DEFECT IDENTIFICATION USING TEXTURE ANALYSIS

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Abstract

This paper focuses the major properties of Texture analysis. The properties are Coarseness, Contrast, Complexity, Strength, Energy, Entropy, Correlation and Homogeneity. These are defined conceptually in terms of spatial changes in intensity. These are then approximated in computational forms. Initially, the input image is divided into sub images and apply all the properties over the sub images. This is mainly, to identity the defect which is present in the input image. The result shows that if any defect present in the input image, will be identified easily. The application used is Department of Textile.

Keywords :- Texture analysis, Texture Properties, Textile department.

1. Introduction

Texture analysis approaches [1] are usually categorized into Structural approach, Statistical approach, Model based approach and Transform methods. Structural approaches represent the texture by well-defined primitives (micro texture) and a hierarchy of spatial arrangements (macro texture) of those primitives. In contrast to structural methods, statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture [2, 3, 4].

Methods based on second-order statistics (i.e., statistics given by pairs of pixels) have been shown to achieve higher discrimination rates than the power spectrum (transform based) and structural methods. Model-based texture analysis using fractal and stochastic models, attempt to interpret an image texture by the use of generative image model and stochastic model respectively. Transform methods of texture analysis such as Fourier, Gabor and wavelet transforms represent an image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture such as frequency or size.

2. Texture Analysis

Haralick et al [6] categorized three groups: the statistical techniques, the structural methods, and the statistical-structural approaches. A major disadvantage of almost all of these approaches is that they do not have general applicability, they cannot be applied to different classes of textures with reasonable success. The statistical techniques are good for microtextures and poor for macrotextures, the reverse is the case for the structural techniques.

M. Amadasun et al [8] characterized the visual properties, namely coarseness, contrast, complexity, texture strength, and busyness as they considered them important for human texture description and proposed conceptual definitions in terms of spatial changes in intensity. These concepts were expressed by formulas extracted out of a neighborhood gray-tone difference matrix. Subjects sorted are some of the textures taken from Brodatz [11] in accordance with each property. The ranking lists were compared with computed ones. A clear correlation between them was established. Further a strong correlation between the features coarseness, texture strength, contrast and complexity was noticed.

Ballard et al [9] measures the texture features as a function on the co-occurrence matrix. Commonly used features are Energy, Entropy, Correlation, Inertia. Tamura et al. [10] attempted to develop textural features which correspond to human visual perception. They established a set of general descriptions of visual texture properties common to all texture images in Brodatz [11], namely Coarseness, Contrast, Directionality, Linelikeness, Regularity, Bloblikeness and Roughness. They defined formulas derived from the co-occurrence matrix for these properties. Their results indicate that Coarseness, Contrast, and Directionality are the most significant features and they found a strong correlation between some of these features: e.g. Linearity and Directionality.

Table 1. Comparison of properties by different authors for Texture Analysis

Properties	**Tamura et al [10]**	**Amadasum et al [8]**	**Rao et al [18]**	**Wu et al [12]**	**Asendorf et al [19]**	**This paper focuses**
Coarseness (I)	X	X		X	X	X
Contrast (II)	X	X		X	X	X
Complexity (III)		X	X	X		X
Strength (IV)		X				X
Energy (V)						X
Entropy (VI)						X
Homogeneity (VII)						X
Correlation (VIII)						X

Wu et al [12] proposed a new statistical feature matrix. They defined formulas for the properties Coarseness, Contrast, Regularity, Periodicity and Roughness and applied them in terms of Brodatz textures and ultrasonic liver images. Rao et al [18] used Directionality, Regularity and Complexity. Asendorf et al [19] used Linelikeness, Bloblikeness, Planarity, Coarseness, Directionality, Regularity and Contrast.

3. Texture Properties

This paper focuses the major properties of texture analysis. The properties are Coarseness, Contrast, Complexity, Strength, Entropy, Energy, Correlation and Homogeneity. Consider the input image of size n x n (where n may be 8,16,32,64,128,etc.,). Divide the input image into sixteen sub images. Apply the properties over all the sub images. With the references of [8] and [9] combined to perform the analysis.

