Texture Classification and Defect Detection by Statistical Features

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Abstract—In order to identify and classify the proper textured region, a decision theoretic method and two types of statistic texture feature are used. The first type features derive from the average co-occurrence matrices: contrast, energy, entropy, homogeneity, and variance. The second type features are the following: the grey level histogram, the grey level difference histogram, and the edge density per unit of area. The algorithms are implemented in Visual C++ and Matlab and allows the simultaneously display of both the investigated region, and the Euclidian distance between this and a reference image. The result is the classification of the tested texture and the defect localization (if a region with defect exists) inside of the divided regions. In order to compare regions, a data base with the reference texture images is created. For the texture defect detecting, a combination between the template matching and the decision theoretic method is used. Our experimental results indicate the fact that the selected features which derive from the average co-occurrence matrices have a good discriminating power both for texture classification and defect localization. The results also confirm the fact that the distances between the regions without defect are relatively small and the distance between a region with defect and a region without defect is relatively great. The image difference histogram has better behavior referring to texture classification than to defect detection and localization.

Keywords—Edge densities, Grey level difference histogram, Average co-occurrence matrix, Texture.

I. Introduction

It is very hard to define rigorously the texture into an image. The texture can be considered like a structure which is composed by many similar elements (patterns) named textons or texels, in some regular or continual relationship.

Texture analysis is made by using various approaches, like statistical type (characteristics associable with grey level histogram, grey level image difference histogram, grey level co-occurrence matrices and the features extracted from them, autocorrelation based features, power spectrum, edge density per unit of area, etc), fractal type (box counting fractal dimension), and structural type. The statistical approach utilizes features to characterize the stochastic properties of grey level distribution in the image.

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There are two important kinds of problems that texture analysis research attempts to solve: texture segmentation and texture classification. Another problem, texture synthesis is often used for image compression application.

Texture classification involves deciding what texture class an observed image belongs to. Thus, one needs to have an a priori knowledge of the classes to be recognized. The major focus of this paper is the classification process, based on statistical features (especially derived from average co-occurrence matrix), and the defect detection and localization, based of texture analysis of regions which are obtained by image partition.

For the purpose of algorithm validation, two experimental studies have been conducted. The first study is focused on region classification of textured images and the second study is focused on defect identification and localization.

With this end in view, the whole image is partitioned in four equivalent regions like in Fig.1. Different textured regions are compared by minimum distance criterion. The measured features are derived from average co-occurrence matrices (contrast, energy, entropy, homogeneity, and variance), from grey level histograms or from contour pixel densities.

$I_i(1)$	$I_i(2)$
$I_i(3)$	$I_i(4)$

Fig.1 four regions image partition

The experimental results indicate that the five features selected from medium co-occurrence matrices have a good discriminating power, both in texture classification applications and in defect detection and localization.

II. Statistical Methods to Texture Analysis

The statistical approach is more useful than structural approach to texture analysis. The simplest statistical features like the mean (1) and standard deviation (3) can be computed indirectly in terms of the image histogram h.

Thus,

$$\mu = \frac{1}{N}\sum_{i=1}^{K} x_i h(x_i) \tag{1}$$

$$N = \sum_{i=1}^{K} h(x_i) \tag{2}$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{K} (x_i - \mu)^2 h(x_i) \tag{3}$$

where $N = n_1 n_2$ is the image dimension, and K is the number of grey levels.

The shape of an image histogram provides many clues to characterize the image, but sometimes it is inadequately to discriminate textures (it is not possible to indicate local intensity differences).

Another simple statistic features is the edge density per unit of area, Den_e (4). The density of edges, detected by a local binary edge detector, can be used to distinguish between fine and coarse texture like in Fig.3. The density can be evaluated by the ratio between the pixel number of extracted edges (which must be tinned – one pixel thickness) and image area (pixel number of region matrix):

$$Den_e = \frac{N_e}{A} \tag{4}$$

In equation (4), N_e represents the number of edge pixels and A is the region area.

