STATISTICAL TEXTURE ANALYSIS OF ROAD FOR MOVING OBJECTIVES

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Obiectivul articolului este acela de a identifica şi de a localiza regiunile importante din imaginile cu textură pentru navigaţia obiectivelor mobile. Sunt analizate două tipuri de trăsături. Primul tip sunt histogramele şi densităţile de pixeli de contur. Trăsăturile de al doilea tip derivă din matricele de co-ocurenţă medii, noţiune ce a fost introdusă de autori. Algoritmii au fost implementaţi în MATLAB. Asfaltul este considerat textură de urmărit (referinţa) iar pietrişul şi iarba sunt considerate texturi de evitat. Rezultatele experimentale au reliefat faptul că trăsăturile ce derivă din matricele de coocurenţă medii prezintă putere de discriminare mare, atât pentru clasificarea, cât şi pentru localizarea regiunilor.

The paper objective is to identify and localize significant regions in textured images for navigating an autonomous agent. Two types of statistic texture features are used. The first type features are the histograms, and the edge density. The second type features derive from the medium co-occurrence matrices, which is a notion introduced by the authors. The algorithms are implemented in MATLAB. The basic texture is considered the asphalt and the different textures are considered the grass and the pebble. The experimental results indicate that the features, which derive from medium co-occurrence matrices, have a good discriminating power both for texture classification and region localization.

Keywords: texture, statistic features, medium co-occurrence matrix, edge densities, grey level histogram

1. Introduction

Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. It is very hard to define rigorously the texture into an image. The texture can be considered like a structure which is composed of many similar elements (patterns) named textons or texels, in some regular or continual relationship. Texture analysis has been studied 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,

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power spectrum, edge density per unit of area, etc.), fractal type (box counting fractal dimension), and structural type. In the last case, the textures are composed of primitives, and an image description is produced by the placement of these primitives according to certain placement rules. The structural approach is suitable to analyze textures with more regularity in the placement of texture elements. The statistical approach utilizes features to characterize the stochastic properties of grey level distribution in the image.

There are two important categories 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. The process, called texture segmentation, consists of similar texture region identification and different texture region separation. 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 route analysis for moving objectives, based on statistical features (especially derived from medium co-occurrence matrix).

For the purpose of algorithm validation, two experimental studies have been conducted. The first study is focused on region classification and localization of textured images composed of asphalt and pebble (Fig. 1, Image I_1), and the second study is focused on route identification and localization form textured images composed of asphalt and grass (Fig. 1, Image I_2).

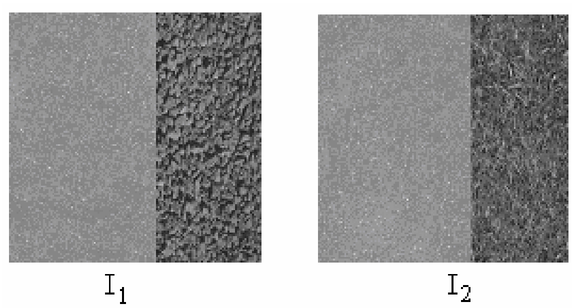

Fig. 1. Analyzed images I_1 and I_2.

With this end in view, the whole image is partitioned in sixteen equivalent regions (Fig. 2). Different textured regions are compared, based on minimum distance between measured features, which are derived from medium co-occurrence matrices (contrast, energy, entropy, homogeneity, and variance). Other texture features, like grey level histograms or contour pixel densities, are also discussed. Image region $I_1(1)$, which contains asphalt texture, is considered the reference texture template. If a region contains another texture or mixed textures, then it is a defect region.

I(1)	I(2)	I(3)	I(4)
I(5)	I(6)	I(7)	I(8)
I(9)	I(10)	I(11)	I(12)
I(13)	I(14)	I(15)	I(16)

Fig.2. Sixteen 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 region detection and localization.

