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DEFECT ANALYSIS USING TEXTURE

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This paper presents an overview of the methodologies and algorithm for statistical texture analysis of 2D images for defect detection. Detection of defects within the inspected texture is performed by partitioning the textured image into non-overlapping sub windows and classifying each sub window as defective or non-defective with various distance measures to present a comparison of various distances on various types of defects. The experimental results indicate the fact that the selected distance measures have a better discriminating power for defect detection.

1. Introduction

Visual inspection constitutes an important part of quality control in industry. Until recent years, this job has been heavily relied upon human inspectors. Development of fast and specialized equipment however, has facilitated the application of image processing algorithms of real world industrial inspection problems.

Traditionally three main texture analysis techniques have been used to study the visual texture: structural, spectral, and statistical model. However the real industrial textured materials such as wood, fabric, steel, rolls, paper, ceramics, etc. are neither completely structural, nor spectral, nor entirely stochastic. However the purely statistical approaches are suitable for modeling many real textures.

2. Texture Defect Detection Using Statistical

Texture refers to properties that represent the surface or structure of an object. Texture consists of texture primitives or texture elements, sometimes called texels. A texture primitive is contiguous set of pixels with some tonal and or regional property and can be described by its average intensity, size, shape etc. Image texture can be described by the number and types of primitives and by their spatial relationship.

Co-Occurrence Matrix: The Co-occurrence matrix (P_d) method of texture description is based on the repeated occurrence of some gray-level configuration in the texture.Texture classification can be based on criteria derived from the Co-occurrence matrix (P_d).

Texture Feature	Formula
Energy	$\Sigma_i \Sigma_j P^2_d(I, j)$
Entropy	$-\Sigma_i \Sigma_j P_d(I, j) \log P_d(I, j)$
Contrast	$\Sigma_i \Sigma_j (i - j)^2 P_d(i, j)$
Homogeneity	$\Sigma_i \Sigma_j (P_d(i, j)/(1 + \|i - j\|))$
Correlation	$\Sigma_i \Sigma_j (i - \mu_x)(j - \mu_y) P_d(i, j)/\sigma_x \sigma_y$

Where P_d = co-occurrence matrix

μ = mean of the co-occurrence matrix P_d

σ = standard variation of co-occurrence matrix P_d

Various distance measures used are:

Given an m-by-n data matrix X, which is treated as m(1– by – n) row vectors x1, x2, ..., xm, the various distances between the vector x_r and x_s are defined as follows:

1. Euclidean distance:

$$d^2_{rs} = (x_r - x_s)(x_r - x_s)'$$

2. Cityblock: Also called Manhattan distance. It is Minkowski distance with power 1.

$$d_{rs} = \Sigma^n_{j=1} |x_{rj} - x_{sj}|$$

3. Cosine: One minus the cosine of the included angle between points (treated as vectors).

$$d_{rs} = (1 - x_r x'_s/(x'_r x_r)^{1/2}(x'_s x_s)^{1/2})$$

4. Correlation: One minus the sample correlation between points (treated as sequences of values).

$$d_{rs} = 1 - [(x_r - \bar{x}_r)(x_s - \bar{x}_s)'/[(x_r - \bar{x}_r)(x_r - \bar{x}_r)']^{1/2}[(x_s - \bar{x}_s)(x_s - \bar{x}_s)']^{1/2}]$$

where

$$\bar{x}_r = 1/n \Sigma_j x_{rj} \text{ and}$$
$$\bar{x}_s = 1/n \Sigma_j x_{sj}$$

5. Seuclidean: Standardized Euclidean distance. Each coordinate in the sum of squares is inverse weighted by the sample variances of that coordinate.

$$d^2_{rs} = (x_r - x_s) D^{-1} (x_r - x_s)'$$

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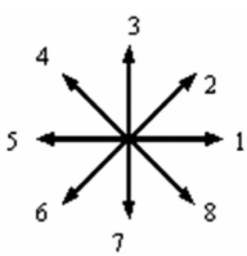
Where D is the diagonal matrix with diagonal elements given by, which denotes the variance of the variable Xj over the m objects.

4. DEFECT DETECTION AND EXPERIMENTAL ANALYSIS

For each pixel we consider increasing (2d + 1)x(2d + 1) symmetric neighborhoods, d = 1, 2, 3,...,10. Inside each neighborhood there are 8 principal directions: 1, 2, 3, 4, 5, 6, 7, 8. We evaluated the co-occurrence matrices P_d, k corresponding to vector distances determined by the central point and the neighborhood edge point in the k direction (k = 1, 2,...,8). For each neighborhood type, an average co occurrence matrix Pd is calculated:

$$P_d = 1/8(P_d1 + P_d2 + P_d3 + P_d4 + P_d5 + P_d6 + P_d7 + P_d8)$$

d = 1, 2,...,10



principal directions for co- occurrence matrix calculus

The whole image is partitioned in four equivalent regions as stated below. Different textured regions are compared by minimum distance criterion. The measured features are derived from average co-occurrence matrices (contrast, energy, entropy, homogeneity, and variance).