In order to characterize textured images, connected pixels must be analyzed. For this reason, correlation function (5), difference image function (6) in certain direction $d = (\Delta x, \Delta y)$,

$$R(x, y) = \frac{\sum_{u=0}^{n_1-1} \sum_{v=0}^{n_2-1} I(u,v)\, I(u+x, v+y)}{\sum_{u=0}^{n_1-1} \sum_{v=0}^{n_2-1} I^2(u,v)} \tag{5}$$

$$I_d(x,y) = I(x,y) - I(x+\Delta x\,, y+\Delta y) \tag{6}$$

and also the co-occurrence matrices (9), must be considered.

From histogram of difference image h_d, one can extract the mean (7) and standard deviation (8):

$$\mu_d = \frac{1}{N}\sum_{i=1}^{K} x_i h_d(x_i) \tag{7}$$

$$\sigma_d^2 = \frac{1}{N}\sum_{i=1}^{K} (\,x_i - \mu_d\,)^2 h_d(x_i) \tag{8}$$

The most powerful statistical method to textured image analysis is based on features extracted from the Grey-Level Co-occurrence Matrix (GLCM), proposed by Haralick in 1973 [1]. GLCM is a second order statistical measure of image variation and it gives the joint probability of occurrence of grey levels of two pixels separated spatially by a fixed vector distance $d = (\Delta x, \Delta y)$. Smooth texture gives co-occurrence matrix with high values along diagonals for small d. The range of grey level values within a given image determines the dimensions of a co-occurrence matrix. Thus, 4 bits grey level images give 16x16 co-occurrence matrices. The elements of a co-occurrence matrix C_d depend upon displacement d:

$$C_d(i,j) = Card\{((x,y),(t,v)) \,/\, I(x,y) = i,\ I(t,v) = j,\ (x,y),(t,v) \in NxN,\ (t,v) = (x+\Delta x, y+\Delta y)\} \tag{9}$$

From the co-occurrence matrix C_d one can draw out some important statistical features for texture classification. These features, which have a good discriminating power, are the following [1], [2]: contrast, entropy, energy, homogeneity, and variance.

III. Local Features Based on Average Co-occurrence Matrix

For each pixel we consider increasing $(2d+1)x(2d+1)$ symmetric neighborhoods, d = 1, 2, 3,...,10. Inside each neighborhood there are 8 principal directions: 1, 2, 3, 4, 5, 6, 7, 8 (Fig. 2). We evaluated the co-occurrence matrices $C_{d,k}$ corresponding to vector distances determined by the central point and the neighborhood edge point in the k direction (k = 1,2,...,8). For each neighborhood type, an average co-occurrence matrix C_d is calculated (10):

$$C_d = 1/8(C_{d,1} + C_{d,2} + C_{d,3} + C_{d,4} + C_{d,5} + C_{d,6} + C_{d,7} + C_{d,8})\ ,\ d = 1,2,...,10 \tag{10}$$

Thus, for 3x3 neighborhood, d = 1; for 5x5 neighborhood, d = 2; for 7x7 neighborhood, d = 3, and so on.

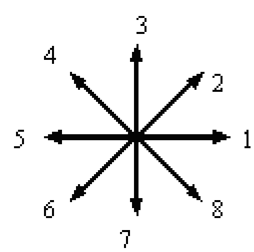


Fig.2 principal directions for co-occurrence matrix calculus

In order to quantify the spatial dependence of gray level values, from average co-occurrence matrices C_d, d = 1, 2,..., 10, we calculated various textural features like Contrast – Con_d – (11), Energy – Ene_d – (12), Entropy – Ent_d – (13), Homogeneity – Omo_d – (14) and Variance – Var_d – (15).

$$Con_d = \sum_{i=1}^{L} \sum_{j=1}^{L} (i-j)^2 C_d(i,j) \tag{11}$$

$$Ene_d = \sum_{i=1}^{L} \sum_{j=1}^{L} C_d(i,j)^2 \qquad (12)$$

$$Ent_d = -\sum_{i=1}^{L} \sum_{j=1}^{L} C_d(i,j) \log(C_d(i,j)) \qquad (13)$$

$$Omo_d = \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{C_d(i,j)}{1+|i-j|} \qquad (14)$$

$$Var_d = \frac{1}{L} \sum_{i=1}^{L} \sum_{j=1}^{L} [C_d(i,j) - \overline{C_d(i,j)}]^2 \qquad (15)$$

In the preceding notations, *LxL* is the dimension of co-occurrence matrices.

