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Texture Feature Extraction Research Based on GLCM-CLBP Algorithm

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Abstract. In view of the existing texture feature extraction method of computational complexity and accuracy problems, this paper proposes a calculation method fused with Complete Local Binary Patterns (CLBP) and Gray-level Co-occurrence Matrix (GLCM). This method uses the rotation invariant CLBP operator to process the texture image and get the CLBP image, then calculate the GLCM of the CLBP image, use the contrast, correlation, energy and inverse difference moment to describe the image texture feature. The experimental results show that the method can reduce the feature parameters at the same time, also improved the texture description ability.

Introduction

Texture is an important visual cue. It is feature which is widespread in the image and difficult to describe. Texture feature extraction is one of the hot topics in computer vision, image processing, image analysis and image retrieval.

T. Ojala in 1996 proposed the Local Binary Patterns algorithm (Local Binary Patterns, LBP) [1], for the description of the texture feature. LBP algorithm is simple and easy to understand, the computational complexity is small, and it can well describe the local texture features of the image. So it attracts the attention of many research scholars. In the past many years, the researchers studied the LBP algorithm, and proposed several improved algorithms such as FLBP, LBP, FPLBP, MS-LBP, CLBP [2] and so on, and it is widely applied in image segmentation, face recognition, image retrieval and other fields. Compared with other improved LBP algorithms, CLBP algorithm is more comprehensive and precise in local texture description and texture feature extraction, and has achieved good results. But the shortcoming of CLBP algorithm is that the feature dimension is large in the process of texture feature description, which brings great difficulty to the calculation, and reducing the feature dimension will inevitably lead to the loss of texture features. Haralick feature is proposed by Haralick for analyzing the 14 features of Gray-level Co-occurrence Matrix (GLCM). It is found that there are only 4 features (contrast, correlation, energy and inverse difference moment) in the 14 texture features, which are not only convenient for calculation, but also can provide a high classification accuracy.

This paper proposes a calculation method fused with CLBP and GLCM, using the rotation invariant CLBP operator to process the texture image and get the CLBP image. At last calculate the GLCM of the CLBP image, and use the contrast, correlation, energy and inverse difference moment to describe the image texture feature.

Local Binary Patterns

Traditional Local Binary Patterns (LBP). The basic idea of LBP is to calculate the LBP operator by comparing the image pixels and the pixels around it. Take this pixel as the center and compare the adjacent pixels. If the gray value of the central pixel is greater than or equal to its adjacent pixels, it marked as 1, otherwise marked as 0. As shown in Fig. 1:

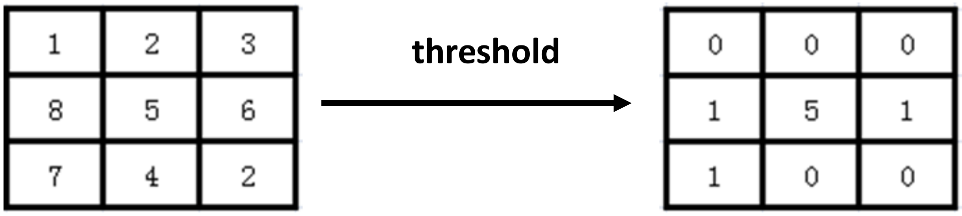


Figure 1. LBP operator example

$$LBP_{P,R} = \sum_{n=0}^{P-1} s(g_n - g_c)2^n \quad (1)$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

In Eq. 1, g_n is the gray value of the neighboring pixels, g_c is the gray value of the central pixel, P is the number of pixels in the field, R is the radius of the neighborhood.

Complete Local Binary Patterns(CLBP). CLBP[3] put forward three kinds of local texture description operator to express texture description operator: window gray difference description operator (CLBP-Sign, CLBP_S), window gradient difference description operator (CLBP-Magnitude, CLBP_M) and the central pixel description operator (CLBP-Center, CLBP_C) The calculation is as follows:

$$CLBP\_S_{P,R} = \sum_{n=0}^{P-1} s(g_n - g_c)2^n$$

$$CLBP\_M_{P,R} = \sum_{n=0}^{P-1} s(D_n - T)2^n$$

$$CLBP\_C_{P,R} = s(g_c - g_N)$$

where

$$D_n = g_n - g_c$$

$$T = \frac{1}{N}\sum_{i=0}^{N-1}\frac{1}{P}\sum_{n=0}^{P-1}(g_n - g_c)$$

$$g_N = \tfrac{1}{N}\sum_{i=0}^{N-1} g_i$$

N is the number of sub windows for image division. From the above formula, we can see that $CLBP\_S_{P,R}$ is LBP.$CLBP\_M_{P,R}$ describes the gradient difference information of the local window through the comparison between the two pixel gray difference value and the average value of the global gray difference. It as the complementary information of $CLBP\_S_{P,R}$. $CLBP\_C_{P,R}$ reflects the central pixel gray information. Compared with LBP, CLBP describes the texture more precise, and the texture recognition accuracy has been greatly improved.

Gray-level Co-occurrence Matrix (GLCM)

GLCM[4] describes the probability of gray-level of two points which satisfy a certain distance and a certain direction in the image. Definition: two pixel which gray-level is i and j, then the probability that the positional direction is θ, distance is d is denoted as P (i,j,d, θ).

