Comparison of texture parameters for colour texture analysis

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Abstract

In this article we present three texture characterisation parameters, the cooccurrence matrices, the auto-covariance matrix and the local-extrema function. The behaviour of these three texture characterisation parameters will be investigated when perturbations such as noise or re-scaling are applied to texture picture that has to be analysed. To achieve the comparison of these parameters, a set of coloured texture from the free texture database 'absolute background texture' was selected, perturbation were applied to this set of textures and then a nearest neighbour classification was performed to determine relative perturbation sensitivity .

Keywords: Texture, Colour, Cooccurrence, Autocovariance, auto-correlation, Local extrema

1. Introduction

The first definition for texture is determinist and is based on the spatial repetition of a basic motif in different directions. This structural approach corresponds to macroscopic vision of textures.

The second definition is probabilistic and characterises the random and homogeneous aspect without any located motif and repetition frequency. It corresponds to a microscopic vision. Texture gives visual information that can be qualitatively described with the following adjectives: coarse, thin, smooth, mottled, granular, marbled, regular or irregular. From a statistical point of view this visual aspect reveals homogeneous and constant spatial properties with translation [2].

For coloured textures, multi- or hyper-spectral, we note a high correlation between the spectral bands of the texture. The object of our study is to determine the less perturbation sensitive of these 3 parameters for coloured textures. Later, this parameter will be extended to more than 3 bands. The parameter choice has to be determined thanks to the sensitivity analysis for different factors that could modify the texture like the noise or the scaling factor.

2. Texture parameters

2.1. Cooccurrence matrices

The cooccurrence matrix was introduced by Haralick &al. [4]. For a grey level texture, for a distance D and a direction θ, the element $MC(i,j)_{D,\theta}$ of the cooccurrence matrix indicates the number of pixels couples, separated by a distance D in the θ direction where I(s)=i and I(t)=j (I(s) is the grey level of the pixel s).

The cooccurrence matrix is generally calculated in the principal direction ($\theta = 0°$, $\theta = 45°$, $\theta = 90°$, $\theta = 135°$) with D=1.

The size of these matrices depends on the number of grey levels in the image and these matrices are so heavy to use. Studies have shown [5] that texture analysis could be carried out with 20 values. These parameters, 5 per matrix are the homogeneity, the contrast, the correlation, the local homogeneity and the entropy.

2.2. Autocovariance matrix

The autocovariance matrix measures the correlation between two pixels for a given distance. Autocovariance matrix is given by the following formulae (1).

$$C(\Delta) = K \times \frac{\sum_{y=ya}^{yb}\sum_{x=xa}^{xb} L^*(x,y)L^*(x+\delta x, y+\delta y)}{(yb-ya)(xb-xa)}$$

$$with: \qquad (1)$$

$$K = \frac{1}{\sum_{y=ya}^{yb}\sum_{x=xa}^{xb} L^{*2}(x,y)}$$

m being the mean of radiances, L*(x,y) is the centred radiance of the pixel (x,y), i.e. L(x,y)-m, δx and δy are the distances between two pixels for the x and y directions, ya and yb, xa and xb are the window limits for the distance Δ(δx, δy).

Gagalowicz [6] used the autocovariance matrix and the histogram for texture synthesis. The method consists of generating a noise image having the required texture size and the same histogram as the original texture. The iterative process consists of modifying the pixels value in order to best fit the autocovariance matrix without too much changing the histogram.

2.3. Local extrema method

Bonnevay [1] developed a method based on the order extrema. The grey level I(s) of a pixel s is a local maximum of the n^{th} order if I(s) is a maximal value of n order neighbourhood of s. The order maxima of a region are counted in a region and a good evaluation of the granularity is then obtained.