III. Experimental results for texture classification by statistical features

For algorithm testing and program validation we used two textured images I_1 and I_2, each partitioned in four regions $I_i(1)$, $I_i(2)$, $I_i(3)$, $I_i(4)$, i=1,2 (Fig. 1). In fact, the regions are 128 x 128 images with 16 grey levels. From these images we considered two regions, $I_1(1)$, $I_1(2)$, for I_1 image, and two regions, $I_2(1)$, $I_2(2)$, for I_2 image (Fig. 3).

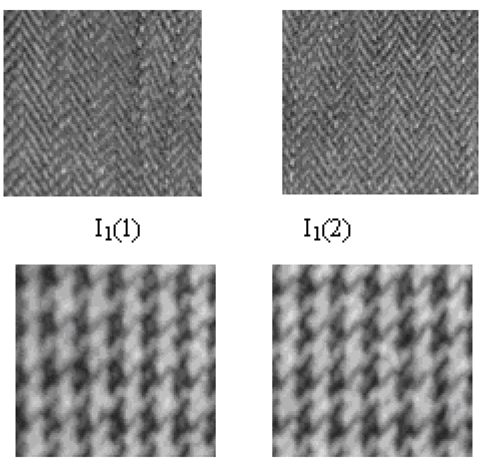


Fig.3 image regions derived from two images (I_1 and I_2) with different textures

Firstly, the analysis of the simple grey level histogram (Fig. 4, Fig. 5, Fig. 6, and Fig. 7) demonstrates that the regions can be discriminated by the aid of the mode location and mode value (histogram peak) which is greater for $I_1(1)$ and $I_1(2)$ than for $I_2(1)$ and $I_2(2)$. Secondly, supposing that the histograms are not so different, another set of texture features makes possible the region classification.

Textural features like Con_d (8), Ene_d (9), Ent_d (10), Omo_d (11), and Var_d (12) are calculated. The normalized results are presented in Table I, for d = 1, 2,..., 10. For the purpose of discriminated power evaluation of the selected features we calculate the Euclidian distances between regions from the same image: $D\{I_1(1),I_1(2)\}$, $D\{I_2(1),I_2(2)\}$, and the Euclidian distances between regions from different images: $D\{I_1(1),I_2(1)\}$, $D\{I_1(1),I_2(2)\}$, $D\{I_1(2),I_2(1)\}$, $D\{I_1(2),I_2(2)\}$.

