Texture Analysis of Brodatz Images Using Statistical Methods

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Abstract

Textures are one of the important features in computer vision for many applications. Most of attention has been focused on the texture features. An important approach to region description is to quantify its texture content. Although no formal definition of texture exists, intuitively this descriptor provides measures of properties such as smoothing and regularity. The principal approaches used in image processing to describe the texture of an image region are statistical, structural, and spectral. In this paper the features were constructed using different statistical methods. These are auto-correlation, edge frequency, primitive-length and law's method; all these methods were used for texture analysis of Brodatz images. The result showed that the law's autocorrelation method yields the best result.

Keywords: Image analysis, texture, feature extraction, statistical textural analysis, image Brodatz.

التحليل النسيجي لصور Brodatz باستخدام الطرق الاحصائيه

الخلاصة

يعد التحليل النسيجي واحد من أهم الخصائص الموجودة في كثير من تطبيقات الحاسوب. واغلب الاهتمامات تركز على خصائص نسيج ألصوره. ومن التطبيقات المهمة لوصف الصورة تكميم المحتوى النسيجي . لا يوجد أي نموذج جاهز لتعريف النسيج. الوصف النسيجي يعطي خصائص حول التنعيم والانتظام. ثلاث خصائص رئيسيه تستخدم في معالجة الصور الرقمية وتصف نسيج الصورة هي الطريقة الاحصائيه والهيكلية والطيفية.
في هذا البحث تم حساب خصائص الصورة اعتمادا على طرق احصائيه مختلفة auto-correlation, law's primitive-length , frequency, وجميع هذه الطرق تم تطبيقها لتحليل نسيج الصورة الماخوذه من البوم Brodatz الماخوذه من الانترنيت. النتائج تشير إلى أن أفضل طريقه لوصف نسيج الصورة هي طريقة Laws auto-correlation.

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1-Introduction

Texture is defined as a pattern that repeated and is represented on the surface of an object [1]. Also it is a property that represents the surface and structure of an image. Texture can be defined as a regular repetition of an element or pattern on a surface.

Image textures are complex visual patterns with characteristics of brightness, color, shape, size, etc. an image region has a constant texture if a set of its characteristics are constant, or slowly change [2]. Texture can be regarded as a similarity grouping in an image.

Texture analysis is an image processing technique by which different region of an image are identified based on texture properties. This process plays an important role in many industrial, biomedical and remote sensing applications. Statistical methods currently dominate the field of texture analysis. However, there is no clear consensus on which statistical methods work best. Randen and Husoy undertook a quantitative evaluation of statistical and frequency- based approaches to texture analysis [3].

Early work utilized statistical and structural methods for texture feature extraction [4]. Gaussian Marko random field and Gibbs distribution texture modules were developed and used for texture analysis [5].

Texture methods used can be categorized as: statistical, geometrical and structural [6].Van Gool etal. [7] Present a detailed survey of various textural methods used in image analysis studies. Weszka etal. [8] Compared the Fourier spectrum, second order gray level statistics, and co-occurrence matrices features. Ojalaetal [8] compared arrange of texture methods using nearest neighbor classifiers including gray level difference method, law's measures and local Binary patterns applying them to Bordatz images.

2-Texture methods

In this paper we analyze the Brodzat image using four different texture extractions. These methods are:

2.1-Autocorrelation

One method of measuring spatial frequency is evaluating the autocorrelation function of a texture. The autocorrelation function of an image can be used to assess the amount of regularity as well as the fineness of the texture present in the image. In an autocorrelation model, texture spatial organization is described by the correlation coefficient that evaluated linear spatial relation ships between primitives.

$$. \ 0 \le y \le N - 1 \quad ....(1)$$

$$F(x, y), 0 \le x \le N$$

We have an image F(x,y) with N×N images size, and G is the gray level the out correlation function of image F(x,y) is

$$g(x, y) = \frac{\sum_{u=0}^{N} \sum_{v=0}^{N} f(u, v) f(u + x, v + y)}{\sum_{u=0}^{N} \sum_{v=0}^{N} f^2(u, v)} \quad .....(2)$$

where x , y is the positional difference in (u,v) direction.[2].

2.2- Edge frequency based texture analysis

The total length of the edges in a region could also be used as a

measure of the coarseness or complexity of a texture. Edges can be detected either as micro edges using small edge operator masks or as micro edges using large masks [9].
The distance depend texture description function g (d) can be computed for any sub image (f) defined as neighborhood N for a variable distance d is

$$g(d)=|F_0-F|+|F_0-F_1|+|F_0-F_2|+|F_0-F_3|+|F_0-F_4| \quad ....(3)$$

Where

$$F_0 = f(i, j)$$
$$F_1 = f(i+d, j)$$
$$F_2 = f(i-d, j)$$
$$F_4 = f(i, j-d)$$

The function g(d) is similar to negative autocorrelation function, it is minimum corresponds to the autocorrelation and maximum corresponds to the autocorrelation minimum[2]
2.3- Primitive length (run length) [10]:

1- $$K=\sum_{a=1}^{L}\sum_{r=1}^{N_r} B(a,r) \quad ....4$$

B (a,r) number of primitive of all directions have length r and gray level (a).
M, N image dimensions.
L number of image gray levels.
N_r Maximum length of primitive
K total number of primitive.

