A New Parallel Scheme for Robust Segmentation of Textured Images

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Abstract

This paper proposes a parallel scheme/algorithm which is based on statistical analyses to fulfilthe robust segmentation of nature texture image. The whole scheme is constructed as the parallel hierarchical network with the recursive mechanism and formed as multi-layered structure. It has segmented a mixed nature texture images made of two sort of sleepskings with success. The result is satisfied and shows that the algorithm is high effective and practical and can be applied in production as an essential software of computer automation recognition system of leather quality.

1. Introduction

Segmentation of a textured image into meaningful regions is one of the important tasks in the computer vision system. The quality of feature extraction and the quality of the segmentation algorithm are the two crucial factors in the system. In the texture image segmentation processing, the follow respects should be taken into consideration[1]: (1) segmentation of real imagery should processes the stochastic texture types and various of feature characteristics; (2) texture images should comprise region boundaries with a certain level of complexity; (3) texture feature evaluation for segmentation purposes implies a comparison of boundary accuracies. In our study, the selection and extraction of texture characteristics is a key step and the result of feature computation procedure. The texture pattern attribution is constructed by mathematical model of two-dimensional random field and represented by vector form. Just on the basis above, the parallel hierarchical network algorithm is proposed and based on the statistical analysis to fulfilthe effective segmentation of natural texture image. The whole algorithm is not only parallel but also non-recursive hierarchical. Therefore, it could overcome the shortcomings of traditional sequence operation such as lower efficiency, higher opeating complication and inferior adaptability, etc.. So the image segmentation can be effectively completed.

2. The Parallel Algorithm

The algorithm is made of three layers:
(1) modeling the parallel random field and extracting texture characteristic;
(2) edge detection based on vector analysis;
(3) edge tracking operation.
Its construction is expressed in Fig.1.

The efficiency and accuracy of texture image processing are directly determined by the result of feature of calculation. The mathematical model is utilized to represent the spatial

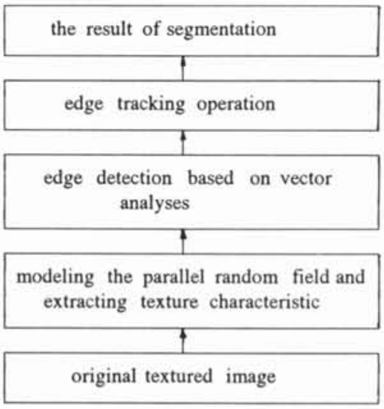

Fig.1

attribution of relevant pattern vector. Through the system parameter identification, we can construct the local texture characteristic vectors which lay a foundation of segmentation and judgement. In the space of characteristic vector, we use the parallel operation of windows as a calculating method, which has advantages such as non-iteration, lower calculating complication and so on. With the aid of judging vector uniform of windows, we can detect the existence of edge which should be marked properly. And then, the continuous texture image region edge will be calculated through the limited edge tracking in the parallel windows and the accurate operation. And now, the image segmentation is effectively completed.

3. Image Segmentation Process

3.1 The Random Modeling

Let $\{ g(x,y);\ x,y=0,1,\ldots,m-1\}$ be a two-dimensional array representing the gray level values of a discrete M*M image. Ifthis image obey a SAR(simultaneous autoregressive) model defined over a M*Mtoroidal lattice, then g(x,y): the gray level of a pixel located at (x,y), is related to the gray levels of its neighboring pixels by:

$$g(x,y)-\mu_g = \sum_{(i,j)\in N} Q(i,j)\,(g(x\oplus i, y\oplus j)-\mu_g)+\sqrt{\rho_n}\,\omega(x,y)$$

where:
μ_g = sample mean of image gray level values.
N = a neighbor set defined in the spatial domain.
Q(i,j) = coefficients of the model characterizing the spatial pattern.
$\oplus$ = addition module M.

$\omega(x,y)$ = independent identically distributed Gaussian random variable with zero mean and unit variance.

ρ_N = overall variance of the noise which is measure of randomness of texture.