Coarseness refers to the quality of being composed of relatively large particles. Example the coarseness of the cloth made it scratchy and uncomfortable. Contrast refers to the opposition or dissimilarity of things that are compared; or the act of distinguishing by comparing differences. Example is the photograph and its negative. Complexity refers the quality of being intricate and compounded. Example, "He enjoyed the complexity of modern computers". Strength refers the property of being physically or mentally strong. Example "Force is the application of power or strength. Entropy stated that it is a measure of "disorder". Energy refers to the capacity of work. Correlation determines the extent to which two or more variables are related among a single group of people. Example pair of score does not come from one person, the correlation between the two persons. Homogeneity refers the quality of being similar.

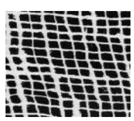

Fig. 1. Sample Texture Image

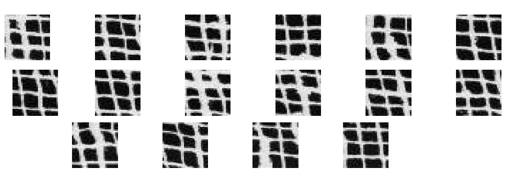

Fig. 2. Sixteen sub images of Fig. 1.

The average intensity value for neighborhood pixels is found by measuring f(x, y), the intensity value i of any pixel at (x, y). Compute the average intensity value A_i over a neighborhood pixel centered at, but excluding (x, y)

$$\overline{A}_i = \overline{A}(x,y) = \frac{1}{W-1}\left[\sum_{m=-d}^{d}\sum_{n=-d}^{d} f(x+m, y+n)\right], \quad (m,n) \neq (0,0) \qquad (1)$$

where d is the distance it specifies the neighborhood size say 1, 2, 3…(eg., if d=1 then it represents a 3X3 matrix, if d=2 then it represents a 5X5 matrix) and $W = (2d + 1)^2$, W is the total number of pixels present in the neighborhood (if d=1 then W = 9, if d=2 then W = 25), m and n are the neighborhood pixels of x and y respectively. Then the i^{th} entry in the neighborhood intensity value difference matrix is

$$c(i) = \sum \left| i - \overline{A}_i \right|, \text{ for } i \in N_i \text{ if } N_i \neq 0, \text{ or } 0 \qquad (2)$$

where N_i is the set of all intensity values, c(i) is the sum of all neighborhood pixels excluding the pixel value of (x, y). Fig. 1 shows the input image. The sixteen sub images are shown in Fig. 2. The values of each property are represented in the Table 2.

1. Coarseness

In a coarse texture, the primitives or basic patterns making up the texture are large. As a result, such a texture tends to possess a high degree of local uniformity in intensity, even over a fairly large area. In other words, the spatial rate of change in intensity is slight. Therefore the intensities of neighboring pixels would tend to be similar; thus there would be small differences between the intensity value of pixels and the average intensity value of their neighborhoods. Hence the summation of such differences computed over all image pixels would give an indication of the level of spatial rate of change in intensity, and thereby in an inverse manner show the level of coarseness of the texture. The computational measure for coarseness property P_{cos} is

$$P_{cos} = \left[\varepsilon + \sum_{i=0}^{G_{max}} p_i c(i)\right]^{-1} \qquad (3)$$

where G_{max} is the highest intensity value present in the image, c(i) is from equation 2, and ε is a small number to prevent P_{cos} becoming infinite, the value for ε is taken as 10^{-7}.

For an N X N image, p_i is the probability of occurrence of intensity value i, and is given by

$$p_i = N_i / n^2, \qquad (4)$$

$$\text{where } n = N - 2d. \qquad (5)$$

The P_{cos} is the reciprocal of normalized sum of the deviations of pixel intensities from their neighborhood average intensities. Large values represent areas where intensity differences are small. The result of the coarseness property is shown in the Fig. 3.

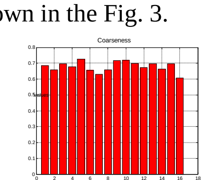

Fig. 3 Coarseness Result

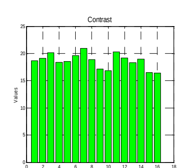

Fig. 4 Contrast Result

2. Contrast

Perceptually, an image is said to have a high level of contrast if areas of different intensity levels are clearly visible. Thus high contrast means that the intensity difference between neighboring of gray scale is large or when it is stretched. Also the spatial frequency of the changes in intensity (i.e., the amount of local intensity variations) will affect the contrast of an image. For instance, a small checkerboard will appear to have a higher contrast than a coarse checkerboard for the same gray scale range.