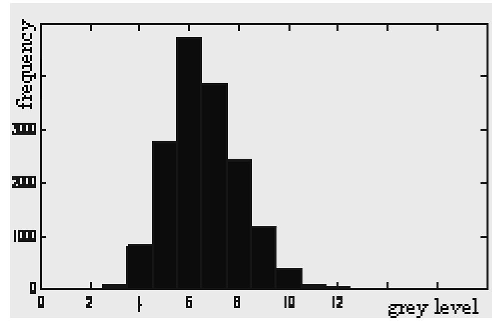


Fig.4 grey level histogram for $I_1(1)$

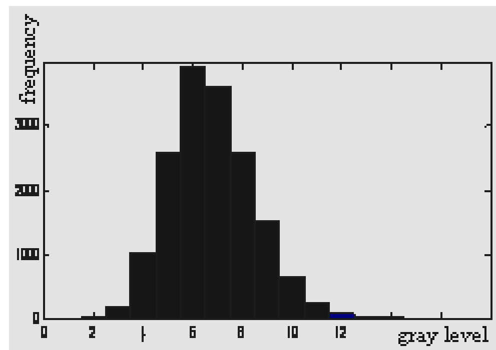


Fig.5 grey level histogram for $I_1(2)$

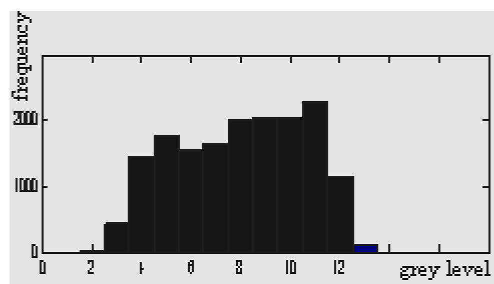


Fig.6 grey level histogram for $I_2(1)$

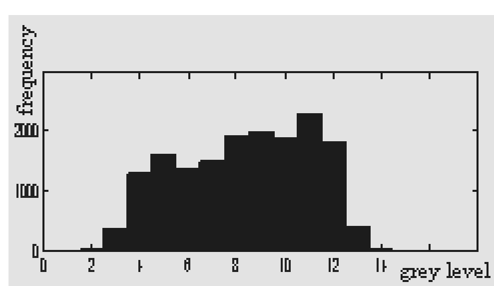


Fig.7 grey level histogram for $I_2(2)$

The Euclidian distance $D\{I_1, I_2\}$ between two images I_1 and I_2, which are characterized by the feature vectors $[C_1,E_1,Et_1,O_1,V_1]^T$ and $[C_2,E_2,Et_2,O_2,V_2]^T$ is expressed by the following relation:

$$D(I_1,I_2)=\sqrt{(C_1-C_2)^2+(E_1-E_2)^2+(Et_1-Et_2)^2+(O_1-O_2)^2+(V_1-V_2)^2}$$

where: C = Con, E = Ene, Et = Ent, O = Omo, V = Var. The results of mentioned distances calculus are presented in the Table II.

TABLEl I
FIVE NORMALIZED STATISTICAL TEXTURES DERIVED FROM CO-OCCURRENCE MATRICES

d	Image	Con_d	Ene_d	Ent_d	Omo_d	Var_d
1	$I_1(1)$	0.39	1.17	1.01	0.93	0.34
1	$I_1(2)$	0.60	0.81	0.96	0.84	0.46
1	$I_2(1)$	0.13	0.98	1.00	1.16	1.04
1	$I_2(2)$	0.15	0.89	0.99	1.13	1.17
2	$I_1(1)$	0.63	1.01	0.98	0.81	0.33
2	$I_1(2)$	0.88	0.73	0.93	0.75	0.45
2	$I_2(1)$	0.38	0.57	0.90	0.92	1.02
2	$I_2(2)$	0.45	0.52	0.89	0.88	1.15
3	$I_1(1)$	0.65	0.99	0.97	0.79	0.33
3	$I_1(2)$	0.89	0.72	0.92	0.73	0.45
3	$I_2(1)$	0.72	0.42	0.85	0.78	1.00
3	$I_2(2)$	0.85	0.38	0.84	0.75	1.14
4	$I_1(1)$	0.64	0.97	0.96	0.79	0.32
4	$I_1(2)$	0.87	0.70	0.91	0.73	0.44
4	$I_2(1)$	1.07	0.34	0.81	0.69	0.99
4	$I_2(2)$	1.25	0.32	0.81	0.66	1.13
5	$I_1(1)$	0.70	0.94	0.94	0.75	0.32
5	$I_1(2)$	0.95	0.68	0.89	0.70	0.44
5	$I_2(1)$	1.41	0.30	0.79	0.62	0.98
5	$I_2(2)$	1.62	0.28	0.79	0.60	1.12
6	$I_1(1)$	0.67	0.91	0.93	0.75	0.32
6	$I_1(2)$	0.90	0.67	0.88	0.70	0.43
6	$I_2(1)$	1.70	0.28	0.77	0.57	0.97
6	$I_2(2)$	1.94	0.26	0.77	0.56	1.11
7	$I_1(1)$	0.60	0.90	0.92	0.76	0.31
7	$I_1(2)$	0.78	0.66	0.87	0.72	0.42
7	$I_2(1)$	1.95	0.27	0.76	0.53	0.96
7	$I_2(2)$	2.21	0.25	0.76	0.52	1.10
8	$I_1(1)$	0.58	0.89	0.90	0.76	0.31
8	$I_1(2)$	0.78	0.64	0.86	0.71	0.42
8	$I_2(1)$	2.16	0.27	0.75	0.50	0.95
8	$I_2(2)$	2.43	0.25	0.75	0.49	1.08
9	$I_1(1)$	0.58	0.88	0.89	0.75	0.30
9	$I_1(2)$	0.78	0.63	0.84	0.70	0.41
9	$I_2(1)$	2.31	0.27	0.74	0.48	0.95
9	$I_2(2)$	2.60	0.25	0.74	0.47	1.07
10	$I_1(1)$	0.54	0.85	0.88	0.76	0.30
10	$I_1(2)$	0.75	0.62	0.83	0.70	0.41
10	$I_2(1)$	2.41	0.27	0.73	0.46	0.93
10	$I_2(2)$	2.72	0.25	0.73	0.46	1.06

