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Texture Image Classification using Multi Resolution Combined Statistical and Spatial Frequency Method

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***Abstract*— Texture Analysis has been an extremely active and fruitful area of research over the past twenty years. Today texture analysis plays an important role in many tasks ranging from remote sensing to medical image analysis.Texture classification is a trendy and catchy technology in the field of texture analysis. Texture classification is important in many applications like image database retrieval, industrial, agricultural and bio-medical applications. Texture classification is based on three different approaches, they are statistical, spectral and structural.The proposed work here is combination of both statistical and spectral approaches for classification of texture images.**

***Index Terms*— Texture, Wavelet, Markov Random Field Matrix, Gray Level Co-occurrence Matrix, Spatial Frequency, MRCSF.**

I. INTRODUCTION

Texture classification plays an important role in the engineering fields and scientific researches. It can be used in image database retrieval, industrial, agricultural and biomedical application. Training phase and Testing phase/Recognition phase are the two different process involved in texture image classification. In the training phase a set of known texture images are trained by feature extraction method and stored in the library or database. In the recognition phase the unknown sample image is tested by using same feature extraction method and compare the values with the already stored features in the database. Based on the classification algorithm the unknown sample can be classified as correctly or sometimes misclassified. Texture classification is a fundamental problem in computer vision with a wide variety of applications. Two fundamental issues in texture classification are how to characterize textures using derived features and how to define a robust distance/similarity measure between textures, which remain elusive despite considerable efforts in the literature. Because images of the same underlying texture can vary significantly, textural features must be invariant to image variations and at the same time sensitive to intrinsic spatial structures that define textures. Because there is no obvious feature common for all texture images, texture features are often proposed based on assumptions for mathematical convenience.

The method of texture analysis chosen for feature extraction is critical to the success of the texture classification. However, the metric used in comparing the feature vectors is also clearly critical. Many methods have been proposed to extract texture features either directly from the image statistics, e.g. co-occurrence matrix, or from the spatial frequency domain Ohanian and Dubes [2] studied the performance of four types of features: Markov Random Fields parameters, Gabor multichannel features, fractal-based features and co-occurrence features. Ma and Manjunath [3] evaluated the texture image annotation by various wavelet transform representations, including orthogonal and bi-orthogonal, tree-structured wavelet transform, and Gabor wavelet transform (GWT). Most of these previous studies have focussed on the features, but not on the metric, nor on modeling the noise distribution.

The co-occurrence features were found to be the best for texture classification This fact is demonstrated in a study by ChellappaR. and Chatterjee[4].In Arivazhagan and Ganesan[1] Haralick features are obtained from wavelet decomposed image yielding improved classification rates. Hiremath and Shivashankar [6] have considered Haralick features for texture classification using wavelet packet decomposition. In Montiel et al [5], texture features are characterized by considering intensity and contextual information obtained from binary images. The conditional cooccurrence histograms are computed from the intensity and binary images. To obtain binary images the fixed thresholds have been used.

Hiremath and Shivashankar [6] proposed a feature extraction algorithm using wavelet decomposed images of an images and its complementary image for texture classification. The characterization defines the features constructed from the different combination of sub-band images. Experimental results show the combination of detail subbands with approximation subband helps to improve the classification rate at reduced computational cost.

Liu and Wang [7] proposed texture classification based on a local spatial/frequency representation. They used spectral histogram as a feature statistic for texture classification. The spectral histogram consists of marginal distributions of responses of a bank of filters and encodes implicitly the local structure of images through the filtering stage and the global appearance through the histogram stage.

Timoojala et al [8] proposed multiresolution approach to gray-scale and rotation invariant texture classification based on local binary patterns and nonparametric discrimination of sample and prototype distributions.

The texture classification algorithm of Varma and Zisserman [9] correctly classifies over 90% of a test set of 2806 images taken from all 61 texture classes with unknown pose and illumination.

The main aim of the proposed work is to improve the classification rate of texture images and rotation invariant texture image classification and also apply the same algorithm in textile industry for fabric defect detection and weed detection in agricultural field. Here the proposed work combines first order and second order statistical properties along with spatial frequency for multi resolution analysis.

II. FEATURE EXTRACTION MRCSF.

MRCSF is Multi Resolution Combined Statistical and Spatial Frequency Method. It is a combination of first order statistical features(like energy, mean, standard deviation and variance) second order statistical features (MRFM, GLCM) and Spatial Frequency for Multi Resolution Analysis[10]

A. Markov Random Field Matrix(MRFM)

Markov Random Field theory is a branch of probability theory for analyzing the spatial or contextual dependencies of physical phenomena F is said to be a Markov random field with respect to a neighborhood system N if and only if the following conditions are satisfied[10-11]

1. Positivity : P (F) > 0 for all F.
2. Markovianity : P (F) all points in the lattice except P (F(i)) neighbors of (i).
3. Homogeneity : P((F(i)) neighbors of (i) depends only on the configuration of neighbors and its translation invariant.