Taking these two factors into consideration, named as i and j then compute the contrast property P_{con} as

$$P_{con} = \left[\frac{1}{N_{diff}\left(N_{diff} - 1\right)} \sum_{i=0}^{G_{max}} \sum_{j=0}^{G_{max}} p_i p_j (i-j)^2 \right] \left[\frac{1}{n^2} \sum_{i=0}^{G_{max}} c(i) \right] \qquad (6)$$

where N_{diff} is the total number of different intensity levels present in the image and p_j is the probability of occurrence of intensity value j.

$$N_{diff} = \sum_{i=0}^{G_{max}} Q_i \quad \text{where } Q_i = 1 \text{ if } p_i \neq 0 \text{ or } 0 \qquad (7)$$

The P_{con} is a product of two terms. The result of the contrast property is shown in the Fig. 4.

The first quantity is the average weighted squared difference between the different intensity values taken in pairs, and is used to reflect the dynamic range of gray scale; the weighting factor is a product of the probabilities of the two intensity values under consideration. The second term is the average difference between pixel intensity values and the average intensity value of their neighborhoods; this quantity increases with the amount of local variation in intensity.

3. Complexity

Complexity refers to the visual information content of a texture. A texture is considered complex if the information content is high. This occurs when there are many blocks or primitives present in the texture, and more so when the primitives have different average intensities. This will depend upon the spatial period of pattern repetition and on the dynamic range of gray scale. Thus complexity is in part correlated with contrast.

Generally textures in which the spatial rate of change in intensity is slight tend to have few different values of intensity values, but with a high probability of each value occurring. Consequently in these textures, there may not be many blocks having different average intensity levels, but the blocks would be large.

Also the resulting high level of local uniformity in intensity will produce few edges. Thus a texture in which there are very rapid spatial changes in intensity is more likely to be complex than a texture that has a high degree of local uniformity in intensity.

Therefore the sizes of primitives and/or probabilities of occurrence of intensity values tend to have inverse relationship with complexity. The measure of the computational complexity property P_{com} is

$$P_{com} = \sum_{i=0}^{G_{max}} \sum_{j=0}^{G_{max}} \left\{ \left(|i-j| \right) / \left(n^2 \left(p_i + p_j \right) \right) \right\} \left\{ p_i c(i) + p_j c(j) \right\},$$

$$p_i \neq 0, \; p_j \neq 0 \qquad (8)$$

The P_{com} is a sum of normalized differences between intensity values taken in pairs. The result of the complexity property is shown in the Fig. 5.

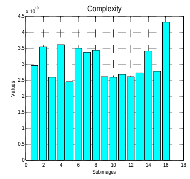

Fig. 5 Complexity Result

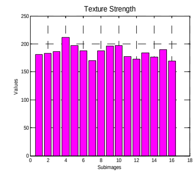

Fig. 6 Strength Result

These differences are weighted by the sum of the probability-weighted entries in the Neighborhood Intensity values Difference Method corresponding to the two intensity values under consideration. High values of P_{com} should indicate a high degree of information content.

Table 2 Values of all Sub Images (SI) for Eight properties

Properties	I	II	III (x10^10)	IV (x10^2)	V	VI	VII	VIII
SI 01	0.0033	18.691	2.9508	1.8117	6.7801	0.0766	0.6835	0.5967
SI 02	0.0031	19.102	3.5309	1.8311	6.6258	0.0665	0.6580	0.5856
SI 03	0.0034	20.129	2.5918	1.8630	6.6260	0.0735	0.6951	0.5959
SI 04	0.0031	18.393	3.5943	2.1136	6.4644	0.0750	0.6766	0.5917
SI 05	0.0036	18.509	2.4412	1.9708	6.7256	0.0781	0.7268	0.6234
SI 06	0.0028	19.658	3.4983	1.8768	6.3834	0.0765	0.6565	0.5929
SI 07	0.0026	20.979	3.3681	1.7005	6.4437	0.0723	0.6297	0.5757
SI 08	0.0031	18.887	3.4223	1.8732	6.5672	0.0695	0.6577	0.5771
SI 09	0.0040	17.175	2.5973	1.9644	6.7683	0.0921	0.7179	0.6222
SI 10	0.0039	16.871	2.5868	1.9687	6.7716	0.0708	0.7196	0.6114
SI 11	0.0033	20.260	2.6783	1.7763	6.5939	0.0737	0.6976	0.6027
SI 12	0.0033	19.222	2.5946	1.7324	6.7010	0.0633	0.6719	0.5806
SI 13	0.0035	18.277	2.7106	1.8381	6.6667	0.0770	0.6949	0.6064
SI 14	0.0030	18.991	3.4076	1.7619	6.6378	0.0682	0.6633	0.5963
SI 15	0.0037	16.485	2.7739	1.8974	6.7012	0.0732	0.6956	0.5991
SI 16	0.0024	16.433	4.3149	1.6891	6.4490	0.0641	0.6069	0.5541

