co-occurrence approach (Haralick, 1979) are used in a our classification experiment. The comparative study is performed on a set comprised of 16 colour images from the VisTex database (VisTex, 2000) using a supervised classifier based on Learning Vector Quantization (Kohonen, 1995). In order to obtain realistic results, the training 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 organized 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 our 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, 1986) 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 transformation selected for this paper is the Discrete Cosine Transform (DCT). The DCT has been widely used, most notably in image coding applications. 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:

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

These vectors are used 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:

$$I_{mn} = I * h_{mn} \qquad (2)$$

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

where

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

represents the average over the filtered image, and '$*$' represents the 2D convolution operator.

In the comparative experiments the DCT approach is evaluated for a filter size of $N = 3$. In our implementation (and after normalization) the 1D DCT filter masks defined in Eq. 1 are $h_0 = \{1, 1, 1\}$, $h_1 = \{1, 0, -1\}$, $h_2 = \{1, -2, 1\}$. Using the outer product outlined previously, a set of 9 mutually orthogonal 2D DCT masks are generated and used to calculate texture features according to Eqs. 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 (Jain and Farrokhnia, 1991) approach has been widely used in texture analysis. This approach is biologically motivated and minimises the joint space frequency uncertainty. We have adopted a basic even-symmetric Gabor filter similar to the approach adopted by Randen and Husøy (1999), this has the form:

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

where parameters (σ_x, σ_y) characterize the spatial extent and the bandwidth of the filter, u_0 is the radial frequency and ϕ is the phase of the filter.

To 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 to be 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:

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

where g_m is a particular Gabor filter defined by Eq. 5. The main issue in the 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 on the human visual system (Pollen and Ronner, 1986) we have employed an octave spaced frequency set of 2, 4, 8 cycles per image size for 4 angular orientations (i.e. the angle between the main and the horizontal axis of the filter) of 0, 45, 90 and 135 degrees, resulting in a set of 12 features. The spread parameters σ_x, σ_y are set to the (number of cycles per image)/2. Since we are only concerned with the discriminatory power of Gabor features we use the energy from a raw Gabor filtered images. Although improved performances could be obtained using a non-linear transformation of filtered images (Jain and Farrokhnia, 1991), this lacks a formal method for determining the parameters of the transformation. For a more complete review of the issues involved in Gabor filter design for texture segmentation, consult Weldon and Higgins (1999).

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 a benchmark in texture analysis. Haralick (1979) extracted a set of 14 features from these matrices, although researchers have tended to rely on a smaller set of attributes, namely Energy (E), Entropy (H), Inertia (I), Local Homogeneity (LH) and Correlation (COR):

$$E = \sum_i \sum_j [f(i,j|d,\theta)]^2 \quad (7)$$

$$H = -\sum_i \sum_j [f(i,j|d,\theta) \log f(i,j|d,\theta)] \quad (8)$$

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

$$LH = \sum_i \sum_j \frac{(i,j|d,\theta)}{1+(i+j)^2} \quad (10)$$

$$COR = \sum_i \sum_j \frac{(i-\mu_x)(j-\mu_y) f(i,j|d,\theta)}{\sigma_x \sigma_y} \quad (11)$$

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. Another problem associated with the co-occurrence approach involves choosing an appropriate quantization level (i.e. the number of bins per image). 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 discussed in Section 3.3, the quantization level was set to 8 bins per image.

2.4. Colour spaces

The concept of colour space refers to a Cartesian space in which the visual sensation of a 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 visualizing the spatial relationship between the colours.

RGB space is perhaps the most common format for digital images and it is compatible with a wide range of computer displays and colour video cameras. 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. A problem with this colour representation is that it is device dependent and excludes some visible colours. For improved colour processing, RGB space is frequently transformed into a range of alternative colour spaces. Along with the RGB space the 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 image 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 this 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 used by means of a classifier. While there are many classification approaches available in pattern recognition literature, we have adopted the Learning Vector Quantization (LVQ) (Kohonen, 1995) supervised technique for the experiments presented in this paper. While it is beyond the scope of this paper to present detailed information about LVQ, the underlying principle of LVQ is to approximate the optimal Bayesian decision borders between different classes with a set of labeled cluster centers (codebook vectors). There are three 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 the VisTex database (VisTex, 2000) 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 (Fig. 1). Each image was divided into a set of 540 overlapped 32×32 subimages resulting in a total of 8640 colour image regions. This approach offered a reasonable compromise between representativity and computation time. As suggested in Randen and Husøy (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.