Generally θ has 4 values: 0°, 45°, 90° and 135°. The probability that the pixel pair M(k, l)=i and M(m, n)=j appear in these four directions are:

P(i,j,d,0°)=#{[(k, l),(m, n)] | k-m=0,|l-n|=d}

P(i,j,d,45°)=#{[(k, l),(m, n)] | k-m=d, l-n=d}

P(i,j,d,90°)=#{[(k, l),(m, n)] | |k-m|=d, l-n=0}
P(i,j,d,135°)=#{[(k, l),(m, n)] | k-m=-d, l-n=-d}
Where # Indicates the number of elements in the collection.

In this paper, the contrast, correlation, energy, inverse difference moment respectively as a feature, recorded f_1,f_2,f_3,f_4, calculated as follows:

$$f_1 = \sum_{i,j} (i-j)^2 P$$

$$f_2 = \frac{\sum_{i,j} (i-\mu_x)(j-\mu_y)P}{\sigma_x \sigma_y}$$

$$f_3 = \sum_{i,j} P^2$$

$$f_4 = \sum_{i,j} \frac{1}{1+|i-j|} P$$

Where

$$\mu_x = \sum_i i \sum_j P$$

$$\mu_y = \sum_j j \sum_i P$$

$$\sigma_x = \sum_i (i-\mu_x)^2 \sum_j P$$

$$\sigma_y = \sum_j (j-\mu_y)^2 \sum_i P$$

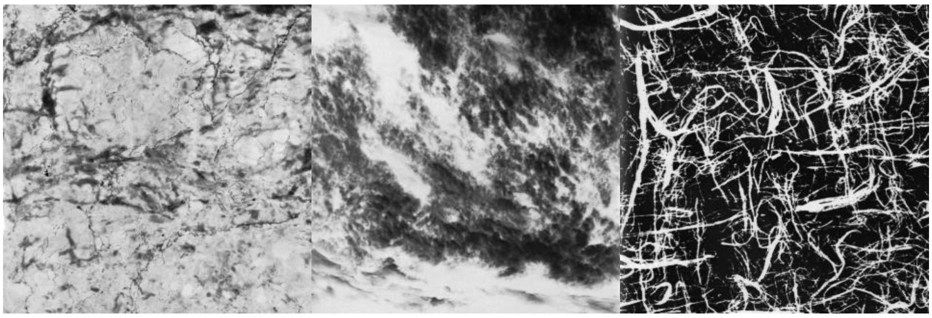
The texture feature extraction method is as follows:
(1) Select the rotation invariant CLBP_M operator, after CLBP operation for each pixel of the image then get the CLBP images.
(2) Calculate the GLCM of CLBP characteristic spectrum, the distances d=1,θ=0°,45°,90° and 135° are selected, at last obtain four GLCM.
(3) The contrast, correlation, energy and inverse difference moment of each GLCM are calculated, and the 4 feature values calculated of each GLCM are cascaded as the texture features of the image, and there are 16 texture features.

In this paper, the number of the characteristic parameters which used to characterize the texture is 16. Compared with the CLBP histogram, the feature dimension is greatly reduced.

Experimental and Result

Five images from the Brodatz texture image library to verify the effectiveness of the proposed method.

D14 D28



D63 D90 D107

Figure 2. Texture Image

The size of the original texture image is 640 * 640 pixels, in the experiment each image will be divided into 64 sub-images that each image 80 * 80, and a total of 320 sub-images. In this paper, the original texture image is rotated 45°, 90°, 135°, 180°, 225°, 270°, 315° in order to test the rotation invariance of the method. Then, eight sub-images with no overlap of 80 * 80 pixels are divided in the center of each rotated image, so that each original image is divided into 64 + 7 * 8 = 80 sub-images, totaling 5 * 80 = 400 sub-images.

Twenty sub-images were randomly selected from each texture image as training samples and the rest as test samples. This method is compared with GLCM, CLBP, Gabor and other mainstream methods.

The GLCM method selects 0°, 45°, 90° and 135° and the distance is 1 to calculate the GLCM. The four feature vectors of contrast, correlation, energy and inverse difference moment are extracted respectively. The 16 feature values calculated are concatenated as the texture features of the image.

The CLBP method uses rotation invariant CLBP_M operator to extract texture features.

The Gabor method uses 5 scales and 8 directional filter banks to extract texture features.

The experimental results are shown in Table 1.

Table 1 Classification Accuracy of Test Set

Method	D14	D28	D63	D90	D107	Average Classification Accuracy(%)
GLCM	92.25	93.25	91.25	95.25	93.75	93.15
CLBP	91.50	93.25	90.25	95.50	94.75	93.05
Gabor	92.50	93.50	90.75	95.25	95.00	93.40
Paper Method	93.50	94.50	90.75	96.75	96.25	94.56

It can be seen that the classification accuracy of the method is improved, and verified the effectiveness of the proposed method in texture image feature extraction.

Conclusion

This paper proposes a texture feature extraction method fused with CLBP and GLCM. Using contrast, correlation, energy and inverse difference moment of GLCM of CLBP image to describe the texture, reduced the feature parameters at the same time, also improved the texture description ability.

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