This is a parametric approach where the texture is modeled as a Markov Random Field. First the type of neighborhood is chosen and then, the parameters on which function s depends characteristic the texture. These are called Markov Parameters

MRF Matrix constructed from the 9 MRF parameters (β_1, β_2, β_3, β_4, γ_1, γ_2, γ_3, γ_4 and ξ). MRF parameters are extracted from that 3x3 size matrix of image gray level.

The procedure consists of the following steps[12-13]:

(1) Find the relationship between the center pixel and its nearest neighbors in the 3×3 matrix.

(2) Obtain 9 different MRF parameters from the 8 neighborhood system.

(3) The parameter of β depends on two pixel relationships, γ depends on three pixel relationship and ξ depends on four pixel relationship.

(4) MRF parameter matrix [M] output contains 9 parameters so the size is 1×9. Obtain the transpose of M matrix [M^T] and multiply with M matrix. It provides 9×9 size MRF matrix.

(5) Obtain MRF features from the MRF matrix.

i_1	i_2	i_3
i_8	i	i_4
i_7	i_6	i_5

Figure 1 Pixel i and its eight neighbors in the second order neighborhood system

B. Gray Level Co-occurrence Matrix(GLCM)

The gray-level co-occurrence matrix C[i, j] is defined by the first specifying a displacement vector d = (d_x, d_y) and counting all pairs of pixels separated by d having gray levels i and j. Count all pairs of pixels in which the first pixel has the value of i and its matching pair displaced from the first pixel by d has a value of j, and also enter this count in the i^{th} row and j^{th} column of the matrix[14]

1. Energy / Uniformity

$$f_1 = \sum_{i,j}^{N} C_{i,j}^2 \qquad (1)$$

where f1 is the energy feature and $C_{i,j}$ is the co-occurrence matrix.

2. Maximum Probability

This property gives an indication of the strongest response to the texture pattern.

$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} Max\, C_{i,j} \qquad (2)$$

3. Element difference moment of order k

This descriptor has a relatively low value when high values of co-occurrence matrix are near the main diagonal because the difference is very small.

$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} C_{i,j}(i-j)^k \quad (3)$$

4. Inverse element difference moment of order k

This has an opposite effect of previous defined one.

$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{C_{i,j}}{(i-j)^k}$$

where i $\neq$ j (4)

5. Entropy

Entropy is a measure of randomness, achieving its highest value when all elements of co-occurrence matrix are equal.

$$-\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} C_{i,j}\log C_{i,j} \quad (5)$$

C. Spatial Frequency

The spatial frequency is used to measure the over all information level in the regions. This is computationally simple and efficient and also can be used in real time applications.[15] The spatial frequency for an M×N block of an image is calculated as follows

$$SF = \sqrt{(RF)^2 + (CF)^2} \quad (6)$$

$$RF = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=2}^{N}[F(m,n) - F(m,n-1)]^2} \quad (7)$$

$$CF = \sqrt{\frac{1}{MN}\sum_{n=1}^{N}\sum_{m=2}^{M}[F(m,n) - F(m-1,n)]^2} \quad (8)$$

Where *RF* and *CF* are the row frequency and column frequency respectively.When the images get more blurred, the spatial frequency also gets reduced accordingly. Higher the value of spatial frequency, higher will be the contrast and quality of the image.

In each sub band, individual pixels or group of pixels of the wavelet transform of the images are compared using spatial frequency (SF) that serves as a measure of activity at that particular scale and space. Other examples of such measures are absolute values of the pixel gray values, maximum absolute gray value of the group of pixels and the variance [16].

III. TEXTURE IMAGE CLASSIFICATION USING MRCSF.

The proposed work introduces a new method for texture image classification called Multi Resolution Combined Statistical and Spatial Frequency (MRCSF). MRCSF is a combination of first order, second order statistical properties along with spatial frequency of Multi resolution analysis. The Classification rate of MRCSF method is compared with other three combinations.

F1 : Wavelet Statistical Features (WSF)

F2 : Combination of wavelet and second order statistical features

F3 : Spatial frequency features

F4 : MRCSF

Initially Image Training was done using 20 images each of 512×512 size and 8 bit monochrome images like bark, bubbles, brick, grass, hole array, leather, pigskin, raffia, rough wall, sand, straw, water, weave, wood, wool etc.

Image Classification was done with 512×512, 256×256, 128×128 and 64×64 size of image regions from the original image. The Features were extracted from the unknown input images and compared with the database, by means of calculating distance vector given in the following equation[15-16].

$$D(i) = \sum_{j=1}^{m} abs[f_j(x) - f_j(i)] \quad (9)$$

The Classification ratio of texture images using various features are given below in Table 1.