The normalized characteristics are necessary because the ranges of initial characteristics can differ too much for efficient Euclidian distance calculation.

From Table II, one can observe that the distances between two different regions, like $D\{I_1,I_2\}$, are greater than distances between two similar regions, like $D\{I_1,I_1\}$ or $D\{I_2,I_2\}$. In order to appreciate the efficiency of the presented algorithm, we analyzed the most unfavorable cases, namely the minimum distance between two regions coming from different images, and the maximum distance between two regions coming from the same image.

These distances are grouped in two categories, for d = 1,2,…,5 and d = 6,7,…,10 (Table III). Thus, $D_{min}\{I_1,I_2\}$ is grater than max$\{D_{Max}\{I_1,I_1\}, D_{Max}\{I_2,I_2\}\}$, especially in large neighborhood case (d = 6,7,…,10).

Towards ameliorate the classification accuracy, a development of the recognition algorithm, consisting in the attachment of new textural features like edge point density per unit of area and statistical features extracted from histogram of difference image, is proposed.

TABLE II
EUCLIDIAN DISTANCES BETWEEN DIFFERENT IMAGES

d	D $\{I_1 1,I_1 2\}$	D $\{I_2 1,I_2 2\}$	D $\{I_1 1,I_2 1\}$	D $\{I_1 1,I_2 2\}$	D $\{I_1 2,I_2 1\}$	D $\{I_1 2,I_2 2\}$
1	0,44	0,16	0,81	0,93	0,83	0,89
2	0,40	0,16	0,87	0,98	0,79	0,86
3	0,39	0,19	0,89	1,04	0,66	0,67
4	0.38	0,22	1,03	1,22	0,70	0,88
5	0,39	0,25	1.18	1,40	0,81	1,04
6	0,36	0,27	1,40	1,65	1,06	1,31
7	0,33	0,29	1,65	1,92	1,36	1,64
8	0,34	0,30	1,83	2,12	1,54	1,83
9	0,34	0,31	1,97	2,27	1,68	1,99
10	0,34	0,34	2,09	2,42	1,79	2,13

TABLE III
MINIMUM AND MAXIMUM DISTANCES

d=1,2,…,5

Images	D_{min}	D_{Max}
$D\{I_1,I_1\}$	0,38	0,40
$D\{I_2,I_2\}$	0,16	0,25
$D\{I_1,I_2\}$	0,66	1,40

d=6,7,…,10

Images	D_{min}	D_{Max}
$D\{I_1,I_1\}$	0,33	0,36
$D\{I_2,I_2\}$	0,27	0,34
$D\{I_1,I_2\}$	1,06	2,42