I1	I2
I3	I4

(Partitioning of image into sub windows)

For experimentation basis, we used the following image which was partitioned in four parts

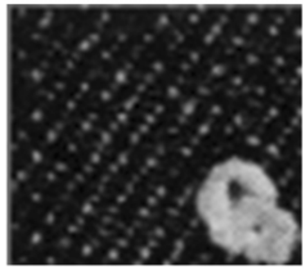


Fig. 1: Original Image

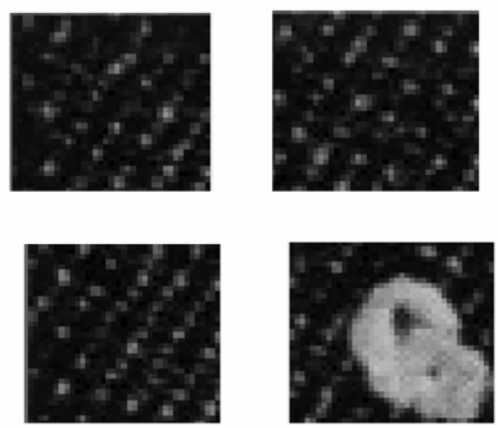


Fig. 2: Image Divided into Four Parts

Textural features like Contrast, Energy, Entropy, Homogeneity and Variance are calculated.

Table 1
For Maximum Distances, For d = 1:5

Pair wise sub windows / Distance Measures	D(I1I2)	D(I1I3)	D(I1I4)	D(I2I3)	D(I2I4)	D(I3I4)
Euclidean (1.0e + 003 *)	0.1344	0.7206	1.7476	0.8549	1.6963	2.4681
City Block (1.0e + 003 *)	0.1345	0.7211	1.7477	0.8556	1.6982	2.4688
Cosine (1.0e – 005 *)	0.0001	0.0024	0.3362	0.0022	0.3400	0.3568
Correlation (1.0e – 005 *)	0.0002	0.0019	0.2451	0.0019	0.2473	0.2440
Seuclidean	1.9366	2.2161	4.0931	3.5723	3.8669	4.4216

Table II
For Minimum Distances, For d=1:5

Pair wise sub windows / Distance Measures	D(I1I2)	D(I1I3)	D(I1I4)	D(I2I3)	D(I2I4)	D(I3I4)
Euclidean (1.0e + 003 *)	0.0223	0.3812	1.6419	0.4035	1.5610	2.0322
City Block (1.0e + 003 *)	0.0224	0.3817	1.6423	0.4040	1.5616	2.0345
Cosine (1.0e – 007 *)	0.0007	0.0863	0.2473	0.1191	0.2100	0.6031
Correlation (1.0e – 007 *)	0.0003	0.0595	0.1038	0.0920	0.0786	0.3085
Seuclidean	0.3332	1.7287	3.1522	2.1232	3.3471	4.1787

Table III
For Maximum Distances, for d = 6:10

Pair wise sub windows / Distance Measures	D(I1I2)	D(I1I3)	D(I1I4)	D(I2I3)	D(I2I4)	D(I3I4)
Euclidean (1.0e + 003 *)	0.0762	0.3861	1.5458	0.3265	1.5778	1.9000
City Block (1.0e + 003 *)	0.0763	0.3867	1.5485	0.3271	1.5807	1.9027
Cosine (1.0e – 005 *)	0.0000	0.0007	0.5450	0.0010	0.5436	0.5549
Correlation (1.0e – 005 *)	0.0000	0.0005	0.4375	0.0008	0.4382	0.4314
Seuclidean	0.9957	2.1688	4.0097	2.4400	4.1282	4.4020

Table IV
For Minimum Distances, For d = 6 : 10

Pair wise sub windows / Distance Measures	D(I1I2)	D(I1I3)	D(I1I4)	D(I2I3)	D(I2I4)	D(I3I4)
Euclidean (1.0e + 003 *)	0.0104	0.2481	1.1753	0.2585	1.1648	1.4234
City Block (1.0e + 003 *)	0.0106	0.2487	1.1798	0.2593	1.1694	1.4279
Cosine (1.0e – 005 *)	0.0000	0.0012	0.7037	0.0022	0.7111	0.7276
Correlation (1.0e – 005 *)	0.0000	0.0008	0.5190	0.0019	0.5308	0.5150
Seuclidean	2.0063	2.4991	4.4486	2.1837	3.9040	4.2290

