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Classification of Textures Based on Features Extracted from Preprocessing Images on Random Windows

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Abstract

Textures are one of the important features in computer vision for many applications. In the literature, most of the attention has been focused on the texture features with minimal consideration of the noise models and window selection. To overcome this, in the present paper the features are constructed on preprocessed methods applied on the texture image by considering different types of windows. These features offer a better classification rate. The experimental results on various Brodatz textures clearly demonstrate the efficiency of the proposed method.

Keywords: *Texture, Feature Extraction, Classification, Preprocessed Methods.*

1. Introduction

The classification problem is basically the problem of identifying an observed textured sample as one of several possible texture classes by a reliable but computationally attractive texture classifier. This implies that the choice of the textural features should be as compact as possible and yet as discriminating as possible. In other words, the extraction of texture features should efficiently embody information about the textural characteristics of the image.To design an effective algorithm for texture classification, it is essential to find a set of texture features with good discriminating power. Most of the textural features are generally obtained from the application of a local operator, statistical analysis, or measurement in a transformed domain. Generally, the features are estimated from co-occurrence matrices, Law's texture energy measures, Fourier transform domain, Markov random field models, local linear transforms etc. A number of texture classification techniques have been reported in literature [1, 2, 3, 4].

Initially, texture analysis was based on the first order or second order statistics of textures. The co-occurrence matrix features were first proposed by Haralick [5]. Weszka [6] compared texture feature extraction schemes based on the Fourier power spectrum, second order gray level statistics, the co-occurrence statistics and gray level run length statistics. The co-occurrence features were found to be the best of these features. This fact is demonstrated in a study by Conners and Harlow [7]. In [8], Haralick features are obtained from wavelet decomposed image yielding improved classification rates. Hiremath and Shivashankar[9] have considered Haralick features for texture classification using wavelet packet decomposition.

The above methods on texture classification were not taken into consideration of the effect of noise and window selection. That's the reason the present paper applies preprocessing methods on the input image and also studies the effect of random window over sequential window.

The paper is organized as follows. Section 2 deals with the proposed method. Section 3 is on the experimental results, followed by conclusions at Section 4.

2. Methodology

The present paper computes statistical parameters derived from gray level co-occurrence parameters on sequential window (SW) and random window (RW). The size P×Q of the SW/RW is chosen based on the conditions 2≤P≤M and 2≤Q≤N. The starting position of the random window on the image is determined based on the equation (1).

$$y(n+1) = ((a \times y(n)) + b)\%M \tag{1}$$

where a, and b are the deciding factors for the number of windows and the M value is computed by the equation (2)

$$M = ((K-P) \times (L-Q)) + 1 \tag{2}$$

The RW may contain parts of the other window (overlapped) and the SW does not contain any overlapped windows (non overlapped). One of the features of preprocessing methods is to improve the image information content by suppressing the undesired distortions or enhancements. For this the present paper is applied on the following preprocessing methods called local maximum, local minimum, local (max-min)/2, local mean, local median, local mod as represented by the equations from (3)- (8) respectively. The preprocessing methods are applied on a mask of size 0…..(m-1)× 0…..(m-1), where m is an odd number. Then (m-1)/2×(m-1)/2 represents the central pixel (CP) of the mask.

$$CP = MAXVAL\left(\mathop{\forall}_{i=0}^{m-1} \mathop{\forall}_{j=0}^{m-1} P(i,j)\right) \tag{3}$$

$$CP = MINVAL\left(\mathop{\forall}_{i=0}^{m-1} \mathop{\forall}_{j=0}^{m-1} P(i,j)\right) \tag{4}$$

$$CP = \left(\frac{MAXVAL\left(\mathop{\forall}_{i=0}^{m-1} \mathop{\forall}_{j=0}^{m-1} P(i,j)\right) - MINVAL\left(\mathop{\forall}_{i=0}^{m-1} \mathop{\forall}_{j=0}^{m-1} P(i,j)\right)}{2}\right) \tag{5}$$

$$CP = \operatorname{int}\left(\frac{\sum_{i=0}^{m-1}\sum_{j=0}^{m-1} P(i,j)}{9}\right) \tag{6}$$

$$CP = \left\{CP / ASCSORT\left(\mathop{\forall}_{i=0}^{m-1} \mathop{\forall}_{j=0}^{m-1} P(i,j)\right)\right\} \tag{7}$$

$$CP = COUNT(MODVAL) \geq \left(\underset{i=0}{\overset{m-1}{\forall}} \; \underset{j=0}{\overset{m-1}{\forall}} \; COUNT(P(i,j)) \right) \quad (8)$$

Where P(i,j) represents the pixel value at (i,j) in the mask.

On the preprocessed images the statistical parameters of GLCM are applied they are given by the equations (9)-(13). The entire process is given by the flowchart shown in Figure 1.