Mavromatis &al. [11] take also into account the texture direction. In this approach, the grey level I(s) of a pixel s is an order n maximum in the θ direction if I(s) is the maximum value of the n neighbourhood in the θ direction. If 8 directions are considered, (0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°) the neighbourhood of 0 to 4 orders in the θ = 90° direction are presented by the figure 1:

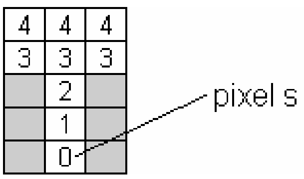

Figure 1 : Neighbourhood of 0 to 4 orders in the θ = 90° direction

The texture is then characterised by a matrix whose each element (n, θ) is the number of order n maxima in the θ direction.

3. Choice of the study texture

In order to benchmark the three parameters, the first step is to select a set of colored texture. This was done within the free database 'absolute background texture'. The choice of texture has been done regardful to their textural properties; the selected sample must provide all the textures properties with different association. Figure 2 presents four representative textures of the selected sample.

2.1: 2.2: 2.3: 2.4:

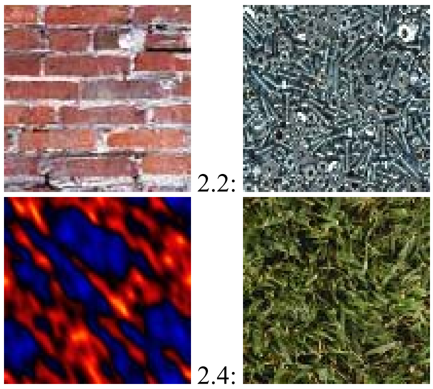

Figure 2: textures from sample.

Subfigure 2.1 represents a bricks wall. It is a very structured texture with red colour dominance.

Subfigure 2.2 is a random texture composed of regular patterns (screws and bolts). Circular and linear patterns can be randomly found. With a grey hue, this texture has no special dominant colour.

Subfigure 2.3 is a bicolour synthetic texture. It presents alternatively red and blue colour dominance.

Subfigure 2.4 is a natural grass texture with green colour dominance.

4. Comparison protocol

First, a parameters database is built with parameters computed onto textures sample. The point is that parameters have to be compared each over. The problem is that, as every texture picture is different size and the values scale of raw parameters is image size dependant. Hence, to allow comparison and according to constancy with translation of statistical properties for a texture, it has been decided to compute parameters onto fixed size windows into pictures. Chosen size being 64*64, each picture is cropped to this size before processing calculation of parameters. Parameters are then computed for each spectral band, in our case, for the three RGB bands of color texture. Obviously, this calculation can be done with M bands of a multi- or hyper-spectral picture. Computed parameters are stocked into a database. Figure 3 shows how it is done.

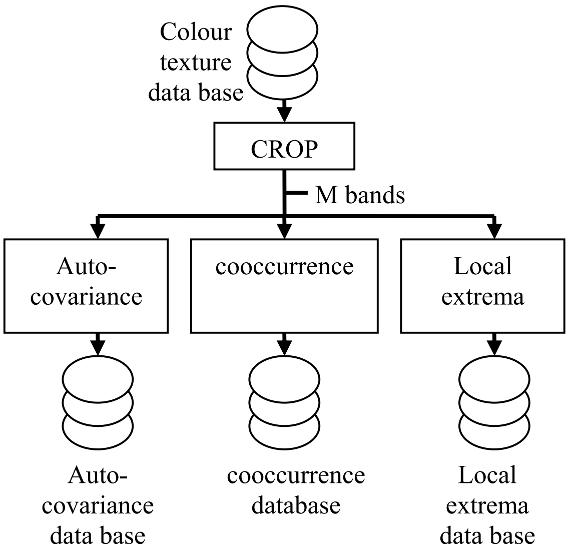

Figure 3: Reference parameters calculation.

As it is wanted to compare parameters it selves, a distance has been chosen between raw parameters data: parameters matrices, which sizes are (17x17) for autocovariance matrix, $(2^n x 2^n)x4$ with n the number of bit quantization, for cooccurrences matrices and (8x6) for local extrema matrix. This distance is defined by the sum of squared differences between each matrices input. An average distance that is the mean distance of the M parameters for the M band of the input picture is then computed.