TABLE IV
EDGE DENSITIES OF THE ANALYZED REGIONS

Region	N_e	*A*	Den_e
$I_1(1)$	5818	16384	0.3551
$I_1(2)$	5820	16384	0.3552
$I_2(1)$	3481	16384	0.2125
$I_2(2)$	3296	16384	0.2012

Thus, we considered an edge extraction algorithm, based on binary image and logical function [11], which gives tinned edges. The edge densities for the analyzed regions $I_1(1)$, $I_1(2)$, $I_2(1)$, and $I_2(2)$ show that this feature has also a good discriminating power (Table IV) and the combination with the previously second order type statistical features will give better results in texture classification.

IV. TEXTURE DEFECT DETECTION

We assumed that there is a texture defect in a region $I(k)$.

Comparing with other image regions, one can decide if the texture of that region is tainted. The comparison in based by minimum Euclidian distance between feature vectors, like in the previous case. We have tested different statistic texture features like: histogram difference, edge density per unit of area, contrast, energy, entropy, homogeneity, and variance.

The method for defect detection and localization is similar with a template matching one. For experimental work we have divided a image with defects, I_3 (Fig. 8), in four regions, like in Fig.1. A region with reference texture (template texture), for example $I_3(4)$, is compared with the others: $I_3(1)$, $I_3(2)$, $I_3(3)$. If one region is not deteriorated, like $I_4(3)$, then the distance $D\{I_3(3),I_3(4)\}$ is small (Table V). If one region is tainted, like $I_3(1)$, then $D\{I_3(1),I_3(4)\}$ is relatively high. The test image I_3 is processed to be grey level type, 256 levels, and 1024x1024 pixels. Consequently, the dimension of the inside regions is 512x512 pixels.

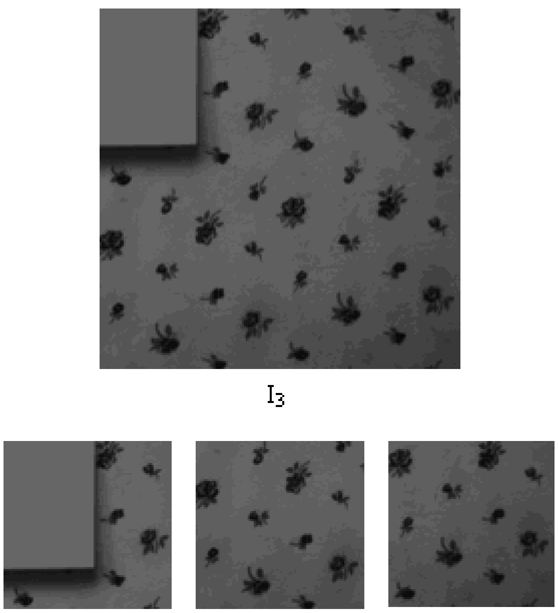


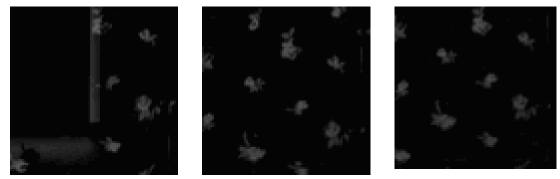
Fig.8 image with defect in texture, I_3 , and three regions inside

The feature vector is composed by five normalized statistical textures derived from average co-occurrence matrices. The defect decision is based upon an error threshold in distance evaluation. If the distance is grater than the threshold, then there is a defect in the tested region. In rest, there is not a defect in the tested region.

Also, we tested the efficiency of the grey level image difference histogram in texture classification and defect detection. With that end in view we have considered the same images form Fig. 8.