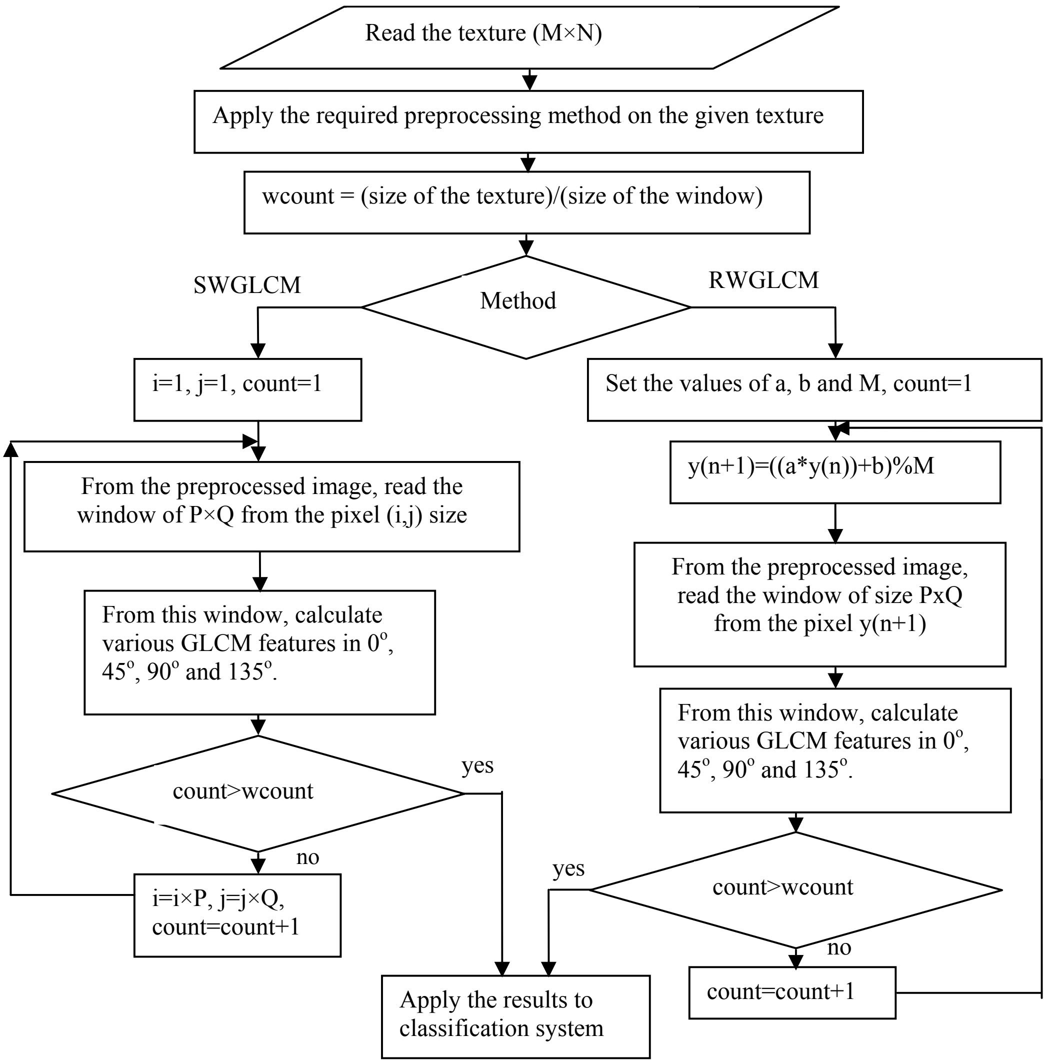

Figure 1. Methodology for texture classification system by preprocessing method

$$Inertia = \sum_{i,j=0}^{n} (i-j)^2 C(i,j) \quad (9)$$

$$TotalEnergy = \sum_{i,j=0}^{n} C^2(i,j) \quad (10)$$

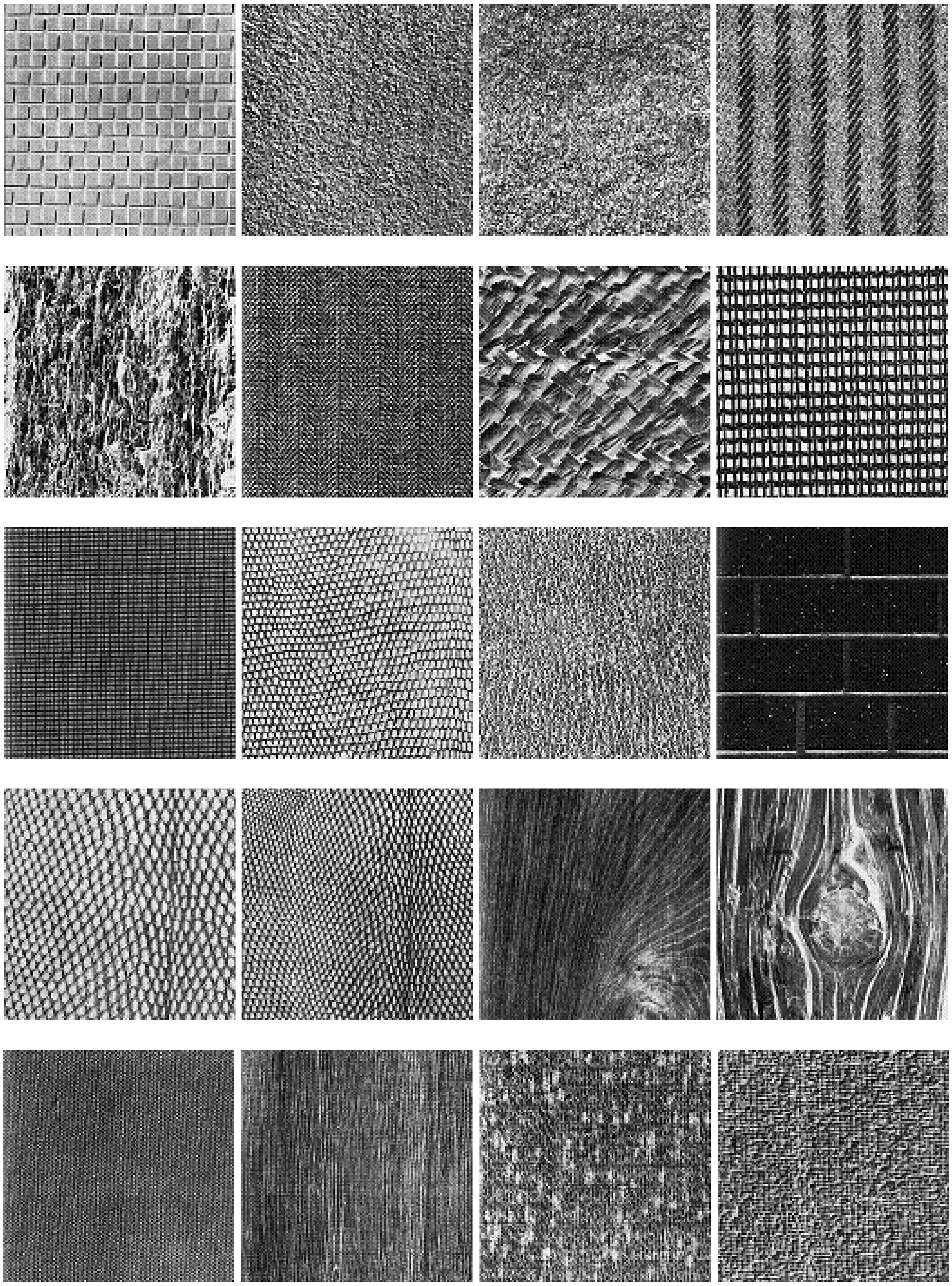

Figure 2. Input images from Brodatz album (D1, D4, D9, D11, D12, D17, D18, D20, D21, D22, D24, D25, D35, D36, D69, D72, D77, D79, D81, D84)

Table 1. Average texture classification rates for RW and SW with out any preprocessing

Texture	Random	Sequential
D1	100.00	100.00
D4	62.50	92.86
D9	75.00	100.00
D11	100.00	100.00
D12	56.25	71.43
D17	93.75	100.00
D18	100.00	92.86
D20	100.00	100.00
D21	100.00	100.00
D22	50.00	57.14
D24	93.75	92.86
D25	100.00	100.00
D35	100.00	92.86
D36	75.00	85.71
D69	100.00	100.00
D72	81.25	57.14
D77	100.00	100.00
D79	100.00	78.57
D81	81.25	57.14
D84	100.00	100.00
	88.44	**88.93**

$$Entropy = \sum_{i,j=0}^{n} C(i,j)\log(C(i,j)) \tag{11}$$

$$Local \quad Homogeneity = \sum_{i,j=0}^{n} \frac{1}{1+(i-j)^2} C(i,j) \tag{12}$$

$$Max.\Pr obability = \max_{i,j} C(i,j) \tag{13}$$

3. Results and Discussions

The experiments are conducted with 20 texture images of each size 256×256, collected from the Brodatz album [10] as shown in Figure 2. In the first method, a sequential window (SW) of size 64×64 is considered. This divides the image into 16 parts and 20 co-occurrence features are obtained by computing inertia, total energy, entropy, local homogeneity and max. probability for four directions (namely 0^o,45^o,90^o,135^o). The average of these features of 16 parts over the set of angles is computed and taken as training set. In the same way a training data is also created for random windows, and they are stored in the texture feature library. The texture classification is implemented by considering the extracted texture feature from the sample X with the corresponding feature values of all the texture classes *v* stored in the feature library using the distance vector formula given by the equation (14)

$$D(v) = \sqrt{\sum_{j=0}^{N} abs(f_j(x) - f_j(k))} \quad (14)$$

where N is the number of features in f, $f_j(x)$ represents the j^{th} texture feature of the test sample x, while $f_j(v)$ represents the j^{th} feature of the v^{th} texture class in the library.