2- Short primitive emphasis

$$K = \sum_{a=1}^{L}\sum_{r=1}^{N_r} \frac{B(a,r)}{r^2} \quad ....(5)$$

3-Long primitive emphasis

$$\frac{1}{k}\sum_{a=1}^{L}\sum_{r=1}^{N_r} B(a,r)r^2 \quad ...(6)$$

4- Gray-level uniformity

$$\frac{1}{k}\sum_{a=1}^{L}\left(\sum_{r=1}^{N_r} B(a,r)\right)^2 \quad .(7)$$

5- Primitive length uniformity

$$\frac{1}{k}\sum_{r=1}^{N_r}\left(\sum_{a=1}^{L_r} B(a,r)\right)^2 \quad ...(8)$$

6- Primitive percentage

$$\frac{K}{\sum_{a=1}^{L}\sum_{r=1}^{Nr} rB(a,r)} = \frac{K}{MN} \quad .....(9)$$

2.4- Law's texture energy measures

are a set of filters designed to identify specific primitive features such as spots, edges and ripples in a local region. The origins of the law's filters are five vectors. The five filters are derived from three simple vectors

$$L_3 = [1\ \ 2\ \ 1]$$
$$E_3 = [-1\ \ 0\ \ 1]$$
$$S_3 = [1\ \ -2\ \ 1]$$

Convolving these vectors with themselves and one another generates five 5×1 vectors.

Level $L_5 = [1,4,6,4,1]$

Edge $E_5 = [-1,-2,0,2,1]$

Spots $S_5 = [-1,0,2,0,-1]$

Ripples $R_5 = [1,-4,6,-4,1]$

Waves $W_5 = [-1,2,0,-2,-1]$

Multiplying these five vectors with themselves and one another produces a set of 25 unique 5×5 masks known as law's masks.
By convoluting the law's with texture image and calculation energy statistics, a feature vector is derived that can be used for texture description [11].

3-The study images
The images which are variable in the internet [12] has been chosen for there homogeneity of texture. Each image is of size 512×512 pixels are split into 5 sub images to increase the samples in each type.

We have use five classes:

1- Leaves with 8 images.
2- Sand with 6 images.
3- Fabric with 20.
4- Terrain with 11.
5- Flower with 8 images.

4-Methodology:

The present paper computes statistical parameters derived from statistical methods. We use four texture methods. In our analysis, we use a linear method of classification and two modified K-nearest neighbor with K=1, 3,3,7,9, then we use the leave one out method.
The first model of K-nearest neighbor is [13].

$$d_i = \frac{1}{E}\sum_{j=1}^{N}\left|(x_j - y_j^{im}\right|$$

The algorithm:

1- Out of n training vectors, defining the k value as odd value.
2- Out of these k sample, identify the number of vectors, that belong to class w_i =1, 2…M.

$$\sum_i k = k_i \ .$$

3- Assign x to the class w_i with the maximum number of k_i samples.

4- If two or more classes w_i, I ∈ [1…M], have an equal number E of maximum nearest neighbors, then we have conflict.

For each class involved in the conflict, determine the distance d_i between test pattern x={ $x_1,.....x_N$ } and class w_i involved in the conflict is represented as $y^{im} = (y_1^{im},....y_N^{im})$ then the distance between test pattern x and class w_i is

$$d_i = \frac{1}{E}\sum_{j=1}^{N}\left|(x_j - y_j^{im}\right|$$

5- Assign x to class C if its d_i is smallest, i.e. x∈ w_c, if $d_c < d_i$ for $\forall_i$, such that C∈ [1..M]and i $\neq C$.

Second model

$$d_i = \frac{1}{E_i}\sum_{j=1}^{N}\left|(x_j - y_j^{im}\right|$$

1- Out of n training vectors, defining the k value as odd value.