TABLE V
DISTANCE BETWEEN REGION PAIRS

Region pairs	Distance D
$I_3(3)$, $I_3(4)$	1,01
$I_3(1)$, $I_3(3)$	5,87
$I_3(1)$, $I_3(4)$	6,75



$I_3'(1)$ $I_3'(3)$ $I_3'(4)$

Fig.9 difference image for some regions inside of I_3

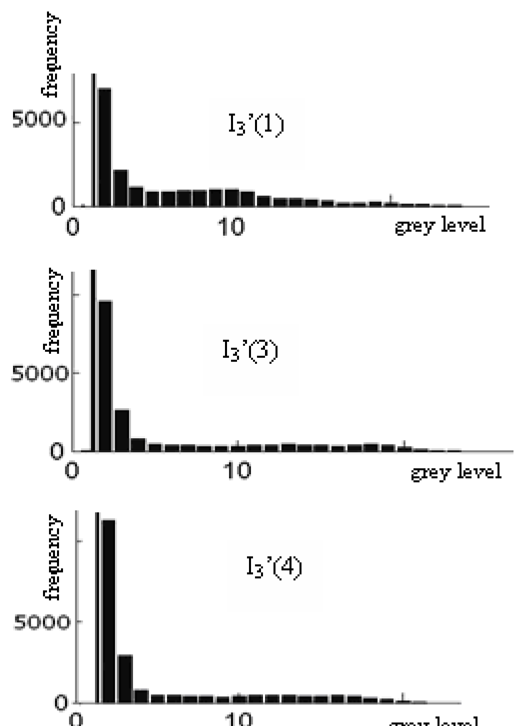
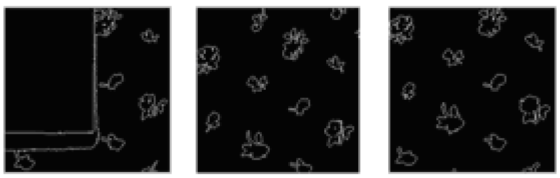


Fig.10 difference image histograms for regions inside of I_3

The difference images in the displacement (x = 20, y = 20) for $I_3(1)$, $I_3(3)$, and $I_3(4)$ are respectively $I_3'(1)$, $I_3'(3)$, and $I_3'(4)$ – Fig.9. The image difference histograms are presented in Fig.10. In graphical histogram representation, the value for gray level 0 is too high and irrelevant comparing with the others. Therefore it is neglected (thin line in graphical representation).

One can observe that the difference image histogram has better behavior referring to texture classification than to defect detection and localization. The basic aspect of the histogram is similar for regions without defect texture, but is dissimilar for region with defect texture. For this reason, the image difference histogram can be also utilized in texture classification by minimum distance criterion.

Another statistical feature analyzed is the edge pixels density per unit of area. With that end in view we have extracted the contour image from initial regions with a proper threshold [11] so that the texture model is not deteriorated (Fig.11). In the case of the image investigated, (I_3) the values for the thresholds and for the pixels densities are given in Table VI. One can observe that this feature has not a good discriminating power in the case of texture defect detection.



$I_3''(1)$ $I_3''(3)$ $I_3''(4)$

Fig.11 contour images for regions inside of I_3

TABLE VI
EDGE PIXEL DENSITY

Regions	Threshold	Density
$I_3(1)$	70	0.119
$I_3(3)$	70	0,175
$I_3(4)$	70	0.180
$I_4(1)$	50	0.024
$I_4(3)$	50	0.025
$I_4(4)$	50	0,025

V. CONCLUSION

Because it is considered an average co-occurrence matrix, the presented algorithm is relatively insensible to image translation and rotation. The results confirm that the statistic second order features, extracted from medium co-occurrence matrices, especially in the case d = 6, 7,…,10, offer a good discriminating power both in texture identification process and in defect detection and identification. The main application of the algorithm consists in texture identification and classification and defect detection in the regions of textured images (like images from satellite or images from video camera of intelligent vehicles). The additional features like difference image histograms and edge pixel density per unit of area increase the power of discriminating for texture identification and classification. The efficiency of the defect detection and localization depends upon the range of image partition and the texture element dimension.

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