ILLUMINATION-INVARIANT MORPHOLOGICAL TEXTURE CLASSIFICATION

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Abstract We investigate the use of the standard morphological texture characterisation methods, the granulometry and the variogram, in the task of texture classification. These methods are applied to both colour and greyscale texture images. We also introduce a method for minimising the effect of different illumination conditions and show that its use leads to improved classification. The classification experiments are performed on the publically available Outex 14 texture database. We show that using the illumination invariant variogram features leads to a significant improvement in classification performance compared to the best results reported for this database.

Keywords: Mathematical morphology, texture, variogram, granulometry, illumination invariance

1. Introduction

The principal tools in the morphological texture analysis toolbox are the variogram, which is a generalisation of the covariance, and the granulometry [19, 20]. These have been used successfully in a number of applications [20]. It is nevertheless desirable to place these tools in the context of current research on texture analysis methods. To this end, we first discuss how they fit into the framework of structural and perceptual properties of texture. Then we compare their performance to that of the best reported method using a standard benchmark. Additionally, an approach to solving the problem of computing illumination-invariant texture features is presented. By illumination invariance we mean that the feature vector describing a texture should be independent of the illumination conditions in which the texture image is captured.

There has recently been much effort at comparing the performance of texture feature calculation methods on standard publically-available databases, such as the Outex databases [13]. This is done for tasks such as texture classification and texture segmentation. Classification results exist, for example, for the Local Binary Pattern (LBP) [14] and the Gabor filter approaches [12]. In this paper, we compare the performance of the standard morphological texture description methods for the task of texture classification.

Texture analysis tools have mostly been applied to greyscale images. Colour textures have however received much attention recently, with many greyscale texture analysis methods being extended to colour images. There are three main approaches to the analysis of a colour texture [15]:

Parallel approach: Colour and texture information is processed separately. The global colour is characterised, usually by means of a colour histogram. The intensity is used with greyscale texture descriptors to characterise the texture.

Sequential approach: Colour information is processed first to create an image labelled by scalars. Greyscale texture algorithms are then applied to this labelled image.

Integrative approach: This can be divided into single- and multi-channel strategies. Single-channel strategies apply greyscale texture analysis algorithms to each colour channel separately, while multi-channel strategies handle two or more channels simultaneously.

Many greyscale texture description techniques have been recast in the integrative framework: cooccurrence matrices [1, 15], run length [5] and Gabor filtering [16]. There is however no agreement yet as to whether the integrative approach functions better [15] or worse [12] than the parallel approach.

We begin with a brief overview of the morphological texture description methods (Section 2), and relate these to the perceptual properties of texture in Section 3. Our proposed transformation allowing illumination invariant classification of textures is presented in Section 4. The experimental setup, texture features used and results are presented in Sections 5, 6 and 7 respectively.

2. Morphological texture processing

We briefly summarise the variogram and granulometry as well as their extensions to colour textures.

Variogram

The variogram is a notion which generalises the covariance [19]. We make use of it here as it is easier to generalise to colour images than the covariance.

To calculate a variogram of an image $f(\mathbf{x})$, a direction α and a unit displacement vector $\hat{\mathbf{h}}$ in this direction must be chosen. For various multiples of vector $\hat{\mathbf{h}}$, written $q\hat{\mathbf{h}}$, the following value

$$V(q,\alpha) = \frac{1}{2}\mathcal{E}\left[f(\mathbf{x}) - f_\alpha\left(\mathbf{x} + q\hat{\mathbf{h}}\right)\right]^2 \tag{1}$$

is plotted against q, where $f_\alpha\left(\mathbf{x} + q\hat{\mathbf{h}}\right)$ is the displacement of image f in direction α by distance q. The expectation value $\mathcal{E}$ of the greyscale differences squared is calculated only in the region in which the original and displaced images overlap.