Reference parameters calculation returns a set of N classes in each parameter space, where N is the number of different input pictures. With this set of N classes and the distance described before, we are able to make a k-NN classification. Obviously, the aim being to retrieve the original texture from a modified one, the number k of studied neighbors is set to 1.
Then, textures pictures are modified, parameters are computed for each modified texture and are sent to the classifier.

Modifications applied to texture picture are:

1) Change adding Gaussian white noise with increasing variance.
2) Adding random noise with increasing density
3) Rescale pictures using increasing scaling coefficients.

Random noise is "salt and pepper" type, it is completely random and no simple statistic can describe it. Hence, different pure random noise picture are not correlated in anyway.

Variances of noise have been chosen following a quadratic law in order to improve discrimination for low noise levels. The used function is: $[(N-1).K]^2$, where N is a level of noise and K a constant value used to set the discrimination level. In this application, $1<N<13$ and $K=0.0425$, hence 12 increasingly noised pictures for each texture are generated. The same values are used as density for uncorrelated noise. Scaling coefficients step has been set to +5% starting to scale 1 and ending to scale factor 2, so, we have 21 increasingly scaled pictures for each texture.

Figure 4 shows how classifier is working using previously generated parameters databases.

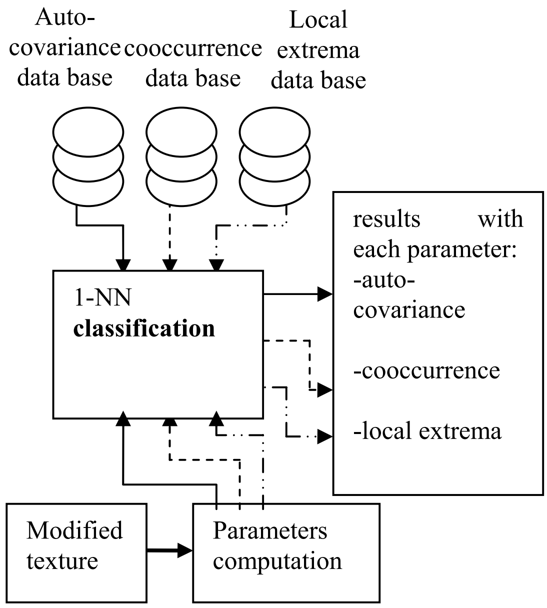

Figure 4: Classifier.

5. Results

Figure 5 represents results obtained with addition of Gaussian zero mean white noise. Y axe represents the standard deviation square root of the added before classifier fails to recognize original texture. X axe is the texture number. Hence, each curve represents one of the 3 parameters and each point of these curves is the best result for a texture.

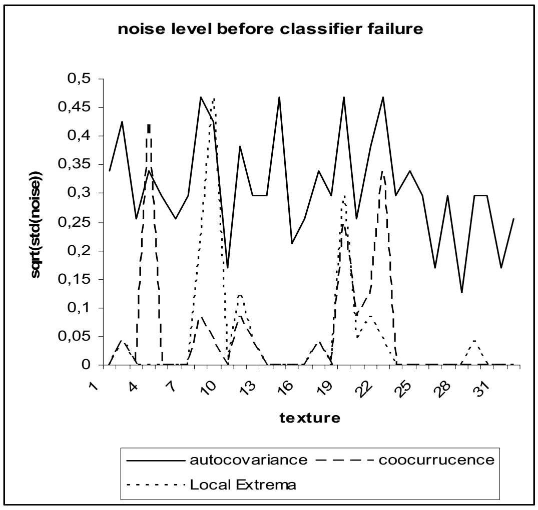

Figure 5: results with Gaussian white noise.