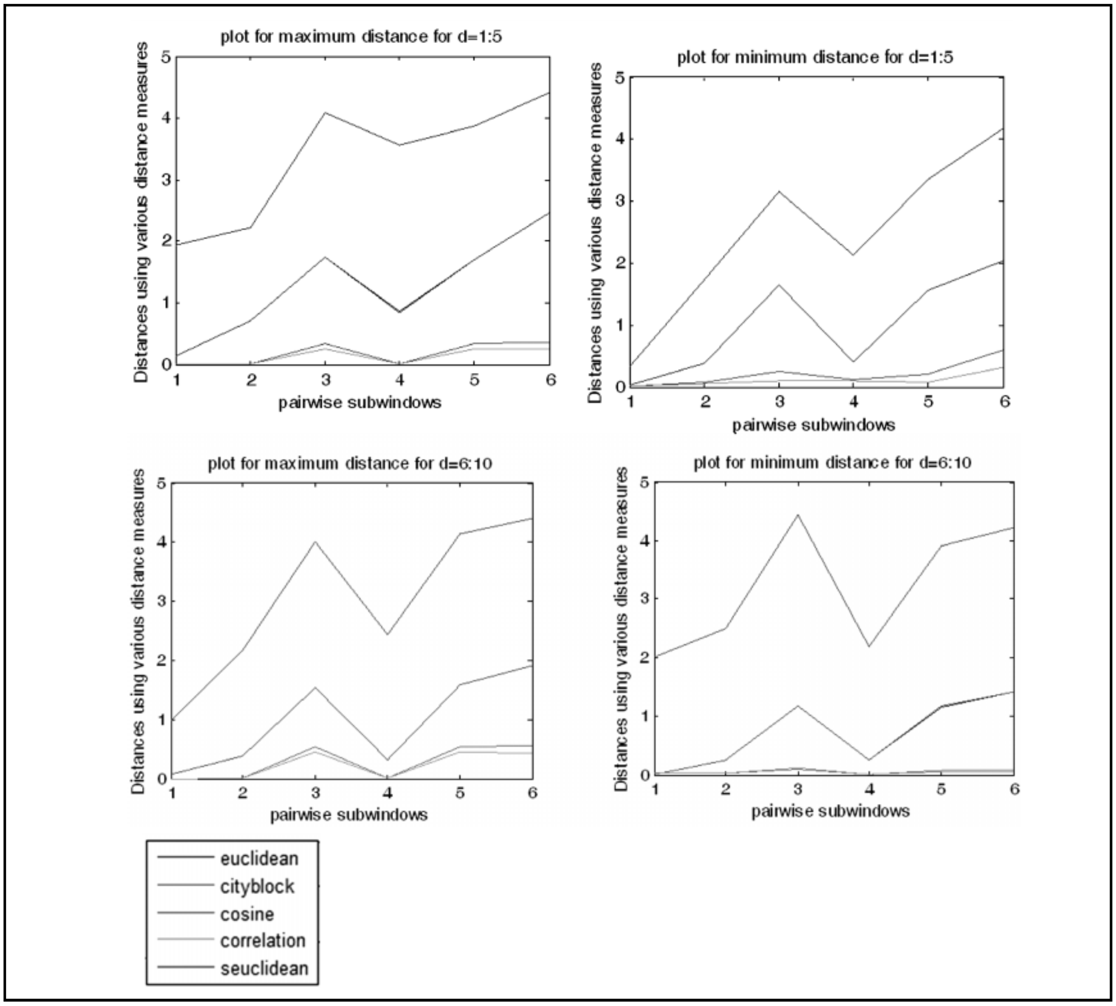


Fig. 3: Plots for Pair Wise Sub Windows v/s Distance Measures Taking Various d Values

From the above tables, one can observe that the distances between two different regions, like D{I1,I4} are greater than distances between two similar regions, like D{I1,I2} or D{I1,I3},thus indicating the presence of defect in I4.

Here, we take into account the maximum and minimum distances between the two sub windows. These distances are grouped in two categories for d = 1, 2…5 and d = 6, 7..10. It can be observed that the d values from 6, 7..10 are better in terms of comparing the distances as it gives greater variations in slope.

Also from the above plots we can decipher that the slope variation of various distances can be taken as a measure to analyze which one is more efficient in various cases. As we observe, seuclidean has the best slope variations between defected and non-defected pairs, while euclidean and cityblock distances do not show significant difference. Cosine distance gives slightly better variations compared to correlation distance.

5. Conclusion

As the above algorithm considers an average co-occurrence matrix, it is relatively invariant to image translation and rotation. It can be concluded that the range of d values 6,7,..10 gives a better discriminating power for texture defect detection.

Also, among the various distance measure techniques, the ones with better slope variations clearly proves to be a better measure for defect detection which in the present case is Seuclidean.

Further, the efficiency of the defect detection algorithm depends upon the range of image partition and texture element dimension.

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