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ROAD ANALYSIS BASED ON TEXTURE SIMILARITY EVALUATION

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Abstract: The paper presents an image processing algorithm based on statistical methods in order to evaluate the road delimiting by textured region similarity measurement and defect texture detection and localization. With the purpose of algorithm validation, the images are divided in sixteen equivalent regions. For the proper region identification and classification, a decision theoretic method and two types of statistic texture feature are used. The first type features derive from the medium co-occurrence matrices: contrast, energy, entropy, homogeneity, and variance, but in normalized form. The second type feature is 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 them and a reference image region. The basic texture (reference) is considered an asphalt one and the different textures are considered like the grass and the pebble. The result is the classification of the tested texture in road and non-road type, based on the similarity evaluation and the localization of the defect regions.

Key-words: Texure similarity, Statistic normalizad features, Medium co-occurrence matrix, Edge densities, Defect localization, Road analysis.

1 Introduction

Image texture, defined as a function of spatial variation in pixel intensity (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. 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 has been studied using various approaches, like statistical type (characteristics derived from grey level histogram, grey level image difference histogram, co-occurrence matrices, autocorrelation, power spectrum, etc.), fractal type (box counting fractal dimension*)*, and structural type.

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 road 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 for textured images composed of asphalt and pebble (Image I_1), like in Fig. 1. The second study is focused on road identification and localization form textured images composed of asphalt and grass (Image 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). Image region $I_1(1)$, which contains only asphalt texture is considered the

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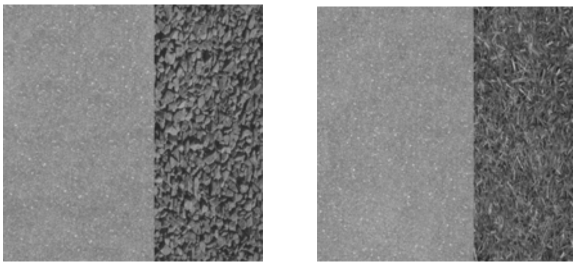
reference texture template. If a region contains another texture or mixed textures, then it is considered a defect region.



I_1 I_2

Fig. 1. Analyzed images I_1 and I_2.

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 Feature based method for texture similarity evaluation

The most powerful statistical method for texture similarity evaluation 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, four bits grey level images give 16x16 co-occurrence matrices. The elements of a co-occurrence matrix C_d (1) depend upon the displacement $d=(\Delta x, \Delta y)$.

$$C_d(i,j) = Card\{((x,y),(t,v))/I(x,y) = i, I(t,v) = j, (x,y), (t,v) \in N \times N, (t,v) = (x+\Delta x, y+\Delta y)\} \quad (1)$$

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, energy, entropy, homogeneity, variance.

For each pixel we can consider $(2d+1)$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 average co-occurrence matrix notion.

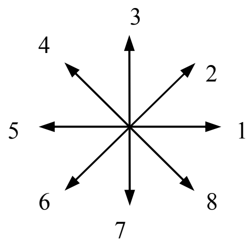


Fig.3. The principal directions for co-occurrence matrix calculus

Thus, for each neighborhood type, we define an average co-occurrence matrix C_d which is calculated by the average of the eight co-occurrence matrices (2).

$$C_d = 1/8(C_{d,1} + C_{d,2} + C_{d,3} + C_{d,4} + C_{d,5} + C_{d,6} + C_{d,7} + C_{d,8}), \; d = 1,2,...,15 \quad (2)$$

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

In order to quantify the spatial dependence of gray level values, from average co-occurrence matrices C_d, we calculate various textural features like Contrast – Con_d – (3), Energy – Ene_d – (4), Entropy – Ent_d – (5), Homogeneity – Omo_d – (6) and Variance – Var_d – (7).