2- Out of these k sample, identify the number of vectors, that belong to class w_i =1, 2, ..., M.

$$\sum_i k = k_i \, .$$

3- Find the average distance d_i that represents the distance between test pattern x= { x_1 ,..... x_N } and E_i nearest neighbors found for class w_i, i=1..M. only include classes for which samples were detected in the first step if the m^{th} training pattern of class w_i found within the hyper here is represented as $y^{im} = (y_1^{im}, \ldots y_N^{im})$, then the distance between the test pattern x and class w_i is

$$d_i = \frac{1}{E_i} \sum_{j=1}^{N} \left| (x_j - y_j^{im} \right| \, .$$

4- Assign x to class C if its d_i is smallest, i.e. x$\in w_c, if \quad d_c < d_i$ for $\forall_i$, such that C$\in$ [1..M]and i$\neq C$. the decision in this model does not depend on the number of nearest neighbors found but solely on the average distance between the test pattern and samples of each class found.

Table (1) shows the first model of K-nearest neighbor, the best result is obtained for the autocorrelation followed by the laws then the edge frequency. The last one is the primitive length method.

Table (2) represents the second model of K-nearest neighbor, the best result is obtained with the laws then the autocorrelation followed by edge frequency and the last one is the primitive length.

Table (3) shows the recognition rate. It gives good recognition rate showing that the data is linearly separated for better quality texture methods like autocorrelation and law's.

5-Conclusions

In this search we have used four different statistical textural methods. One deals with edge detector, the primitive length texture gives indication about the gray level and direction, the laws texture provided information about the image form in which the energy is measured. Our result finds that the best result obtained with the autocorrelation and laws. It appears that different texture methods capture different aspect of the image texture. Figure (6) and figure (7) shows the distribution of the texture methods and the recognition rate it appears that the best methods is the autocorrelation and the laws.

6-References

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Table (1): The K-nearest neighbor using the first model

Texture method	K=1	K=3	K=5	K=7	K=9
Autocorrelation	89.8%	83.2%	84%	83%	79%
edge frequency	71.8%	73.3%	79.1%	72%	69%
Primitive length	55.2%	59.9%	59.9%	62.9%	64%
Law's	76.9%	82.3%	82.3%	83%	85%

Table (2): The K-nearest neighbor using the second model

Texture method	K=1	K=3	K=5	K=7	K=9
Autocorrelation	80.4%	82.3%	79.2%	79.9%	79.5%
edge frequency	68%	67%	69%	68%	70.9%
Primitive length	58.3%	55.2%	60%	61%	59%
Law's	76%	81%	82%	85%	80.1%

Table (3): The Recognition rate for each texture method

Texture methods	Recognition rate
Autocorrelation	67%
edge frequency	69%
Primitive length	53%
Law's	87%

Figure (1): Fabric Brodatz images.

Figure (2): Flower Brodatz images.

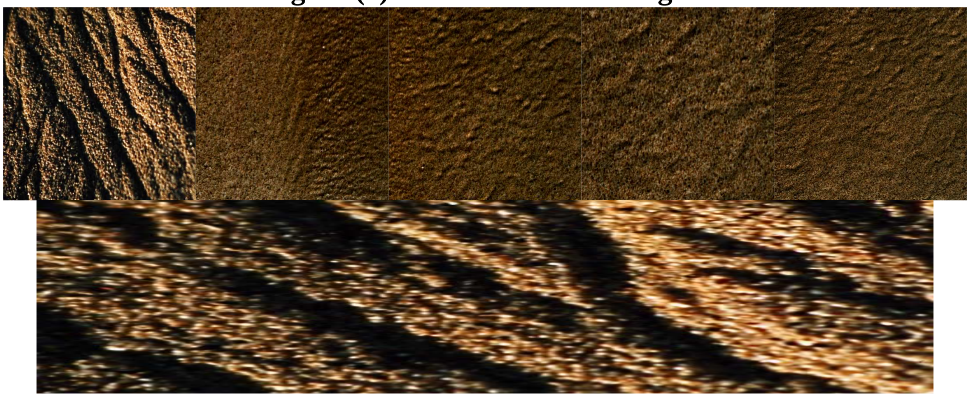

Figure (3): Sand Brodatz images.

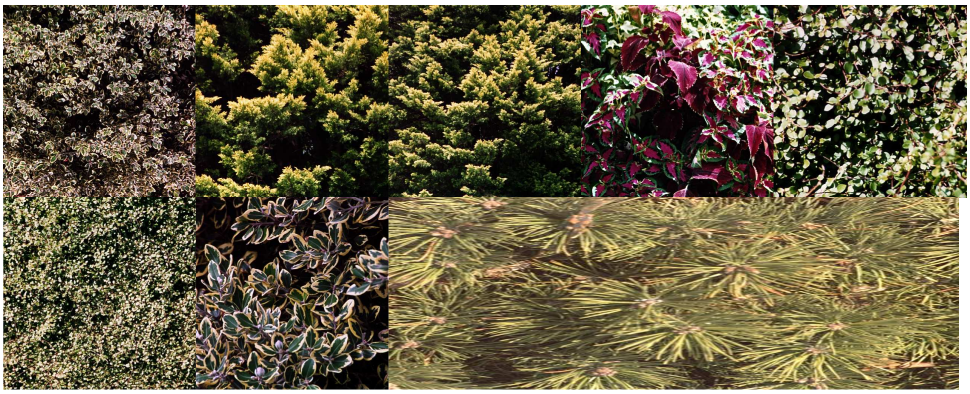

Figure (4): Leaves Brodatz images.

