DETECTION OF LOCAL NOISE IN THE TEXTURAL IMAGES

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ABSTRACT. The paper presents a classification and identification method for the local noise in the textural images. To identify local noise in the textural images, a reference database with the textural images is used. For the region recognition with local noise, a decision theoretic method is used. The features are of the statistic type and derive from the medium co-occurrence matrices: contrast, energy, entropy, homogeneity, and variance. The algorithm is implemented in a mathematical software and allows the simultaneously display of both the investigated regions pairs, and the Euclidian distance between them. Our experimental results indicate that the five selected features for texture classification give good results to identify the local noise. The results also confirm that the distances between the similar regions are relatively small and the distances between regions from different textured images with local noise are relatively great.

Keywords: textural features, co-occurrence matrix, identify local noise.

1. Introduction

Texture is a feature that can help to segment images into regions of interest and to classify those regions. In some images, it can be the defining characteristic of regions and critical in obtaining a correct analysis. Texture gives us information about the *spatial arrangement* of the colors or intensities in an image. Texture is a set of primitive *texels* in some regular or repeated relationship. Texture relates to the surface or structure of an object and depends on the relation of contiguous elements. Wilson (Wilson and Spann, 1988) emphasis that textured regions are spatially extended patterns based on more or less accurate repetition of some unit cell; the origin of the term is related with the craft of weaving. Gonzalez (Gonzalez and Woods, 1992) relates texture to other concepts like *smoothness, fineness, coarseness, graininess* and describes the three different approaches for texture analysis: statistical, structural and spectral. The statistical methods rely on the moments of the grey level histogram; mean, standard deviation, flatness etc. These can give interesting information about the image but have the drawback that there is no information about the relative position of the pixels. Structural methods look for a basic pattern in the image, a texture element, and then describe the region according to the repetition of the pattern.

In order to classify the regions with local noise of an image, we have used the distances between all partitions of the image. We used a classic distance computed with some feature (contrast, energy, entropy, homogeneity, correlation) extracted form co-occurrence matrix

2. Texture information as integrated image feature

Co-occurrence matrices

A *co-occurrence* matrix is a two-dimensional array C in which both the rows and the columns represent a set of possible image values V.For example, for gray-tone images, Vcan be the set of possible gray tones and for color images, Vcan be the set of possible colors. The value of $C(i, j)$indicates how many times value i co-occurs with value j in some designated spatial relationship. For example, the spatial relationship might be that value i occurs immediately to the right of value j. To be more precise, we will look specifically at the case where the set $V$is a set of gray tones and the spatial relationship is given by a vector $d$that specifies the displacement between the pixel having value i and the pixel having value j.

Let d be a displacement vector *(dr, de)* where *dr* is a displacement in rows (downward) and *de* is a displacement in columns (to the right). Let Vbe a set of gray tones. The gray-tone co-occurrence matrix *Cd* for image 1is defined by

$$Cd(i,j) = |\{(r, \mathrm{c})\ |I(r,c) = \mathrm{i}\ \mathit{and}\ I(r + dr,\ c + dc) = \mathrm{j}\}|\ (1)$$

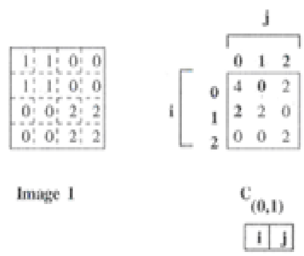


Figure 1 illustrates this concept with a 4 x 4 image 1and three different co-occurrence matrices for 1 :$C_{(0,l)}$, $C_{(1,0)}$,and $C_{(1,l)}$.

Fig. 2. Three different co-occurrence matrices for a gray-tone image. In C(0,l)note that position (1,0) has a value of 2, indicating that j= 0 appears directly to the right of i = 1 two times in the image. However, position (0, 1) has a value of 0, indicating that j= 1 never appears directly to the right of i = 0 in the image. The largest co-occurrence value of 4 is in position (0, 0), indicating that a 0 appears directly to the right of another 0 four times in the image.