The generalisation of the variogram to colour images was suggested by Lafon et al. [10]. It is an integrative multi-channel strategy in which the difference in Equation 1 is replaced by the Euclidean distance in the CIELAB colour space. The CIELAB space was designed such that this distance corresponds to the perceptual difference between two colours expressed in CIELAB coordinates. We also use the Euclidean distance in the RGB space.

Granulometry

The granulometry in materials science, which is used to characterise granular materials by passing them through sieves of increasing mesh size while measuring the mass retained by each sieve, is transposed to image data by opening the image with a family of openings γ_λ of increasing size λ [20]. The mass is replaced by the image volume Vol, i.e. the sum of the pixel values. The normalised granulometric curve of an image f is a plot of $\mathrm{Vol}\left[\gamma_\lambda(f)\right]/\mathrm{Vol}(f)$ versus λ. The most useful structuring elements are discs and lines. Negative values of λ are interpreted as a closing with a structuring element of size λ.

Due to the extremely large number of ways of applying an opening to a colour image [7], we decided to use an integrative single-channel strategy and apply the granulometry to each channel of the image in the RGB and CIELAB spaces.

3. Structural properties of texture

Texture has been characterised in terms of two sets of properties: spatial relation properties and perceptual properties. Rao [17] developed a taxonomy of textures based on their spatial relations. He defined the following four texture classes, examples of which are shown in Figure 1:

Strongly ordered: Textures made up of a specific placement of primitive elements, or of a distribution of a class of elements.

Weakly ordered: Textures exhibiting a certain level of specificity of orientation at each position.

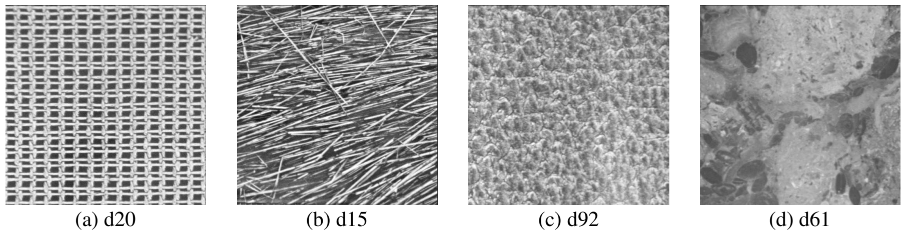

Figure 1. Examples of the four texture classes defined by Rao: (a) Strongly ordered. (b) Weakly ordered. (c) Disordered. (d) Compositional. The reference number of each texture in the Brodatz album [2] is shown below each image.

Disordered: These textures are not oriented or repetitive, and could be described based on their roughness.

Compositional: Textures which do not fit completely into one of the above three texture classes, but can be described as a combination of them.

Perceptual properties are those which humans take into account when looking at texture. Rao and Lohse [18] performed an experiment designed to find the high-level texture characteristics which are important in the perception of texture by humans. They asked 20 people to each classify 30 greyscale textures from the Brodatz album [2] into an unspecified number of classes, and then to group similar classes so as to create a tree of texture similarity. Using an analysis by multidimensional scaling, the authors determined that the most important characteristic is regularity, followed by the degree of orientation specificity and lastly descriptional complexity. Mojsilović et al. [11] did a similar experiment in which 28 people were asked to specify numerically the similarity between every combination of 20 colour textures obtained from a textile catalogue. Using multidimensional scaling, they identified five important perceptual characteristics, of which two are specific to colour textures and three correspond to those of Rao and Lohse. They are, in order of decreasing importance: overall colour, directionality and orientation, regularity and placement, colour purity and complexity and heaviness. Chetverikov [3] relates orientation specificity to anisotropy and points out that regularity and anisotropy are hierarchical — a periodic texture is always anisotropic as characteristic orientations are defined by the directions of the periodicity.