Table I

Texture Image Classification using MRCSF

S.No	Texture Images	Correct Classification Ratio (%)			
		F1	F2	F3	F4
1	Bark	95	80	100	100
2	Bubbles	98	95	87.5	100
3	Brick	90	85	75	100
4	Calf Leather	95	87.5	100	95
5	Carpet	100	90	100	100
6	Grass	95	87.5	75	93

7	Hole Array	100	95	100	100
8	Metal Gate	100	80	100	100
9	Pigskin	90	85	100	100
10	Raffia	90	75	75	90
11	Rough Wall	95	88	100	100
12	Sand	90	90	87.5	93
13	Straw	85	95	50	93
14	Tile	90	98	87.5	93
15	Water	95	90	87.5	100
16	Weave	96	78	87.5	100
17	Wire Mesh	93	90	100	100
18	Wood	95	90	87.5	100
19	Wood Grain	98	90	100	100
20	Wool	80	85	100	100
	Over All Correct Classification Rate	**93.6 %**	**87.75 %**	**90%**	**98%**

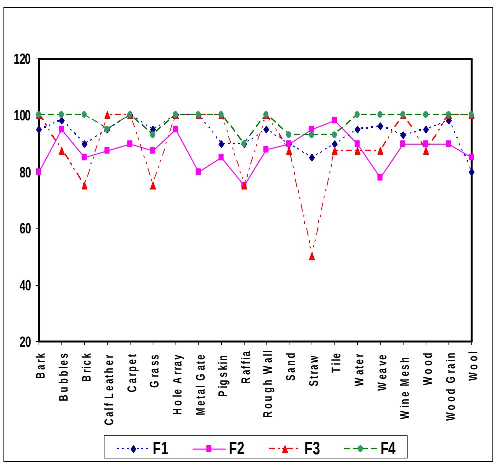

Figure 2 Compartive Analysis of Texture Image Classification using MRCSF

Table 2 Brodatz test samples for MRCSF analysis

S.No	Size of the Sample	No of Samples for single image	No of Samples for 112 Brodatz database
1	512 × 512	1	112 × 1 = 112
2	256 × 256	4	112 × 4 = 448
3	128 × 128	16	112 ×16 = 1792
4	64 × 64	20	112 × 20 = 2240
Total			**4592**

No. of Correct Classification (NCC) = 4252

No. of Error Classification (NEC)

Total Samples-NCC = 4592-4252

= 340

Classification rate = (NCC/Total Samples) × 100

= (4252/4592) ×100

= 92.6%.

Table 2 shows the classification rate for all 112 texture images using MRCSF.

IV. APPLICATION OF TEXTURE IMAGE CLASSIFICATION

The proposed work was suited to an application, particularly for the textile industry and agricultural field. Defect detection in textile fabrics was done using Multi Resolution Combined Statistical and spatial Frequency [16], the main objective of the defect detection method is to check whether the fabric material is defective or not, if it is defective then identify the location and type of the defect[16-17] .

Weed control has a major effect on agriculture. A large amount of herbicide has been used for controlling weeds in agriculture fields, lawns, golf courses, sport fields, etc. Random spraying of herbicides does not meet the exact requirement of the field. Certain areas in field have more weed patches than estimated. An automated visual system that can discriminate weeds from the image of the field which will reduce or even eliminate the amount of herbicide used. This would allow farmers to not use any herbicides or only apply them when and where are needed[11-13] A machine vision precision automated weed control system could reduce the usage of chemicals in crop fields. Here, an intelligent system for automatic weeding strategy using Multi Resolution Combined Statistical and spatial Frequency is used to identify the weed and also discriminate the weed types namely as narrow, little and broad.[12-13]

V. CONCLUSION

Texture image classification is now used in remote vision and it is a fast developing field. The implementation in this field is continuing as a process of classifying a segment of unknown image and is compared with stored database. The experimental results show that the WSF has much better performance than GSF.

GLCM approach is a combination of wavelet and co-occurrence matrix features. It provides 94.15% mean success rate of classification. MRMRFM based approach is a combination of wavelet and MRFM features. It provides 97.2% mean success rate of classification for 20 images in the Brodatz texture data base. So, MRMRFM provides better classification rate than compare to GLCM. The work was extended to all 112 texture images in the Brodatz database and the classification rate is 89.79% for Multi-resolution Markov Random Field Matrix.

Texture Image Classification using Multi Resolution Combined Statistical and spatial Frequency (MRCSF) provides 98% classification rate for 20 images from Brodatz album. MRCSF is a combination of first order statistical properties like mean, energy, variance and entropy, second order statistical properties like Markov Random Field Matrix, Gray level co-occurrence matrix combined with spatial frequency of Multi resolution analysis. The Classification rate for MRCSF technique is 92.6% for 112 images.

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