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# One Dimensional Object Segmentation and Statistical Features of an Image for Texture Image Recognition System

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***Abstract*****—**Traditional object segmentation methods are time consuming and computationally difficult. In this paper, one-dimensional object detection along the secant lines is applied. Statistical features of texture images are computed for the recognition process. Example matrices of these features and formulae for calculation of similarities between two feature patterns are expressed. And experiments are also carried out using these features.

***Keywords*****—**1-D object segmentation, secant lines, object-occurrence (frequency) matrix, contiguity matrix, statistical features.

## I. INTRODUCTION

IN the practical applications can frequently be seen image classification and analysis problems. Texture images do not contain precisely expressed objects and cannot be considered as a sense with certain physical, technical or other meaning. Such images contain randomly located figures (objects) with different form, orientation and brightness. Examples of such texture images are :

- the extremely increased histological images (Fig.1*a*) used in medical and biological researches;
- results of sounding from the satellite to a surface of the Earth by means of a radar in different ranges of wave lengths;
- the decorative art pictures, deprived substantial objects on the image (Fig.1*b*), and so forth.

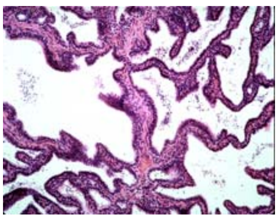

Fig. 1. *a*) Histological image

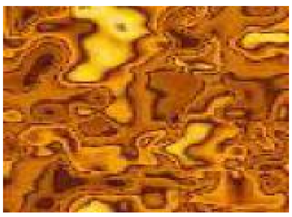

Fig. 1. *b*) Decorative patterns

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These textures are different each other in the patterns containing base elementary figures (structural primitives) in various scale, orientation, light exposure and, probably regularities.

## II. OVER VIEW OF THE SYSTEM

Digital processing of texture images is a difficult methodological and computational problem. In the theory and practical of texture image processing and recognition, the significant contribution have been made by Haralick, Gonzalez, Rosenfeld, Shapiro, Hawkins, and Zhang J., etc. Nevertheless, it is not yet created theoretical bases and algorithmic decision making in the field of texture image processing which really meet the practical needs.

In this work, the new methodological approach to texture processing based on concept of secant lines of an image. This approach allows solving the following problems connected with texture recognition process:

- How to construct a set of informative features which fully describe color intensity and structural properties of texture images;
- How to provide feature invariants of rotation, scale and light exposure of a scene at image registration;

## III. SECANT LINES OF AN IMAGE AND ONE-DIMENSIONAL OBJECT SEGMENTATION

Let's understand a secant line on an image $Q$ as an arbitrary cross straight line on a plane($x$, $y$) and its end points are at the edge of the image. Let $N_Q$ randomly generated secant lines on the image, $Q_i,\ i=\overline{1,N_Q}$ .

Consider $Q$ one of the secant lines, $Q_i,\ i=\overline{1,N_Q}$ , which goes along the coordinate *z.* Color intensity space $I(x,y)$ of image along the line can be expressed as function $I(z)$ ,

where $z=\alpha_Q x+\beta_Q y+\gamma_Q$ ,

$\alpha_Q,\beta_Q,\gamma_Q$ – parameters of secant lines,

$x\in[x_1,x_2]$, $y\in[y_1,y_2]$,

$(x_1, y_1)$ and $(x_2, y_2)$ - end point of a cross line *Q*. A fragment of an image with a secant line crossing through bright objects on the darker background is displayed in Fig(2). Along that secant line, various object segments and backgrounds are detected.

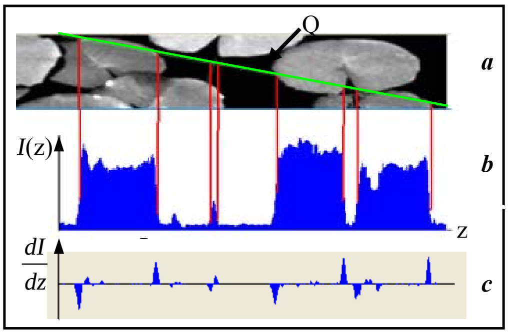


Fig. 2. A fragment of an image with a secant line *Q* (*a*), function *I*(*z*) (*b*), and differential $\frac{dI}{dz}$ (*c*) along that line.

With the aim of the experimental research work, a program is developed for texture image recognition problem. Experiments shows that in the typical research work of texture image recognition system, from 300 to 500 lines should be used for getting the enough statistical samples.

Random character of secant lines allows statistical property invariant of detected segments related to texture rotation in the vision of registered camera. An example of a texture image with random secant lines is shown in the following Fig3.