$$Con_d = \sum_{i=1}^{L}\sum_{j=1}^{L}(i-j)^2 C_d(i,j) \quad (3)$$

$$Ene_d = \sum_{i=1}^{L}\sum_{j=1}^{L} C_d(i,j)^2 \quad (4)$$

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$$Ent_d = -\sum_{i=1}^{L}\sum_{j=1}^{L} C_d(i,j)\log(C_d(i,j)) \qquad (5)$$

$$Omo_d = \sum_{i=1}^{L}\sum_{j=1}^{L} \frac{C_d(i,j)}{1+|i-j|} \qquad (6)$$

$$Var_d = \frac{1}{L}\sum_{i=1}^{L}\sum_{j=1}^{L}[C_d(i,j) - \overline{C_d(i,j)}]^2 \qquad (7)$$

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

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

$$D(I_1,I_2)=\sqrt{(C_1-C_2)^2+(E_1-E_2)^2+(Et_1-Et_2)^2+(O_1-O_2)^2+(V_1-V_2)^2} \qquad (8)$$

where: $C = Con$, $E = Ene$, $Et = Ent$, $O = Omo$, $V = Var$.

Another simple statistic features is the edge density per unit of area, Den_e (9). The density of edges, detected by a local binary edge detector, can be used to distinguish between fine and coarse texture, like in Fig.1. 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:

$$Den_e = \frac{N_e}{A} \qquad (9)$$

In (9), N_e represents the number of edge pixels (tinned edges, with one pixel thickness) and A is the region area (pixel number of image region).

4 Experimental results for texture classification and road identification by statistical features

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

From these images we have considered 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).

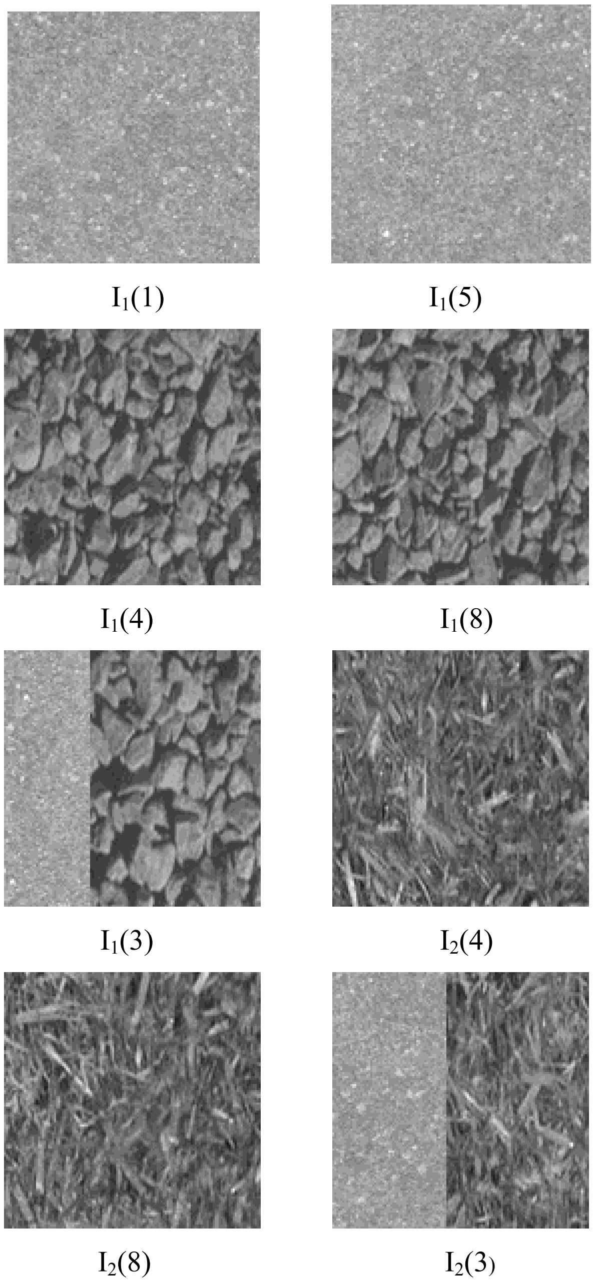

Fig. 4. Selected regions from I_1 and I_2.