2. Statistical methods to texture analysis

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

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

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

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

$N = n_1\, n_2$ 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 inadequate 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. Den_e 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 image region):

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

In (4), N_e represents the number of edge pixels (tinned edges, with one pixel thickness) 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 (6) in certain direction $d = (\Delta x, \Delta y)$, and co-occurrence matrices (9), must be considered:

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

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

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

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

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

The most powerful statistical method for 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 $d=(\Delta x, \Delta y)$:

$$C_d\,(i,j) = Card\{((x,y),(t,v))/I(x,y) = i,\ I(t,v) = j,$$

$$(x,y),\ (t,v) \in N \times N,\ (t,v) = (x+ \Delta x,\ y+ \Delta y)\} \tag{9}$$

From a co-occurrence matrix C_d one can draw out some important statistical features for texture classification. These features, which have a good discriminating power, were proposed by Haralick: contrast (11), energy (12), entropy (13), homogeneity (14), variance (15). The contrast measures the coarseness of texture. Large values of contrast correspond to large local variation of the grey level. The entropy measures the degree of disorder or non-homogeneity. Large values of entropy correspond to uniform GLCM. The energy is a measure of homogeneity.

3. Local features derived from mean co-occurrence matrix

For each pixel we consider increasing $(2d+1)x(2d+1)$ symmetric neighborhoods, d = 1, 2, 3,...,15. Inside each neighborhood there are 8 principal directions: 1, 2, 3, 4, 5, 6, 7, 8 (Fig. 3) and 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). With a view to obtain statistical feature insensitive relatively to texture rotate, we introduce the *mean co-occurrence matrix* notion. For each neighborhood type, the mean co-occurrence matrix C_{dm} is calculated by averaging the eight co-occurrence matrices (10):

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

Thus, for 3x3 neighborhood, d = 1; for 5x5 neighborhood, d = 2; for 7x7 neighborhood, d = 3; for 9x9 neighborhood, d = 4, and so on.

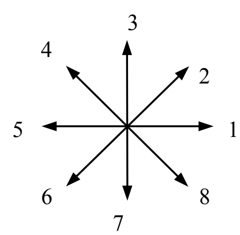

Fig.3. The principal directions for co-occurrence matrix calculus.

In order to quantify the spatial dependence of the gray level values from the average co-occurrence matrices C_{dm}, d = 1, 2,..., 10, it is necessary to compute 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).

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

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

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

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

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

In the preceding relations, *LxL* represents the dimension of co-occurrence matrices.

4. Experimental Results for Texture Classification and Route Identification by Statistical Features

For algorithm testing and program validation we used two textured images I_1 and I_2 (Fig. 1), each partitioned into sixteen regions $I_i(1)$, $I_i(2)$,. . . , $I_i(15)$, $I_i(16)$, i=1,2. The considered regions have 128 x 128 pixels, and 16 grey levels.

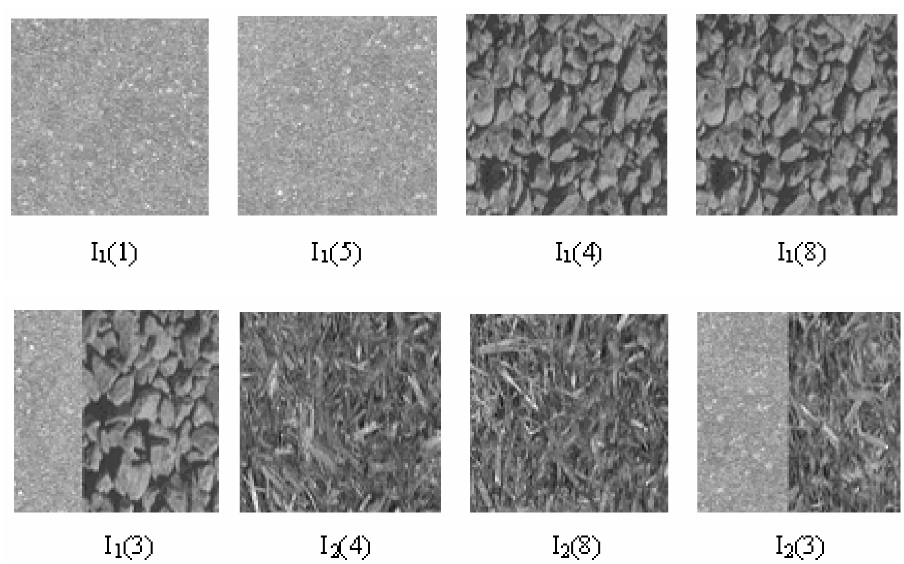

Fig. 4. Selected regions from I_1 and I_2.