4. Strength

The term strength is a difficult concept to define concisely. However a texture is generally referred to as strong when the primitives that comprise it are easily definable and clearly visible. Such textures generally tend to look attractive, as they present a high degree of visual feel. But the ease with which distinctions can be made between the component primitives of a texture depends to a considerable extent upon the sizes of the primitives and the differences between their average intensities.

For instance it may be possible to distinguish between large primitives even with small differences between their average intensities. Thus, in part, strength may be correlated with coarseness and contrast. The strength of the property P_{str} is measured as

$$P_{str} = \left[\sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{\max}}\left(p_i + p_j\right)(i-j)^2\right] / \left[\varepsilon + \sum_{i=0}^{G_{\max}} c(i)\right],$$

$$p_i \neq 0, \; p_j \neq 0 \qquad (9)$$

This expression involves two terms. The result of the strength property is shown in the Fig. 6.

The numerator is a factor stressing the differences between intensity levels, and therefore it may reflect intensity differences between adjacent primitives, particularly as the intensities are weighted by the sum of their probabilities of occurrence; these probabilities would tend to be high for large primitives.

Also the denominator can convey information about the size of texture primitives, as it is essentially a sum of the difference between a pixel intensity value and the average intensity value in its neighborhood over all pixels. Its value would be small for coarse textures, and large for fine textures.

The expression would therefore tend to emphasize the boldness or distinctiveness of the primitives. Hence a high value of texture strength P_{str} would correspond to a strong texture. ε is a small number.

5. Entropy

Entropy is the amount of energy in a system that is no longer available for doing work [20]. Entropy calculated from the probability that a state could be reached by chance alone. Entropy states that it is a measure of "disorder" or Randomness.

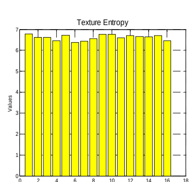

Fig. 7 Entropy Result

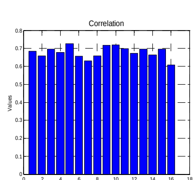

Fig. 8 Correlation Result

Entropy is an important principle in statistics for constructing a probability distributions p on a set of random variables X. The Entropy principle suggests that a good choice of the probability distribution is the one that has the maximum entropy [21]. The entropy property P_{entr} is measured as

$$P_{entr} = -\sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{\max}} p(i,j) \times \log\left(p(i,j)\right) \qquad (10)$$

Inhomogeneous scenes have first low order entropy, while a homogeneous scene has a high order entropy. The result of the entropy property is shown in the Fig. 7.

6. Correlation

A causal, complementary, parallel, or reciprocal relationship, especially a structural, functional, or qualitative correspondence between the two comparable entities [5]. The simultaneous change of two numerical values random variables. An act of correlating or the condition of being correlated. They are used to determine the extent to which two or more variables are related among a single group of people (although sometimes each pair of score does not come from one person).

There is no attempt to manipulate the variables (random variables). A correlation has direction and can be either positive or negative. With a positive correlation, individuals who score high (or low) on one measure tend to score similarly on the other measure. A correlation can differ in the degree or strength of the relationship [7]. The result of the correlation property is shown in the Fig. 8.