Table 2. Average texture classification rates for SW with preprocessing techniques

Texture	Maximum	Minimum	(Max-Min)/2	Mean	Median	Mod
D1	37.50	18.75	56.25	100.00	50.00	43.75
D4	31.25	37.50	75.00	87.50	43.75	25.00
D9	18.75	25.00	75.00	100.00	31.25	50.00
D11	62.50	93.75	75.00	100.00	87.50	93.75
D12	6.25	62.50	87.50	100.00	75.00	43.75
D17	87.50	56.25	62.50	93.75	81.25	56.25
D18	100.00	56.25	87.50	93.75	56.25	81.25
D20	56.25	87.50	62.50	100.00	87.50	62.50
D21	75.00	50.00	100.00	100.00	87.50	81.25
D22	37.50	93.75	75.00	100.00	68.75	87.50
D24	62.50	81.25	81.25	100.00	56.25	43.75
D25	25.00	37.50	68.75	93.75	75.00	81.25
D35	87.50	56.25	43.75	93.75	62.50	56.25
D36	100.00	81.25	75.00	100.00	87.50	62.50
D69	62.50	100.00	100.00	100.00	100.00	100.00
D72	81.25	81.25	81.25	62.50	56.25	50.00
D77	81.25	56.25	62.50	93.75	87.50	56.25
D79	68.75	81.25	62.50	75.00	100.00	87.50
D81	43.75	62.50	68.75	100.00	100.00	100.00
D84	100.00	87.50	100.00	100.00	93.75	100.00
	61.25	**65.31**	**75.00**	**94.69**	**74.38**	**68.13**

Then the test texture is classified as v^{th} texture, if the distance D(v) is minimum among all the texture classes available in the library. Based on the distance function the percentage of correct classification with out any preprocessing for RW and SW are calculated and are represented in table1. The same is also applied for various preprocessed images and it is shown in table 2 and 3 for RW and SW respectively.

Table 1 clearly indicates that on average RW and SW exhibits similar classification rate for any non preprocessed textures. Table 2 and 3 clearly indicates that except preprocessing by mean, all other preprocessing methods exhibits a poor classification rate for both RW and SW methods. The mean preprocessing step has got an advantage, because it exhibits a higher classification rate than non preprocessing methods for both SW and RW.

Table 3. Average texture classification rates RW with preprocessing techniques

Texture	Maximum	Minimum	(Max-Min)/2	Mean	Median	Mod
D1	57.14	57.14	64.29	85.71	78.57	71.43
D4	57.14	21.43	85.71	92.86	42.86	42.86
D9	14.29	42.86	64.29	71.43	28.57	85.71
D11	50.00	85.71	64.29	100.00	35.71	92.86
D12	7.14	57.14	100.00	100.00	35.71	42.86
D17	57.14	92.86	35.71	100.00	50.00	92.86
D18	35.71	7.14	57.14	85.71	57.14	50.00
D20	100.00	92.86	92.86	92.86	57.14	78.57
D21	85.71	100.00	100.00	100.00	92.86	71.43
D22	50.00	64.29	64.29	100.00	64.29	85.71
D24	64.29	92.86	64.29	92.86	14.29	35.71
D25	14.29	57.14	71.43	92.86	92.86	85.71
D35	64.29	64.29	85.71	85.71	78.57	78.57
D36	57.14	78.57	50.00	78.57	92.86	92.86
D69	64.29	100.00	100.00	92.86	100.00	100.00
D72	64.29	71.43	64.29	85.71	57.14	57.14
D77	92.86	50.00	57.14	100.00	35.71	57.14
D79	28.57	57.14	28.57	100.00	85.71	92.86
D81	35.71	50.00	50.00	71.43	92.86	57.14
D84	85.71	71.43	100.00	100.00	92.86	100.00
	54.29	**65.71**	**70.00**	**91.43**	**64.29**	**73.57**

4. Conclusions

Various preprocessing methods applied on RW and SW. The RW on both preprocessed and non preprocessed methods exhibits same percentage of classification as in the case of normal SW method. Though preprocessing is a time consuming process, but the classification rate after preprocessing by mean shows a better result. The preprocessing becomes an essential step when textures are collected from different places and backgrounds.

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