N neighbor set is defined as the neighborhood around each pixel and consists of a set of integer pairs excluding (0,0). The different selection of the neighbor constructs the correspondent modeling for different estimation process. The six features are desired from two different SAR models. The feature set could be represented as: { Q(0,1),Q(1,0),ρ_{N1},Q(1,1),Q(-1,1),ρ_{N2}}. The first three come from a SAR model with symmetric neighbor set: N1= {(1,0),(0,1),(-1,0),(0,-1)}. These features capture texture characteristics in { horizontal, vertical } directions. The remaining three are calculated using: N2= {(1,1),(-1,1),(-1,-1),(1,-1)} which focus on { diagonal, off-diagonal } directions[2].

For the pattern discrimination and classification, the hierarchical procedure should be considered. The correspondent definition and stepwise asymptotical computational operations are proceeded also.

3.2 Parallel Clustering

3.2.1 Unsupervised Mechanism

Based on the local clustering and distribution of the clusters, the unsupervised criteria S could be defined as:

$$S = C_S * S_I * S_B * S_P \qquad (1)$$

where Cs is the coefficient to make the S values in [0.00,1.00].

$$S_I = \frac{n_{cl}}{\sum_{l=1}^{n_{cl}} \delta_l^2} \qquad (2)$$

where δ_l^2 is the region intensity variance of clustering,n_{cl} is the number of clusters.

$$S_B = \frac{\sum_{i=1}^{n_{cl}}\sum_{j=1}^{n_{cl}} \| L_{PK}^{(i)} - L_{PK}^{(j)} \|^2}{n_{cl}(n_{cl}-1)} \qquad (3)$$

$L_{PK}^{(i)}$-----the center position of ith cluster
$L_{PK}^{(j)}$-----the center position of jth cluster

$$S_P = \frac{\sum_{i=1}^{n_{cl}}\sum_{j=1}^{n_{cl}} (C_{PK}^{(i)} - C_{PK}^{(j)})^2}{n_{cl}(n_{cl}-1)}, \quad (i \neq j) \qquad (4)$$

$C_{PK}^{(i)}$-----the probability value of ith cluster center
$C_{PK}^{(j)}$-----the probability value of jth cluster center
Thus,

$$S = C_S * S_I * S_B * S_P$$
$$= \frac{n_{cl}\sum_{i=1}^{n_{cl}}\sum_{j=1}^{n_{cl}} \| L_{PK}^{(i)} - L_{PK}^{(j)} \|^2}{\sum_{l=1}^{n_{cl}} \delta_l^2 \, n_{cl}(n_{cl}-1)} \cdot \frac{\sum_{i=1}^{n_{cl}}\sum_{j=1}^{n_{cl}} (C_{PK}^{(i)} - C_{PK}^{(j)})^2}{n_{cl}(n_{cl}-1)},$$
$$(i \neq j) \qquad (5)$$

And finally we obtain:

$$S = \frac{\sum_{i=1}^{n_{cl}}\sum_{j=1}^{n_{cl}} \| L_{PK}^{(i)} - L_{PK}^{(j)} \|^2 \sum_{i=1}^{n_{cl}}\sum_{j=1}^{n_{cl}} (C_{PK}^{(i)} - C_{PK}^{(j)})^2}{n_{cl}(n_{cl}-1)^2 \sum_{l=1}^{n_{cl}} \delta_l^2} \qquad (6)$$

where 1/S< S_T (given accuracy), the optimal region cluster could be achieved and the final clustering finished[5].

3.2.2 Supervised Mechanism

For the purpose of specific classification task, the supervised mechanism is used to construct the machine learning process. And the correspondent performance could be improved. The sample set of leather images with limited number is used as input to the hierarchical system. The principal characteristics of textured images could be enhanced and extracted. So the asymptotical speed can be increased and optimal result obtained in the maximum likelihood mode. The efficient and accurate boundaries are detected, described and recognized by the system. The meaningful regions are labelled by the algorithm.