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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 (I_1) and Table 2 (I_2), for d = 10.

Table 1. Normalized statistical texture features for I_1 and d = 10.

Region Index	Ent	Ene	Con	Omo	Var
1	1.00	1.00	1.00	1.00	1.00
3	0.85	0.20	4.84	0.73	0.48
4	0.85	0.17	5.31	0.65	0.48
5	1.00	0.98	1.00	1.00	1.01
8	0.85	0.17	5.25	0.66	0.48

The normalized characteristics are necessary for efficient Euclidian distance calculation, because the ranges of initial characteristics can differ too much. The normalization is refered to refference texture (region $I_1(1)$).

Table 2. Normalized statistical features for I_2 and d = 10

Region Index	Ent	Ene	Con	Omo	Var
3	0.93	0.31	2.81	0.90	0.71
4	0.94	0.26	5.72	0.81	0.46
8	0.93	0.27	4.00	0.78	0.46

The results of the Euclidian distance calculus between template $I_1(1)$ and mentioned different regions distances have the following values:

$D\{I_1(1),I_1(3)\} = 3.96$

$D\{I_1(1),I_1(4)\} = 4.43$

$D\{I_1(1),I_1(5)\} = 0.02$

$D\{I_1(1),I_1(8)\} = 4.37$

$D\{I_1(1),I_2(3)\} = 1.96$

$D\{I_1(1),I_2(4)\} = 4.81$

$D\{I_1(1),I_2(8)\} = 4.11$

One can observe that the distances between two different regions, like $D\{I_1(1),I_1(4)\}$, $D\{I_1(1),I_1(8)\}$, $D\{I_1(1),I_1(3)\}$, $D\{I_1(1),I_2(4)\}$, $D\{I_1(1),I_2(8)\}$, $D\{I_1(1),I_2(3)\}$, are greater than distances between two similar regions, like $D\{I_1(1),I_1(5)\}$. 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 textures, and the maximum distance between two regions coming from the same texture. Thus, minimum value for dissimilar textures,

$$min\{D\{I_1(1),I_1(3),D\{I_1(1),I_1(4)\},D\{I_1(1),I_2(4)\}, D\{I_1(1),I_2(3)\},....\} = 1.82,$$

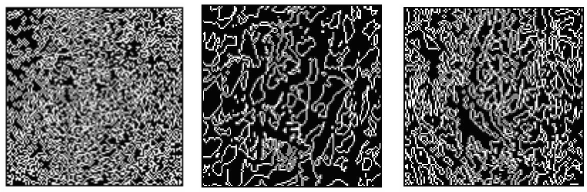
is grater than maximum value for similar textures,

$$max\{D\{I_1(1),I_1(2)\}, D\{I_1(1),I_1(5)\},...\} = 0.10,$$

in large neighborhood case (d = 5,10,15).

Also, we can observe that the most important features, with greater discriminating power, both in texture similarity evaluation and in defect region detection and identification, are the contrast and the energy.

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 is analyzed. Thus, we considered an edge extraction algorithm, based on binary image and logical function [11], which gives tinned edges (Fig. 5).



$I_1(5)$ $I_1(4)$ $I_2(4)$

Fig. 5. Contour image for some image regions

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

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Table 3. Edge densities for some regions

Region	*Den_e*
I_1 (1)	0.406
I_1 (5)	0.401
I_1 (4)	0.188
I_1 (3)	0.195
I_2 (4)	0.251
I_2 (3)	0.199

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, in the case d = 5, 10, 15, offer a good discriminating power both in texture similarity evaluation and in 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 discriminating for texture identification and classification. The efficiency of the road following and defect region detection and localization depends upon the range of image partition. The most important features, with greater discriminating power, both in texture similarity evaluation and in defect region detection and identification, are the contrast and the energy.

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