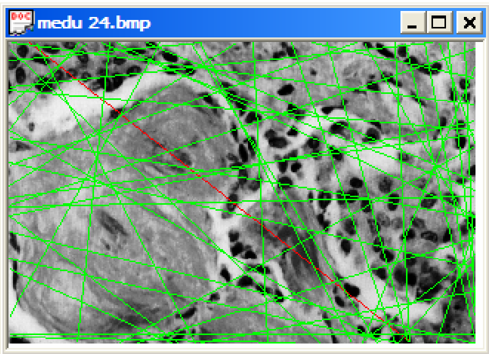


Fig. 3. Random secant lines on a texture image ( $N_Q$ = 200)

One-dimensional object segmentation is carried out for detection edges of the segments using differential $\frac{dI}{dz}$. For differential approximation $\frac{dI}{dz} = I'$ in this work optimal discrete linear filter "moving average" with the limited impulse characteristic [6],

$$\phi = (\phi_k, k \in [-2, 2]) = \left(\frac{2}{7}, -\frac{1}{7}, -\frac{2}{7}, -\frac{1}{7}, \frac{2}{7}\right)$$

$$I'(z_i) = \sum_{k=-2}^{2} \phi_k \; I(z_{i-k}),$$

where $z_i = i \Delta z$, $i \in [i_{\min}, i_{\max}]$

Example processing result of function $I'(z)$ using this filter is displayed above in the Fig(2*c*). For the noise image and blur object edges, a filter with impulse characteristic $\phi = (0.2, 0.1, 0, -0.1, -0.2)$, having great coefficient to reduce noises, can be used.

Sequentially, impulse values o differential $I'(z)$ characterize as the edges of one-dimensional segments. We can delete low values of $I'(z)$ not greater than the given threshold for reducing misdetection in the segmentation process.

Segmentation along all the secant lines of the image is carried out to create an array $P_S$ of segments $S_n$, $n = \overline{1, N_S}$. Each element of these segments characterize as coordinates of central point $c_n^{(x)}$, $c_n^{(y)}$ in the (*x*, *y*) coordinate system, angle to the horizontal axis $\varphi_n$, length $L_n$ and average intensity $I_n$, $n = \overline{1, N_S}$ :

$$P_S = \left\{ \left( c_n^{(x)}, c_n^{(y)}, \varphi_n, L_n, I_n \right),\; n \in \overline{1, N_S} \right\}.$$

This array is considered as statistical sample based on statistic having color and structural properties of texture image. If there is a need of invariance to recognition system concerning variations of light exposure and image scale, it is necessary to transform features length *L* and brightness *I* of segments to some standardized scales. This is carried out by means of functional transformations of segment characteristics *L* and *I*.

## IV. THE FREQUENCIES TABLE OF SEGMENTS DISTRIBUTION BY LENGTH AND BRIGHTNESS

The simple statistic used for texture image recognition, characterizes the law of probability distribution of the first order for random brightness fields. We will consider the two-dimensional histogram of local relative frequencies of segment hits $S_n$, $n = \overline{1, N_S}$, into the given classes – fixed intervals by length and brightness.

On Table1, the example of such histogram, in which number of classes by length $N_L = 10$ and by brightness $N_I = 10$ is presented. Classes non-uniformly cover possible value intervals of segment length from 1 to $L_{\max}$ and brightness from 0 to $I_{\max}$.

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Frequency table $H$ is a matrix with the size of $N_L \times N_I$ elements in which $h_{ij}$ represents the relative frequency hitting segments into a class with a range of length $[(L_{i-1}+1),\ L_i]$ and brightness value $[(I_{j-1}+1),\ I_j]$. Thus,

$$\sum_{i=1}^{N_L}\sum_{j=1}^{N_I} h_{ij} = 1$$

TABLE I RELATIVE FREQUENCY HIT BY SEGMENTS INTO A FIXED CLASS OF LENGTH AND BRIGHTNESS.

| $L \backslash I$ | 0-$I_1$ | ($I_1$+1)-$I_2$ | --- | ($I_9$+1) – $I_{max}$ = $I_{10}$ |
|---|---|---|---|---|
| < $L_1$ | 0.06 | 0.009 | --- | 0.0204 |
| ($L_1$+1)-$L_2$ | 0.17 | 0.0504 | --- | 0.00021 |
| : | : | : | --- | : |
| : | : | : | --- | : |
| : | : | : | --- | : |
| $L_9$< | 0.00 | 0.0001 | --- | 0.0003 |

The table of frequencies H objectively characterizes the law of first order probability distribution only if for its construction, sufficient amount sample is used. Usually in statistical researches it is recommended to choose such number of classes of the histogram in order to the average of each class is not less than ten selective values. In this case, that requirement is expressed by a following inequality:

$$N_S > 10 \cdot N_L \cdot N_I$$

This defines the amount of lines made on image and contained $N_S$ segments.