3.3 Robustness

Because of the noisy case, the various types of the image changes the intensity distribution at different ranges. The noisy simulating sources has been contained in the feature extraction. But the noisy factor should be handled by the dynamic techniques.

The Pearson's method has been applied in the system. Let:

$$g(x) = P_1 f_1(x/\mu_1, \delta_1) + (1-P_1) f_2(x/\mu_2, \delta_2) \qquad (7)$$

where g(x) dedicates image, f_1,f_2 represents two kinds of normal distribution, P_1 is the probability of f_1. The parameters of normal distribution f_1 and f_2 are determined by the following algorithm:

1) Computing the jth order center moment:

$$\mu_j = \frac{\sum_{i=1}^{N}(x_i - M)^j}{N}, \; j = 2, 3, 4, 5, 6 \qquad (8)$$

where M is the variance of the mixed distribution, N is the total number of the pixels in the window.

2) Computing the following statistics:

$$\begin{aligned} \beta_1 &= \mu_3^2/\mu_2^2 \\ \beta_2 &= \mu_4/\mu_2^2 \\ \beta_3 &= \mu_3\mu_5/\mu_2^4 \end{aligned} \qquad (9)$$

$$\begin{aligned} \alpha_1 &= (3-\beta_2)/2 \\ \alpha_2 &= 10\beta_1 - \beta_2 \end{aligned} \qquad (10)$$

3) Solve the equation:

$$\sum_{i=0}^{9} A_i X^i = 0 \qquad (11)$$

where:

$$A_0 = -\beta_1^3 \;,\quad A_1 = 8\beta_1^2\alpha_1$$
$$A_2 = 3(\beta_1\alpha_2 - 7\beta_1\alpha_1^2/2)$$
$$A_3 = 3(4\beta_1^2 - 3\alpha_1\alpha_2 - 3\alpha_1^3)$$
$$A_4 = -(37\beta_1\alpha_1 + 3\alpha_2^2/4\beta_1)$$
$$A_5 = -3(\alpha_2 - 5\alpha_1^2)$$
$$A_6 = 3\beta_1/2 \;,\quad A_7 = -7\alpha_1$$
$$A_8 = 0 \;,\quad A_9 = 1$$

4) For every non-negative real root X, solve the equation:

$$\tau^2 - \left(\frac{Y\sqrt{\mu_2}}{x}\right)\tau + x\mu_2 = 0 \tag{12}$$

where,

$$Y = \sqrt{\beta_1}\left(\beta_1 - 6\alpha_1 x - \frac{3\alpha_2}{2\beta_1}x^2 - 4x^3\right) / (2\beta_1 - 3\alpha_1 x + x^3)$$

5) Computing the parameters of the two normal distribution:

$$\begin{aligned} P_1 &= \tau_2/(\tau_2 - \tau_1) \\ P_2 &= 1 - P_1 \\ m_1 &= m + \tau_1 \\ m_2 &= m + \tau_2 \\ \delta_1^2 &= \mu_2(1+x) - \mu_2/3\tau_2 - Y\tau_1\sqrt{\mu_2}/3x \\ \delta_2^2 &= \mu_2(1+x) - \mu_3/3\tau_1 - Y\tau_2\sqrt{\mu_2}/3x \end{aligned} \tag{13}$$

where, τ_1 and τ_2 ($\tau_1 < \tau_2$) are the roots of the equation (12).

6) Computing 6th order moment:

$$\begin{aligned} \mu_6^* &= P_1(15\delta_1^6 + 45m_1\delta_1^4 + 15m_1^4\delta_1^2 + m_1^6) \\ &\quad + P_2(15\delta_2^6 + 45m_2^2\delta_2^4 + 15m_2^4\delta_2^2 + m_2^4) \\ d &= \mu_6^* - \mu_6 \end{aligned} \tag{14}$$

go to step 4), until no negative real roots exist.

7) Select the parameters of two normal distribution with the smallest d value and the correspondent parameters as the results.