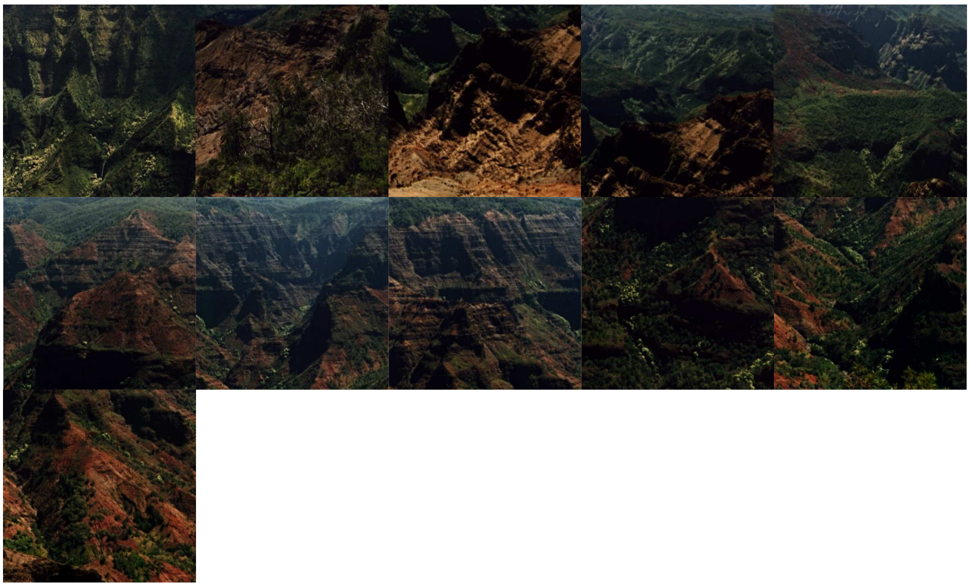

Figure (5): Terrain Brodatz images.

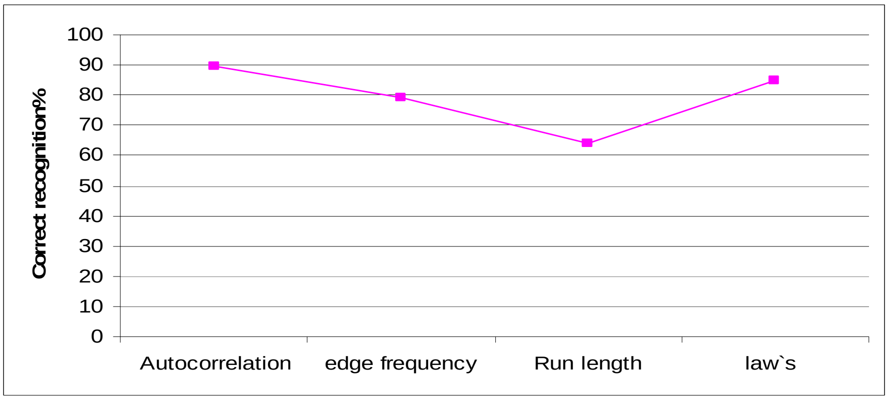

Figure (6): The best neighbors' classifier for using the first model.

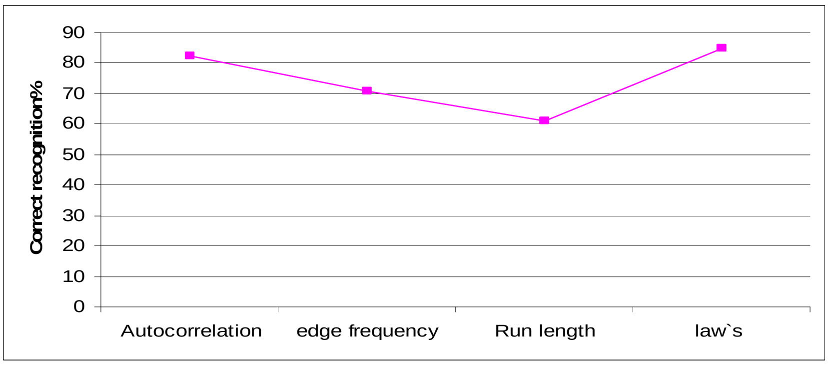

Figure (7): The best neighbor's classifier for using the second model.