The morphological texture descriptors described above are both well adapted to describing regularity and orientation specificity. The variogram of a regular texture should have a visible periodicity. An orientation specificity will be characterised by different variograms for different directions. The granulometry by discs is well suited to identifying regularity — regular structures should have the same size and/or be separated by structures having the same size. Orientation specificity can be detected by computing granulometries using linear structuring elements in a number of directions. The granulometry should also be able to extract useful information from textures which are not periodic and not orientation specific, such as those made up of a random distribution of differently sized grains.

4. Illumination invariance

Even though colour is the most appealing feature [11], it is also the most vulnerable image indexing feature when the illumination under which image content is captured is varied. The problem of illumination variance has been addressed for the last few years, but there is no solid model for textures that provides illumination invariant features. It is obvious that a change in illumination does not change the texture content and hence should not change the texture features. However, the majority of texture analysing algorithms are sensitive to illumination changes. Even in conjunction with popular colour constancy normalization schemes (such as those proposed by Funt, Chatterjee and Finlayson [4]), colour histogram based classification methods and integrative single channel texture analyzing strategies fail to perform well for the Outex 14 database [13]. Overall, the average classification score under illumination varying conditions drops by 25% compared to constant illumination conditions [12].

In this work we propose to use Minvariance Model [9], in which the change in the pixel values is modelled as a function of relative change in two interdependent variables. In general using Lambert's Law, one can determine the resultant colour coefficients using the following equation:

$$\vec{\rho} = \int_w \mathcal{S}(\lambda) E(\lambda) \mathcal{F}(\lambda) d\lambda \tag{2}$$

where λ is wavelength, $\vec{\rho}$ is the sensor responses (the resultant *RGB* pixel values), $\mathcal{F}$ is the visual apparatus response function, E is the incident illumination and $\mathcal{S}$ is the surface reflectance at location *x* on the texture surface. Under the assumption that local surface reflectance is a constant at location *x*, the *RGB* pixel values can be expressed as a product function of sensor response function and illumination. We rewrite Equation 2 as a continuous function Ψ of two functions Ω and χ that are implicitly connected by the third variable λ,

$$\vec{\rho} = \Psi(\Omega, \chi) \tag{3}$$

$$\Omega = \mathcal{F}(\lambda), \chi = E(\lambda) \tag{4}$$

Using the chain rule of differentiation, we can write the total differential coefficient of $\vec{\rho}$ as

$$d\vec{\rho} = \frac{\partial \vec{\rho}}{\partial \Omega} \cdot d\Omega + \frac{\partial \vec{\rho}}{\partial \chi} \cdot d\chi \tag{5}$$

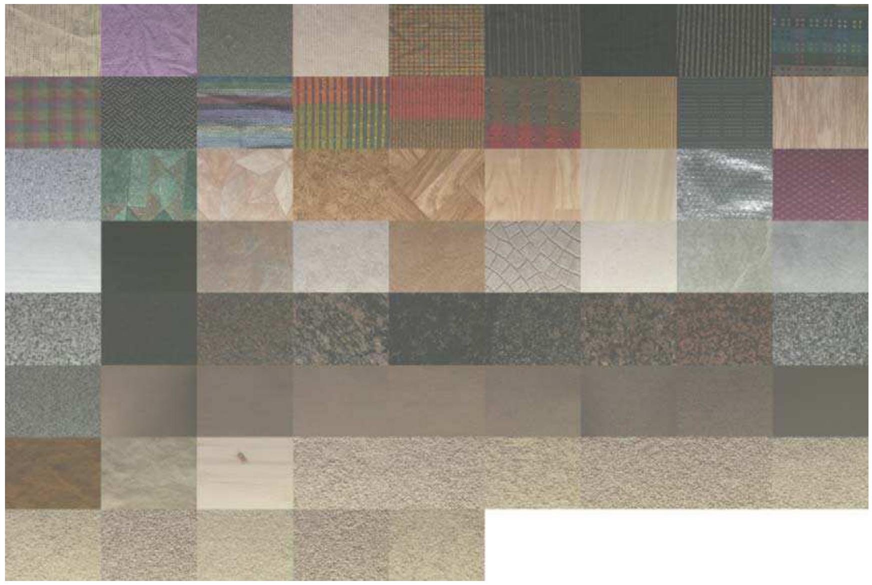

Figure 2. An example of each of the 68 Outex 14 textures (from [12]).