Correlation is a measure of gray level linear dependence between the pixels at the specified position relative to each other. The correlation property P_{cor} is measured as

$$P_{cor} = \sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{\max}} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j}, \qquad (11)$$

$$\mu_i = \sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{\max}} ip(i,j), \qquad (12)$$

$$\mu_j = \sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{\max}} jp(i,j) \qquad (13)$$

$$\sigma_i = \sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{\max}} (i-\mu_i)^2 p(i,j), \qquad (14)$$

$$\sigma_j = \sum_{i=0}^{G_{\max}}\sum_{j=0}^{G_{ma}} (j-\mu_j)^2 p(i,j) \qquad (15)$$

Where μ and σ are the mean and standard deviations of p(i,j) for correlation property.

7. Energy

Energy is the capacity of work or vigorous activity, vigor, power. The capacity of a physical system to do work; the units of energy are joules or ergs, "energy can take a wide variety of forms". It returns the sum of squared elements in average intensity value for neighborhood pixels. It ranges from 0 to 1. Energy is 1 for a constant image. The energy property P_{ene} is measured as

$$P_{ene} = \sum_{i=0}^{G_{\max}} \sum_{j=0}^{G_{\max}} p(i, j)^2 \qquad (16)$$

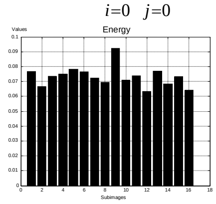

Fig. 9 Energy Result

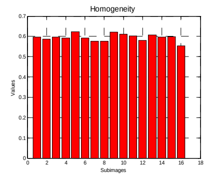

Fig. 10 Homogeneity Result

The energy property result is shown in the Fig. 9.

8. Homogeneity

Homogeneity is the state or quality of being homogeneous. The quality of being similar or comparable in kind or nature; "there is a remarkable homogeneity between the two companies". The quality of being uniform throughout in composition or structure. The homogeneity property $P_{\hom}$ is measured as

$$P_{\hom} = \sum_{i=0}^{G_{\max}} \sum_{j=0}^{G_{\max}} \frac{p(i, j)}{1 + |i - j|} \qquad (17)$$

It returns a value that measures the closeness of the distribution of elements in the average intensity value for neighborhood pixels to the diagonal pixel values.

It ranges from 0 to 1. Homogeneity is 1 for diagonal average intensity value for neighborhood pixels. The result of the homogeneity property is shown in the Fig. 10.

The running time for the input image is 2.45 seconds on an Intel Pentium III Processor, 1 Ghz Clock Speed, 256MB RAM, using MATLAB code. The time varies according to the images. For any image, complete analysis can be done within the maximum of one minute.

4. Defect Identification

Texture Analysis is done for the defected image. The defected image is shown in the Fig. 11. The sixteen sub images are shown in the Fig. 12. Threshold value is set to all properties. The values of each block is checked with the threshold value, if it is greater than the threshold value then that block is a defected block [16, 17].

If the value is less than the threshold value, then the block is not affected by the defect. Then it is named as a normal. From the result of the properties the defect is identified clearly.

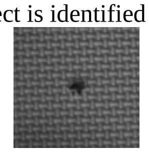

Fig. 11 Defected Input Image

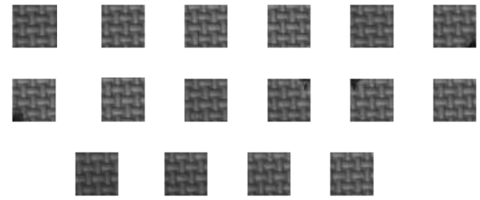

Fig. 12 The sixteen sub images for the defected image

5. Results and Discussion

The result of each property is shown through the Bar chart and the values are represented in the Table 3

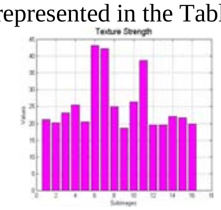

Fig. 13 Strength Result

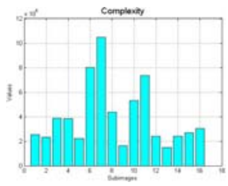

Fig. 14 Complexity Result

For the Strength property the threshold value set as 30. Fig. 13 clearly shows that the defected blocks are 6th, 7th and 11th. For the complexity property, the threshold value set as 6×10^8**.** So the defected blocks are 6th,7th and 11th blocks. The results are shown in the Fig. 14.