There are two important variations of the standard gray-tone co-occurrence matrix. The first is the *normalized* gray-tone co-occurrence matrix N_d defined by:

$$N_d(i,j) = \frac{C_d(i,j)}{\sum i \sum j Cd(i,j)} \tag{1}$$

which normalizes the co-occurrence values to lie between zero and one and allows them to be thought of as probabilities in a large matrix. The second is the *symmetric* gray-tone co-occurrence matrix $S_d(i,j)$defined by

$$S_d\,(i,j) = C_d\,(i,j) + C_{-d}\,(i,j) \tag{2}$$

this groups pairs of symmetric adjacencies.

Co-occurrence matrices capture properties of a texture, but they are not directly useful for further analysis, such as comparing two textures. Instead, numeric features are computed from the co-occurrence matrix that can be used to represent the texture more compactly. The following are standard features derivable from a normalized co-occurrence matrix.

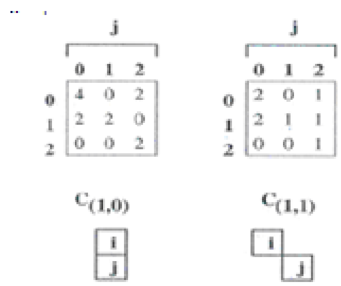
$$Energy = \sum_i \sum_j N_d^2(i,j) \tag{3}$$

$$Entropy = -\sum_i \sum_j N_d^(i,j) \log l2 N_d(i,j) \tag{4}$$

$$Contrast = \sum_i \sum_j (i-j)^2 N_d(i,j) \tag{5}$$

$$Homogeneity = \sum_i \sum_j \frac{N_d^(i,j)}{1+|i-j|} \tag{6}$$

$$Correlation = \frac{\sum_i \sum_j (i-\mu_i)(j-\mu_i) N_d(i,j)}{\sigma_i \sigma j} \tag{7}$$



where μ_i, μ_j are the means and σ_i, σ_j are the standard deviations of the row and column sums $N_d(i)$and $N_d(j)$defined by

$$N_d(i) = \sum_j N_d(i,j) \tag{8}$$

$$N_d(j) = \sum_i N_d(i,j) \tag{9}$$

For the textural images, the color and the texture are more important of perceptual point of view because there are not group of objects.

The regions of textural images tend to spear in whole image, in time that the non-textural images are usual partition in-group regions.

(1) *Distance between two images*

There will be associated five characteristics to each image. Therefore, we will define the distance between two images.

Considering two images I1 and I2 characterized by *Con1, Ene1, Ent1, Omo1, Cor1* and *Con2, Ene2, Ent2, Omo2, Cor2.*Then the distance between I1 and I2 is:

$$d(I1, I2) = \sqrt{\begin{array}{l}(Con1 - Con2)^2 + (Ene1 - Ene2)^2 \\ +(Ent1 - Ent2)^2 + (Omo1 - Omo2)^2 + (Cor1 - Cor2)^2\end{array}} \tag{10}$$

Considering the images I1 and I2 we obtain the next characteristics:

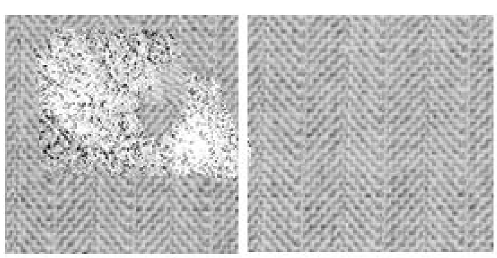


Fig.2 Textural images with noise

Contrast: 6.983	Contrast: 2.237
Energy: 70.004	Energy: 8.319
Entropy: 6.790	Entropy: 7.530
Homogeneity: 2.375	Homogeneity:2.111
Correlation: 1.970	Correlation: 1.827

According to the formula defined above the distance between I1 and I2 will be: d(I1,I2)=61.873.