given the condition $\triangle\lambda \rightarrow 0$, $\triangle\Omega \rightarrow 0$, and $\triangle\chi \rightarrow 0$, where $\triangle$ indicates the change in the corresponding parameter. We obtain the following condition for illumination invariant pixel values by equating the above equation to zero. That is

$$d\Omega = \mathcal{T}(\vec{\rho})^{-1} \cdot d\chi \tag{6}$$

where $\mathcal{T}$ denotes the ratio between partial derivaties, i.e. the ratio between the partial change in pixel values due to a change in illumination and the partial change in pixel values due to a change in sensor sensitivity. In practice, a histogram stretching technique [6] is used to achieve the above condition on colour textures. A detailed description of the Minvariance Model can be found in [9]. A similar approach to illumination invariance using histogram equalisation has been suggested in [8]. We have derived a similar technique, but using a different theoretical model.

5. Experimental setup

Classification experiments were performed on the Outex 14 texture database [13], which contains 68 textures. An example of each texture is shown in Figure 2. The training set was obtained by acquiring a 100dpi image of size 746×538 pixels of each texture illuminated by a 2856K incandescent CIE A light source. Each image was then divided into 20 non-overlapping sub-images, each of size 128×128 pixels, producing 1360 training images. The test set is made up of differently illuminated samples of the same textures, once again with 20 sub-images per texture. The illumination sources used are a 2300K horizon sunlight and a 4000K fluorescent TL84. For each illumination source, 1360 images are available, making a total of 2720 test images. The textures have the same rotations under the three light sources.

6. Texture features and classification

Granulometry and Variogram texture feature vectors were calculated on three images: colour images represented in the RGB (RGB) and CIELAB (Lab) colour spaces, and a greyscale image containing luminance values (L), the latter being the L^* values in the CIELAB space. To transform the RGB images into the CIELAB space, the first step was done using the RGB to XYZ transformation matrix calibrated to the CIE A white point given in [12].

Four variograms are calculated for each image in directions $\alpha = 0°, 45°, 90°$ and $135°$ for values of $q = 1, 2, 3, \ldots, 50$ using Equation 1. These four variograms are then concatenated to form the variogram feature vector. For the greyscale image L, Equation 1 is used directly. For the colour images RGB and Lab, the subtraction in Equation 1 is replaced by the Euclidean distance. The feature vectors for both greyscale and colour images therefore contain 200 features.

The granulometry feature vector is the granulometry curve using linear structuring elements in four directions, as for the variograms. We use the convention that a linear structuring element of size ℓ has a length of $2\ell + 1$ pixels. For a granulometric curve in a single direction, the structuring elements range in size from -25 (i.e. a closing with a linear structuring element of length 49 pixels) to size 25 in steps of size 2. For the greyscale image L, the feature vector therefore contains 104 features. For the colour images RGB and Lab, the granulometry curves for each channel were concatenated to form a feature vector containing 312 features.

Computing a variogram feature vector on a 128×128 image requires on average 0.68 seconds for a greyscale image and 1.16 seconds for a colour image. A granulometry feature vector requires on average 10.7438 seconds for a colour image. The experiments were done in a MATLAB 6.1 environment, using a personal computer with an AMD $Athlon^{[TM]}$ MP 1800^+ 1.5GHz processor and 1GB RAM.

Textures were classified using a kNN classifier, in which the distance between feature vectors was calculated using the Kullback-Leibler distance, which is well suited to comparing probability distributions. The Kullback-Leibler distance between two vectors $\mathbf{p}$ and $\mathbf{q}$ having components p_k and q_k is:

$$d = \sum_k p_k \log_2 \frac{p_k}{q_k} \tag{7}$$

Table 1. Classification scores for Outex 14. The methods are the granulometry $\mathcal{G}$ and Variogram $\mathcal{V}$. The subscript indicates the colour space used.