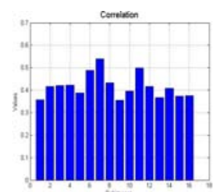

Fig. 15 Correlation Result

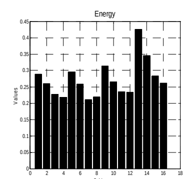

Fig. 16 Energy Result

The threshold value of the Correlation property is 0.45. The result of the Correlation property is shown in Fig.15. Energy property is opposite to other properties. By default it says that if the energy is less, then there is a defect or some fault. The minimum value of the block identifies that there is a defect. The threshold value is 0.25. If the block value is less than the threshold value then there is a defect. Otherwise there is no defect. The result is shown in the Fig. 16. Contrast property will show the minimum value as a defect because of the intensity variation in the image. It is shown in the Fig. 17. Relatively large particles will be shown in the coarseness property. The minimum values will be taken as a defected block. The result is shown in the Fig. 18.

Entropy property will show the disorder values. Maximum value of the block identifies the defects. Result is shown in the Fig. 19. Homogeneity property shows the minimum values of the blocks are defected blocks. The result is shown in the Fig. 20. Any type of defect can be identified through this texture analysis.

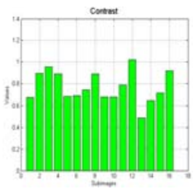

Fig. 17 Contrast Result

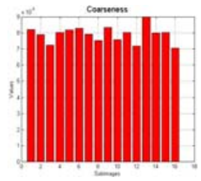

Fig. 18 Coarseness Result

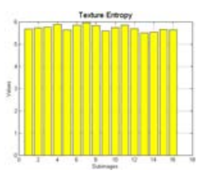

Fig. 19 Entropy Result

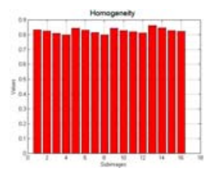

Fig. 20 Homogeneity Result

Table 3 Values of the Defected image

Properties	I	II	III ($x10^{10}$)	IV ($x10^{2}$)	V	VI	VII	VIII
SI 01	0.0082	0.6734	2.5485	20.985	0.2888	5.6702	0.3567	0.8328
SI 02	0.0079	0.8958	2.3429	20.226	0.2594	5.7316	0.4161	0.8245
SI 03	0.0072	0.9542	3.8736	22.914	0.2273	5.7667	0.4207	0.8101
SI 04	0.0080	0.8894	3.8487	25.355	0.2178	5.8805	0.4237	0.7980
SI 05	0.0082	0.6796	2.2151	20.406	0.2955	5.6383	0.3873	0.8427
SI 06	0.0083	0.6904	8.0322	43.028	0.2589	5.8546	0.4872	0.8299
SI 07	0.0079	0.7436	10.467	42.128	0.2118	5.9641	0.5402	0.8146
SI 08	0.0075	0.8900	4.3527	24.843	0.2196	5.8284	0.4326	0.7974
SI 09	0.0083	0.6776	1.6259	18.587	0.3135	5.5822	0.3552	0.8437
SI 10	0.0076	0.6768	5.3058	26.226	0.2647	5.7467	0.3963	0.8269
SI 11	0.0080	0.7892	7.3620	38.569	0.2354	5.8486	0.4977	0.8208
SI 12	0.0072	1.0204	2.4014	19.503	0.2340	5.6906	0.4169	0.8120
SI 13	0.0090	0.4907	1.4751	19.478	0.4258	5.5014	0.3675	0.8609
SI 14	0.0080	0.6479	2.3962	21.847	0.3455	5.5267	0.4086	0.8470
SI 15	0.0080	0.7137	2.6743	21.467	0.2839	5.6541	0.3744	0.8285
SI 16	0.0070	0.9181	3.0419	19.812	0.2609	5.6487	0.3755	0.8222

6. Conclusion

The texture defect can be identified using texture analysis. Texture properties are used for complete analysis. The major properties are taken. Initially, the input image can be divided into sixteen sub images. All properties are applied to each sub images for thorough analysis. The defect can be clearly visible in the Strength, Complexity, Correlation and Energy property. Drastic change is shown in these properties for identification of the defect. But in the remaining properties, slight changes are shown, because of the nature of the property. Major application is for Textile industry.

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