Selection of the best amount of intervals is just an optimization problem not discussed here.

## V. CONTIGUITY MATRIX BY LENGTH AND BRIGHTNESS

Today's well-known texture analysis methods use descriptor based on intensity distribution of each pixel or 2 pixels contiguous with each other relating on the given distance by vertically and horizontally [1]. First type of distribution is only brightness variation on the plane (contrast, "smoothness" or "roughness" of a texture). Second type o distribution allows to make a decision about mutual positioning of pixels having given brightness. Such type of distribution is in the form of contiguity matrix of pixel brightness.

If interval count of brightness is $N_I$, then contiguity matrix of pixel brightness $A$ has a size $N_I * N_I$. To construct it, a positioning parameter $P = (p_x, p_y)$ must be given. Element $a_{lk}$ of that matrix $A$ is defined as a number, when a pixel in the position $(i, j)$ have brightness $I_l$ and at the same time next pixel at $(i + p_x, j + p_y)$ have the value $I_k$, where $i = \overline{1,(N_x - p_x)}$, $j = \overline{1,(N_y - p_y)}$, $N_x * N_y$ – size of image, $l,k = \overline{1,\ N_I}$.

In this paper feature matrices are calculated just based on segments $P_S$, not based on pixels. Examples of these matrices are as follow:

| L\L | 0-5 | 6-10 | 11-20 | 21-30 | 31-50 | 51-80 | >81 |
|---|---|---|---|---|---|---|---|
| 0-5 | 1034 | 993 | 572 | 245 | 155 | 76 | 37 |
| 6-10 | 958 | 1077 | 624 | 259 | 162 | 75 | 32 |
| 11-20 | 558 | 650 | 376 | 147 | 89 | 53 | 18 |
| 21-30 | 289 | 226 | 120 | 46 | 59 | 30 | 12 |
| 31-50 | 148 | 154 | 96 | 43 | 38 | 24 | 14 |
| 51-80 | 59 | 71 | 57 | 30 | 16 | 11 | 5 |
| >81 | 30 | 40 | 22 | 8 | 10 | 2 | 1 |

Fig. 4. Example contiguity matrix by length of detected segments (Lines=500, Image size=400 * 300)

| L\I | 25 | 50 | 75 | 100 | 125 | 150 | 175 | 200 | 225 | 255 |
|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 360 | 193 | 243 | 189 | 177 | 81 | 42 | 8 | 0 | 0 |
| 6 | 780 | 234 | 261 | 321 | 331 | 200 | 84 | 66 | 29 | 0 |
| 9 | 302 | 37 | 38 | 107 | 221 | 77 | 35 | 38 | 46 | 7 |
| 12 | 95 | 22 | 11 | 62 | 177 | 63 | 27 | 16 | 23 | 20 |
| 15 | 46 | 6 | 5 | 46 | 144 | 63 | 26 | 7 | 4 | 20 |
| 24 | 54 | 6 | 4 | 66 | 360 | 130 | 40 | 19 | 21 | 57 |
| 33 | 12 | 0 | 0 | 43 | 278 | 101 | 20 | 8 | 15 | 46 |
| 70 | 5 | 3 | 0 | 41 | 543 | 255 | 41 | 28 | 37 | 129 |
| 107 | 0 | 0 | 0 | 6 | 133 | 65 | 13 | 4 | 17 | 14 |
| 165 | 0 | 0 | 0 | 0 | 14 | 12 | 1 | 3 | 5 | 7 |

Fig. 5. Example frequency matrix of detected segments (Lines=500, Image size=400 * 300)

| I\I | 0-35 | 36-71 | 72-107 | 108-143 | 144-179 | 180-215 | 216-256 |
|---|---|---|---|---|---|---|---|
| 0-35 | 78 | 107 | 492 | 878 | 95 | 47 | 99 |
| 36-71 | 131 | 56 | 287 | 321 | 34 | 18 | 28 |
| 72-107 | 493 | 262 | 475 | 441 | 64 | 19 | 30 |
| 108-143 | 745 | 339 | 424 | 651 | 140 | 104 | 64 |
| 144-179 | 112 | 31 | 46 | 76 | 56 | 70 | 44 |
| 180-215 | 138 | 29 | 16 | 51 | 21 | 23 | 18 |
| 216-256 | 99 | 51 | 43 | 49 | 25 | 15 | 7 |

Fig. 6. Example contiguity matrix by average intensity of detected segments. (Lines=500, Image size=400 * 300)

## VI. PROCESS OF STATISTICAL FEATURE OF A TEXTURE IMAGE

$Q_i,\ i = \overline{1, N_Q}$ - $i^{th}$ secant line,

$N_Q$ - overall amount of lines,

$S_n$ - detected segments,

$A_{LI} = \{a_{ij}, i, j = \overline{0,9}\}$ - object occurrence matrix by length and brightness

$A_L = \{a_{ij}, i, j = \overline{0,6}\}$ - contiguity matrix by length,

$A_I = \{a_{ij}, i, j = \overline{0,6}\}$- contiguity matrix by average intensity.