	No minvariance			With minvariance		
Methods	TL84	horizon	Average	TL84	horizon	Average
$\mathcal{G}_{RGB}$	41.54	47.13	**44.34**	60.44	65.59	**63.02**
$\mathcal{G}_{Lab}$	37.43	56.10	**46.77**	69.04	72.13	**70.56**
$\mathcal{G}_{L}$	16.40	22.72	**19.56**	24.41	19.41	**21.91**
$\mathcal{V}_{RGB}$	73.46	65.66	**69.56**	65.59	60.44	**63.02**
$\mathcal{V}_{Lab}$	65.76	73.75	**69.76**	74.12	55.22	**64.67**
$\mathcal{V}_{L}$	70.07	73.01	**71.54**	77.35	78.82	**78.09**
Best result from [12]			**69.5**			

We used a value of $k = 3$. For the results in [12], with which we are comparing our results, a value of $k = 1$ was used. However, for the experiments in [12], the classifier was trained and tested using only half of the images in the benchmark database. As we are using the full database, we use $k = 3$ to make the comparison more fair. The classification performance is measured as the percentage of test set images classified into the correct texture class.

7. Results

The results of the texture classification experiments are shown in Table 1. The left part of the table shows the results without illumination invariance and the right part with illumination invariance. For each feature extraction method, the classification performance on the two halves of the test database corresponding to different illuminants (TL84 and horizon) are shown. Finally, the average of these two values is shown in bold. For comparison, the best result of classification on the Outex 14 database, reported in [12], is given. This value of 69.5% was obtained using the Local Binary Pattern (LBP) texture features.

The granulometry features for the colour images gave consistently better classification rates than those for the greyscale images. Furthermore, the use of the illumination invariant features with the granulometry improved the classification significantly for the colour images, but little for the greyscale images.

The variogram applied to the non-illumination invariant images produced superior results to the granulometry. These results all have the same magnitude as the best result by the LBP method [12]. The use of the illumination invariant features had the undesired effect of lowering the classification rate for the colour images, but raising it significantly for the greyscale images. It can be assumed that the transformation used to produce the illumination invariance distorts the distances in the RGB or CIELAB spaces which are used in the colour version of the variogram, thereby leading to lower classification rates, but this remains to be investigated further. The use of illumination invariant features for the greyscale images leads to a significant improvement. The best result of 78.09% is obtained by applying the variogram to the illumination invariant luminance images. This is an improvement of 8.6% with respect to the best LBP result.

8. Conclusion

We have discussed the standard morphological texture characterisation tools, the variogram and granulometry, in terms of the structural and perceptual properties of texture, and compared their performance for texture classification. In general, it is can be seen that classification using feature vectors based on the variogram performs better than that using granulometric curves. On average, the use of our proposed illumination invariant features improves the classification for all features except for the colour variogram features. The illumination invariant variogram features applied to the luminance image results in a significant improvement in classification performance compared to the best performance reported in the literature.

Due to the theme of the conference, we have concentrated on comparing classification results using the standard morphological approaches, and have shown that the use of illumination invariant features can lead to a significant improvement in classification. It still remains, of course, to investigate the improvement in the classification results when using the LBP with our proposed illumination invariant features.

The fact that the best classification performance is obtained for greyscale images supports the assertion of Mäenpää et al. [12] that colour information usually only improves texture classification marginally. However, the performance of the texture classification using the colour granulometry features is better than that using the greyscale features, which counters this assertion. We therefore also plan to investigate if the application of the variogram in an integrative single-channel way (i.e. concatenating the variogram of each colour channel to produce the feature vector, as done for the granulometry features) leads to an improvement over the integrative multi-channel strategy used.

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