From these images we chosen five regions for I_1 image: $I_1(1)$ – reference texture, asphalt; $I_1(5)$ – tested region, asphalt; $I_1(4)$ – tested region, pebble; $I_1(8)$ – tested region, pebble $I_1(3)$ – tested region, asphalt and pebble, and three regions for I_2 image: $I_2(4)$ – tested region, grass; $I_2(8)$ – tested region, grass; $I_2(3)$ – tested region, asphalt and grass (Fig. 4).

Firstly, the analysis of the simple grey level histograms (Fig. 5) demonstrates that the regions can be discriminated with the aid of the vectors of the histogram values. The distance between the histogram vectors of the regions $I_1(1)$ and $I_1(5)$ is smaller than the distance between the histogram vectors of the regions $I_1(1)$ and $I_1(3)$ or between the histogram vectors of the regions $I_1(1)$ and $I_2(3)$.

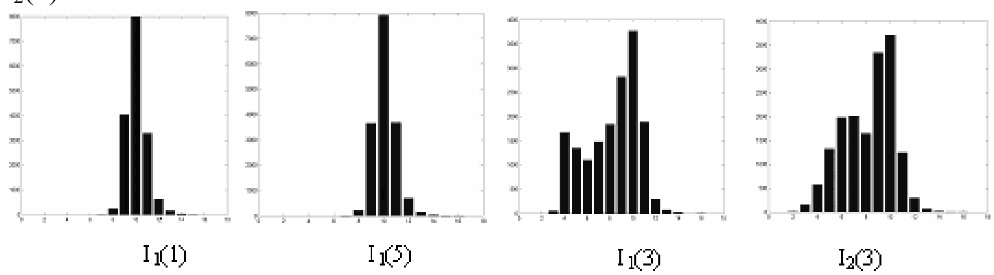

Fig.5. Grey level histogram

It was also tested the efficiency of the grey level image difference histogram in texture classification and defect region detection. With that end in view, we have considered the same images $I_1(1)$, $I_1(5)$, $I_1(3)$, $I_2(3)$. The image difference histograms in the displacement $x = 10$, $y = 10$ are presented in Fig. 6. In the graphical histogram representation, the value for gray level 0 is too high and irrelevant comparing with the others. Therefore it is neglected. One can observe that the difference image histogram has a better behavior referring to texture classification than to defect region detection and localization.

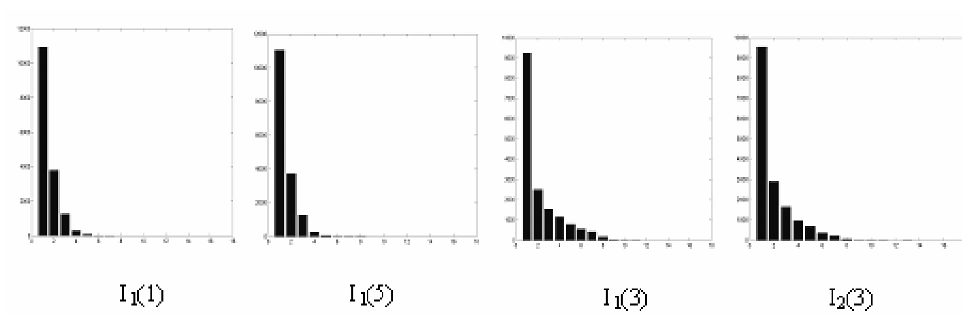

Fig.6. Grey level difference histogram

Secondly, supposing that the histograms are not so different, another set of statistical texture features makes possible the region classification. Thus, we can consider the co-occurrence matrices and the features derived from them. Textural features like Con_d, Ene_d, Ent_d, Omo_d, and Var_d are calculated from average co-occurrence matrices for different distances d. The normalized results are presented in Table 1, for d = 10. The normalized characteristics are necessary because the ranges of initial characteristics can differ too much for efficient Euclidian distance calculation.

For the purpose of the evaluation of the discriminating power of the selected features, we have calculated the Euclidian distances between regions with similar texture~~:~~, $D\{I_1(1),I_1(5)\}$, and the Euclidian distances between regions with different textures: $D\{I_1(1),I_1(4)\}$, $D\{I_1(1),I_1(3)\}$, $D\{I_1(1),I_2(4)\}$, $D\{I_1(1),I_2(3)\}$.