The first thing is that the three parameters work each well on 25% of the 32 texture sample (textures 4, 8, 9, 11, 19, 20, 21 and 22) and only autocovariance gives good results on the remaining 75%, where cooccurrence and local extrema noise level tolerance tends to be zero. Average results for the best 25% are respectively 0.4, 0.18 and 0.16 for autocavariance, cooccurrences and local extrema parameters.

The second type of modification is addition of totally uncorrelated noise. The density of this noise is increasingly modified with the same values that have been used for variance modification of Gaussian noise. Figure 6 shows the maximum noise density before classifier failure. Y axe is noise density root square. X axe is the texture number. Each curve represents highest results before classifier failure for each 32 texture.

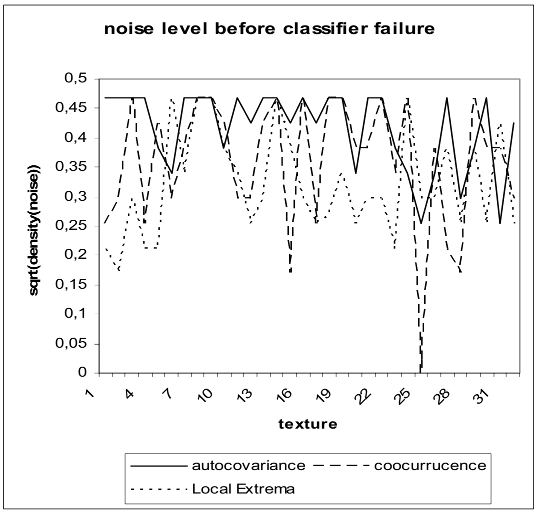

Figure 6: results with uncorrelated noise.

With totally uncorrelated noise, parameters performances are more balanced. Texture 25, which is not recognized with uncorrelated noise according to cooccurrence parameter, is a low frequency monochromatic blue texture.

Average results are respectively 0.42, 0.36 and 0.32 for autocavariance, cooccurrence and local extrema. With uncorrelated noise, autocovariance parameter keeps a certain advance in term of statistics.

Last modification applied is re-scaling. Figure 7 shows the results obtained. Y axe represents the maximum scale factor before classifier fail to recognize original texture from rescaled one.

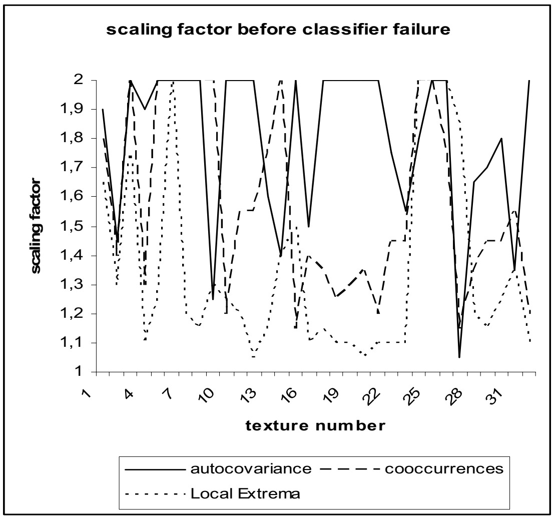

Figure 7: results with re-scaling

Average results are respectively 1.8, 1.57, and 1.34 for autocovariance, cooccurrences and local extrema. It is interresting to see that the lower autocovariance result is obtained with texture 27 while local extrema obtains its second ranking result with this texture. This texture is, after looking more carefully, really poor quality: color planes are granular. It seems that this picture was too loss full compressed before.

6. Conclusion

The first conclusion should be that, according to these results, autocovariance matrix parameter is less sensitive to noise than the two other parameters. However, if noise is totally random, all three parameters perform well.

These results should be discussed; actually, it is difficult to conclude that autocovariance is the best of these three parameters. Noisy textures are actually impossible to recognize according to eyes judgment if noise is higher than N(T, O). N is the maximum noise that allows recognition. N is a function of texture picture T and also a function of the observer O.