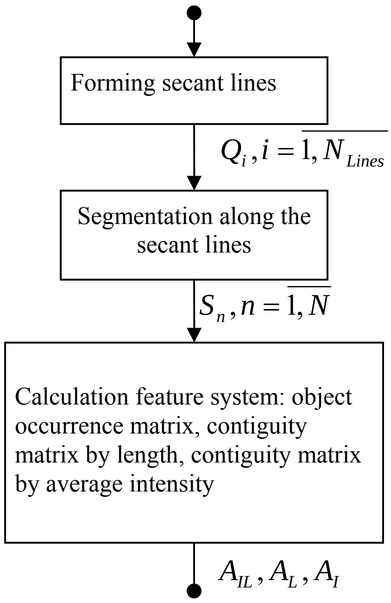



Fig. 7. Stages of feature construction

## VII. Recognition using obtained features

For input image pattern, similarities (or distance) are calculated with each stored patterns of a database. Following criteria are considered as a result output image among the patterns stored in Database.

Root mean square:

$$F_k = \sum_{i=1}^{N_L}\sum_{j=1}^{N_I}\left(h_{ij}(cur) - h_{ij}^k(ptn)\right)^2,$$

$$\sum_{i=1}^{N_L}\sum_{j=1}^{N_I} h_{ij} = 1,$$

Entropy:

$$F_k = \sum_{i=1}^{N_L}\sum_{j=1}^{N_I} h_{ij}(cur)\ln\frac{h_{ij}(cur)}{h_{ij}(ptn)} \quad \text{or}$$

$$F_k = \sum_{i=1}^{N_L}\sum_{j=1}^{N_I} h_{ij}(ptn)\ln\frac{h_{ij}(ptn)}{h_{ij}(cur)},$$

$$\arg\left(\min_{k=\overline{1,K}} F_k\right) = k^*,$$

where,

$F_k$ - distance of relative frequency matrix between $k^{th}$ pattern and input pattern,

$h_{ij}$ - relative frequency hit of segments in the range of $(i,j)$,

$N_L$ - number of intervals by object length,

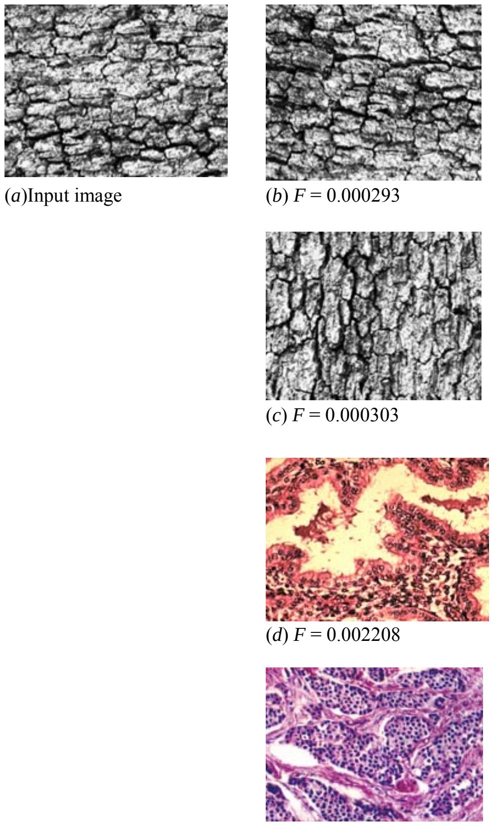
$N_I$ - number of intervals by average intensity,

$k = \overline{1, K}$, $K$ – pattern count in the pattern database,

$k^*$ – pattern number of database similar to input image.

## VIII. Sample experimental result using by Root-mean square method

The following images are the results coming out from texture image recognition system using Root-mean-square method in Figure 7.



(*a*)Input image

(*b*) $F = 0.000293$

(*c*) $F = 0.000303$

(*d*) $F = 0.002208$

(*e*) $F = 0.002446$

Fig. 7. Example result (with calculated root-mean square values) of most similar texture images from database (testing DB with 200 images)(*b-e*) to the input texture image (Bark of a tree)(*a*).

## IX. Conclusion

Detected matrices can fully present as an informative pattern of a texture image having the form of brightness and structural properties. We developed a system using these features set to recognize texture images and results showed that these are enough for typical texture image recognition systems or practical use.

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