It is obvious that the distance between two identical images is zero.

The method of search and classification for textural images with noise presumes the divisions of images in blocks of same dimension (usually squares) witch are compared one with other based on algorithm established. The textural images from the square blocks are initial pre-processed and bridged in a white-black spectrum using only gray-tone.

Because is working directly with the pixels value from square blocks of images then the computations are not complicated and the characteristics are directly extracted.

One advantage of this method is that is not need to make a redetection to a number very small of gray-tone. The co-occurrence matrix is a square matrix with the lines number equal with gray-tone. The method make a good distinction between the images with a fine texture and a roughly texture and it is useful to identify the noise in the texture.

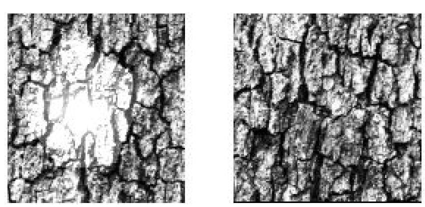
3. Image processing

For the identification of the local noise in the textural images the following operations for every image is applied:

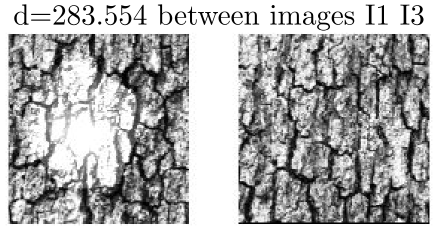
- -read original image
- -convert image in 256 gray tones
- -split in four equal parts the original image
- -for every partition of the image computes 256 gray-level co-occurrence matrix
- -for every partition of image compute the features extracted from the co-occurrence matrix using the formulas (3)-(7) and retains the values for the computing the distance between tow images
- -make all possible combination between two partitions of the image and compute distance using formula (10)
- -identify the image with the local noise where the difference between the values of the distances are great

4. Experimental results

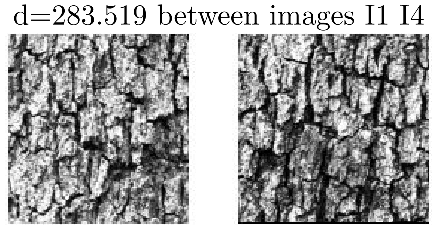
For our analysis we used 20 sets of images, four of them are shown below. For each set, we computed the distance between two images value. We obtained the results listed below:



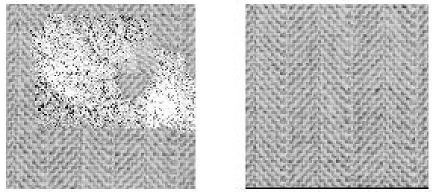
d=283.554 between images I1 I3



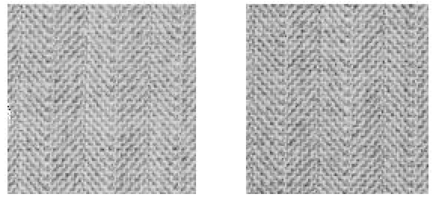
d=283.519 between images I1 I4



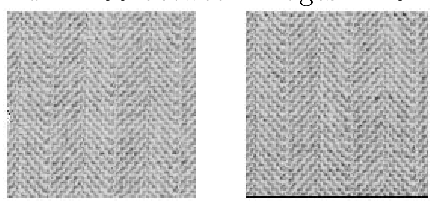
d=0.266 between images I2 I3



d=62.771 between images I1 I4



d=1.450 between images I2 I3



d=1.153 between images I2 I4

5. Conclusions

The analysis has been made on 20 sets of images and the results proves that distance extracted from co-occurrence matrix of the partitions of image may be used for classifying (regions of) images composed with similar gray levels and to identify the textural images with local noise. The main application of the algorithm consists in texture identification and classification of the regions in multi-textured images (like images from satellite or images from video camera of intelligent vehicles).

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