8) Solve the t value that satisfies formula:

$$P_1 f(t/m_1, S_1) = P_2 f(t/m_2, S_2)$$

where f(y) is normal distribution probability functions, P_1, P_2 are the correspondent weight value, m,s is the average value and variance respectively. The t value is used as the decision boundary in the minimum classification error condition. By the guidance of the mechanism mentioned above, if some region obtained by the previous parallel algorithm is with great mount of noise, the Pearson's method is applied to do the refine segmentation[3].

3.4 Structure of the Algorithm

The algorithm is arranged as the parallel hierarchical network with decision making mechanism. The correspondent structure provides the high-speed computational performance because the algorithm is parallel. The system could be optimized by unsupervised/supervised mechanism. And so the satisfactory result could be achieved by the parallel hierarchical network. The spacial reflection is proceeded by the scheme and recognition ability is satisfactory for the robust segmentation of textured images.

4. Experimental Result

The algorithm discussed above has been simulated with Turbo-C languages in computer system. By which, a mixed nature texture image made of two sort of sheepskin and it's noisy image have been successfully segmentated (refer to Fig.2, Fig.3, Fig.4, Fig.5). The result is satisfied and shows that the algorithm is high effective and practical and can be applied in production as an essential software of computer automation recognition system of leather quality.

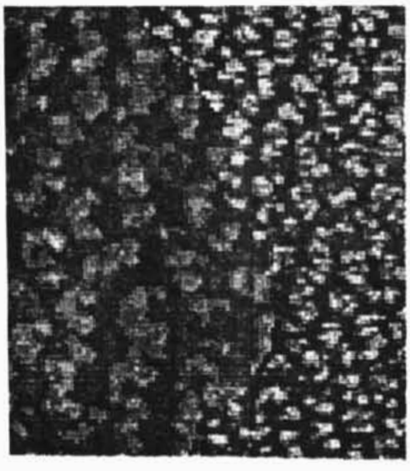

Fig.2 original texture image

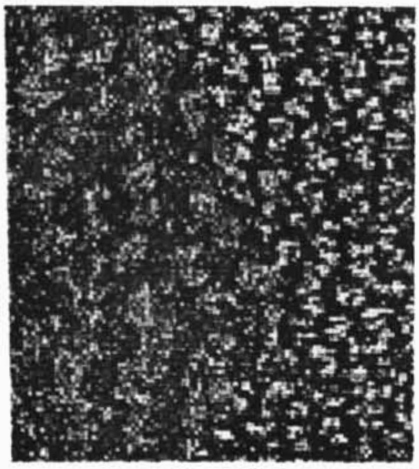

Fig.3 noisy image

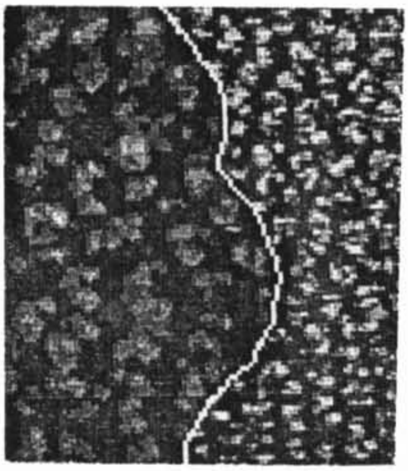

Fig.4 the result of segmentation

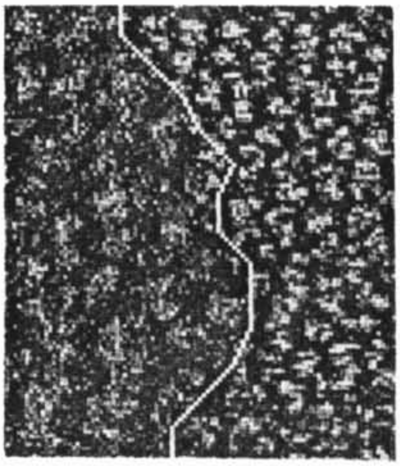

Fig.5 the result of segmentation of noisy image

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