3.3. Experiments and Results

The first experiment evaluates the performance of the grey scale 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 with Eqs. 1 to 11, this leads to 9 DCT, 12 Gabor, 5 co-occurrence grey level features and a corresponding 27 DCT, 36 Gabor and 15 co-occurrence colour features. These results are illustrated in Table 1 (e.g., line 1 of this table shows that the DCT approach has a classification accuracy of 81.2% using grey level intensity only, and 90.6% when using the DCT features generated from each R, G, B plane).

The results presented in Table 1 indicate that the incorporation of colour information into the texture features increases the accuracy of the classification process. At this point, we can only

Table 1
Classification results for grey level and colour images.

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

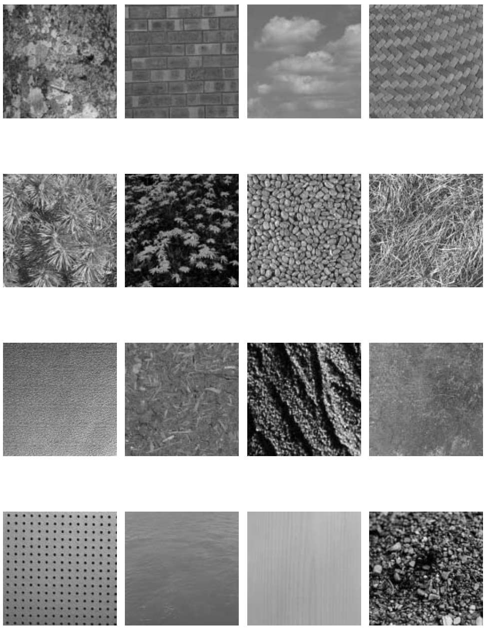

Figure 1. The VisTex images used in the experiments.

compare the results obtained for grey scale images. There are no comparative studies available for colour texture features. The DCT features produced the highest classification accuracy, followed by Gabor filter and the co-occurrence approach. This is the same order as in Randen and Husøy (1999) although 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 extraction techniques was higher since the Gabor filters have relatively large kernels and the calculation of the co-occurrence matrices are computationally expensive.

The second experiment has two key aims. Firstly it allows an investigation in to the effect of using a range of different colour spaces for feature extraction. Secondly, these experiments allow a comparison of the texture features computed using the following approaches:

Three band features: Texture features extracted from each of the colour bands separately.

Texture and pure colour features: Texture features extracted from intensity plane along with pure colour (chrominance) features extracted from the colour components of the related colour space (e.g. hue and saturation in the case of the HSI colour space).

The original RGB images are first converted into HSI, CIE XYZ , YIQ and CIE Lab colour spaces. The *three band features* illustrated in Table 2 are computed from each of the colour bands

Table 2
Classification results for the second experiment.

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 %

using the DCT method exactly as presented in the first experiment, leading to a total number of 27 colour texture features. The *texture and pure colour features* illustrated in Table 2 are computed from the 9 grey level DCT texture features extracted from the luminance information (when available) together with two colour features computed as the variance of the two chrominance planes.

Analyzing the results displayed in Table 2, one can draw the conclusion that none of the colour spaces investigated proved sufficiently superior. This is in agreement with the findings outlined by Skarbek and Koschan (1994). The high classification accuracy was obtained using the YIQ colour space may be attributable to the fact that this transform is nearly orthogonal.

The *three band* and the *texture and pure colour* classification results outlined in Table 2 are quite similar. 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 selection technique which only retains those features with relevant information. This was not implemented in our experiments.

The classification percentages obtained in this study are of minor importance. The important finding is that the inclusion of colour can increase the classification results without significantly complicating 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 research was to examine the contribution of colour to texture features by means of a comparative study. Although colour is a primary source of information in computer vision, texture analysis research has generally been confined to grey scale images. The experiments outlined in this paper illustrate that the use of colour improves the performance of standard grey level texture analysis techniques.

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