Table 1

Statistical texture features for d = 10

Region Index	Ent	Ene	Con	Omo	Var
$I_1(1)$	2.017	4.976	0.324	1.320	2.391
$I_1(3)$	1.693	1.005	1.547	0.973	1.596
$I_1(4)$	1.706	0.843	1.699	0.861	1.150
$I_1(5)$	2.013	4.876	0.325	1.323	2.420
$I_2(3)$	1.849	1.542	0.898	1.186	1.691
$I_2(4)$	1.867	1.543	1.183	1.072	1.104
$I_2(8)$	1.847	1.327	1.279	1.032	1.102

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:

$$D\,(I_1, I_2) = \sqrt{(C_1 - C_2)^2 + (E_1 - E_2)^2 + (Et_1 - Et_2)^2 + (O_1 - O_2)^2 + (V_1 - V_2)^2} \qquad (16)$$

where: $C = Con$, $E = Ene$, $Et = Ent$, $O = Omo$, $V = Var$. The results of the mentioned distances calculus are presented in Table 2.

Table 2

Euclidian distances between template $I_1(1)$ and different regions

d	$D\{I_1(1),I_1(5)\}$	$D\{I_1(1),I_1(4)\}$	$D\{I_1(1),I_1(3)\}$	$D\{I_1(1),I_2(4)\}$	$D\{I_1(1),I_2(3)\}$
5	0.120	5.050	4.629	4.001	3.773
10	0.105	4.563	4.257	3.577	3.448
15	0.121	4.117	3.919	3.183	3.104

One can observe that the distances between two different regions, like $D\{I_1(1),I_1(4)\}$, $D\{I_1(1),I_1(3)\}$,$D\{I_1(1),I_2(4)\}$,$D\{I_1(1),I_2(3)\}$, are greater than the distances between two similar regions, like $D\{I_1(1),I_1(5)\}$. In order to evaluate the efficiency of the presented algorithm, we analyzed the most unfavorable cases, namely the minimum distance between two regions coming from different textures, and the maximum distance between two regions coming from the same texture. Thus, the minimum value for dissimilar textures,

$$min\{D\{I_1(1),I_1(3),D\{I_1(1),I_1(4)\},D\{I_1(1),I_2(4)\},D\{I_1(1),I_2(3)\}\} = 3.104,$$

is greater than the maximum value for similar textures,

$$max\{D\{I_1(1),I_1(5)\}\} = 0.121,$$

in the large neighborhood case (d = 5,10,15). To 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, is analyzed. Thus, we considered an edge extraction algorithm, based on binary image and logical function [11], which gives tinned edges (Fig. 7).

Unfortunately, the edge densities for the analyzed regions $I_1(5)$, $I_1(3)$, $I_1(4)$, $I_2(3)$, and $I_2(4)$ show that this feature has not a good discriminating power (Table 4). The combination with the previous second order type statistical features will give better results in texture classification. Another disadvantage of this algorithm is the dependence of the results on the threshold level for edge extraction.

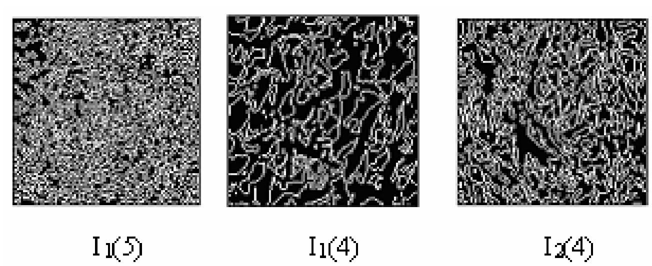

Fig. 10. Contour image for some regions.

Table 4.

Edge densities for some regions

Region	I_1 (5)	I_1 (4)	I_1 (3)	I_2 (4)	I_2 (3)
Den_e	0.401	0.188	0.195	0.300	0.199

5. Concluding remarks

Because it is an average co-occurrence matrix, the presented algorithm is relatively insensitive to image translation and rotation. The results confirm that the statistic second order features, extracted from medium co-occurrence matrices, in the case d = 5, 10, 15, offer a good discriminating power both in the texture identification process and in the defect region detection and identification. The main application of the algorithm consists in road (asphalt) identification and defect region detection (pebble or grass) in textured images (like images from fixed camera or images from video camera of intelligent vehicles). The additional features, like difference image histograms and edge pixel density per unit of area, can increase the power of discrimination for texture identification and classification. The efficiency of the route following and defect region detection and localization depends upon the range of image partition.

R E F E R E N C E S

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