Hence, the question is: Does a parameter perform well if it allows recognition that eyes do not allow? Actually, it is difficult to answer to this question because it is difficult to define precisely the frontier between true and false recognition.

For re-scaling textures, autocovariance performs the best. This is probably due its statistical view of picture where local extrema and cooccurrence look directly pixels relations.

7. References

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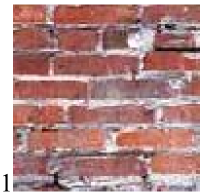
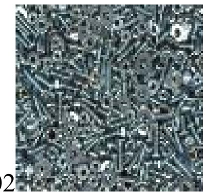
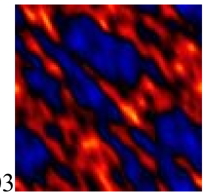
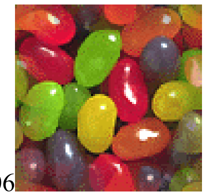
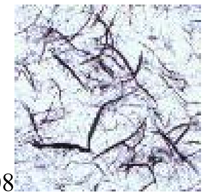
8. Texture sample

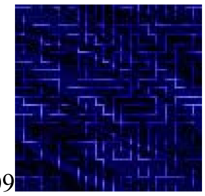
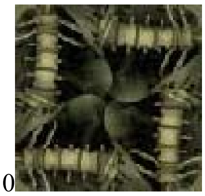
Figure 8.01-8.32 represents used sample of texture with associated number ID.

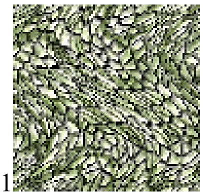
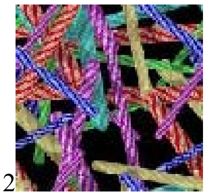
8.01  8.02 

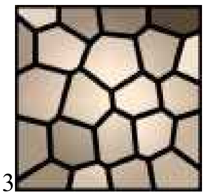
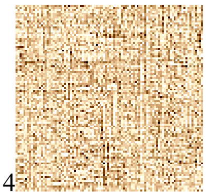
8.03  8.04 

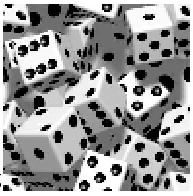
8.05  8.06 

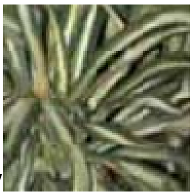
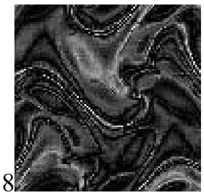
8.07  8.08 

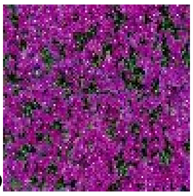
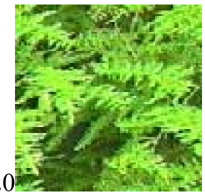
8.09  8.10 

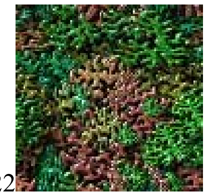
8.11  8.12 

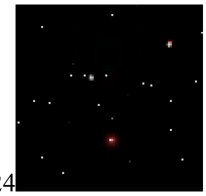
8.13  8.14 

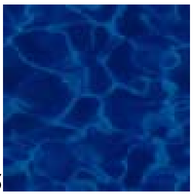
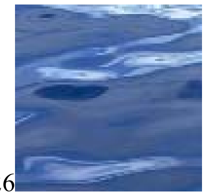
8.15  8.16 

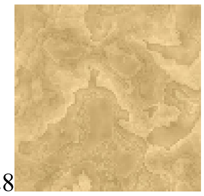
8.17  8.18 

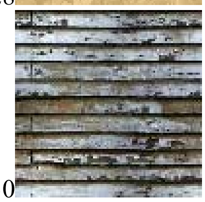
8.19  8.20 

8.21  8.22 

8.23  8.24 

8.25  8.26 

8.27  8.28 

8.29  8.30 

8.31  8.32 

Figure 8: textures sample