HIGHER ORDER STATISTICS BASED TEXTURE ANALYSIS METHOD FOR DEFECT INSPECTION OF TEXTILE PRODUCTS*

Birkan Aras[1], Ayşın Ertüzün[1], Aytül Erçil[2]
[1]Department of Electrical and Electronic Engineering, [2]Department of Industrial Engineering
Boğaziçi University, 80815, Bebek, İstanbul, Turkey
ertuz@boun.edu.tr, ercil@boun.edu.tr

ABSTRACT

Texture analysis is an important approach in textile quality control. Higher order statistics have been very useful in problems where non-Gaussianity, nonminimum phase, colored noise or nonlinearity is important. In this work, higher order statistical analysis is applied to texture defect detection problem. A neighborhood definition is proposed for cumulant lags of higher order statistics and it is used to form higher order statistical feature sets. These higher order statistical feature sets and some hybrid feature sets composed of both second and higher order statistics are used to detect defects on textural images of textile fabrics. The results are compared with methods based only on second order statistics both from performance and computational complexity points of view.

1. INTRODUCTION

Quality control, designed to ensure that defective products are not allowed to reach the customer, is a topical issue in manufacturing. 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 to real-world industrial inspection problems.

Since in many areas the quality of a surface is best characterized by its "texture", texture analysis plays an important role in the automated visual inspection of surfaces. There have been a number of applications of texture processing to inspection problems. Some of these are as follows: Erçil and Özüyılmaz [1] have proposed a model based technique to detect and locate the various kinds of defects that might be present in a given painted surface. Jain *et. al.* [2] have used the texture features computed from a bank of Gabor filters to automatically classify the uniformity of painted metallic surfaces. Chen and Jain [3] have used a structural approach to defect detection in textured images. Conners [4] has utilized texture analysis methods to detect defects in lumber wood automatically. Siew *et.al.* [5] have proposed a method for the assessment of carpet wear. Dewaele *et.al.* [6] have employed signal processing methods to detect point and line defects in texture images.

Signal processing tools that depend on second order statistics of textures have been used in texture analysis for years [7]. In recent years, there is a tendency in signal processing to replace the methods based on second order statistics by higher order statistics [8-9]. Higher order statistics have been very useful in problems where non-Gaussianity, nonminimum phase, colored noise or nonlinearity is important. Tsatsanis and Giannakis [10] have used higher order statistics based methods to classify textures.

In this work, higher order statistical analysis is applied to texture defect detection problem [11]. A neighborhood definition is proposed for cumulant lags of higher order statistics and it is used to form higher order statistical feature sets. In the feature extraction part of the defect detection scheme, the feature vectors are computed. These vectors consist of either higher order statistical feature sets or hybrid feature sets composed of both second and higher order statistics. Then, in the feature analysis section, a mahalonobis distance classifier classifies the textures as defective or nondefective. The proposed method is tested on real fabric images acquired in a laboratory environment. The results are compared with methods based only on second order statistics both from performance and computational complexity points of view.

2. BACKGROUND MATERIAL ON HIGHER ORDER STATISTICS

2.1 Definitions

In signal processing methods based on second order statistics and/or spectrum, the phase information between the frequency components are not considered. These methods are blind to the phase information as well as they can not fully describe non-Gaussian processes. Recently, higher order statistics and spectra have been used to accurately describe stochastic processes and to extract phase information.

Given a set of n real random variables $\{x_1, x_2, \ldots, x_n\}$, their joint cumulants of order $r = k_1 + k_2 + \ldots + k_n$ are defined as [9]

$$Cum\left[x_1^{k_1}, x_2^{k_2}, \ldots, x_n^{k_n}\right] = (-j)^r \left. \frac{\partial^r \ln \Phi(w_1, w_2, \ldots, w_n)}{\partial w_1^{k_1} \partial w_2^{k_2} \ldots \partial w_n^{k_n}} \right|_{w_1 = w_2 = \ldots = w_n = 0} \quad (1)$$

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where

$$\Phi(w_1, w_2, \ldots w_n) = E\left\{\exp\left(j(w_1 x_1 + w_2 x_2 + \ldots + w_n x_n)\right)\right\} \quad (2)$$

is their joint characteristic function and $E\{.\}$ denotes the expectation operator.

If $\{X(k)\}, k = 0, \pm 1, \pm 2 \ldots$ is a real, stationary discrete-time signal, then

$$m_n^x(\tau_1, \tau_2, \ldots \tau_{n-1}) = E\{X(k)X(k+\tau_1)\ldots\ldots X(k+\tau_{n-1})\} \quad (3)$$

represents the nth order moment function of the signal which depends only on the time differences $\tau_1, \tau_2, \ldots \tau_{n-1}, \tau_i = 0, \pm 1, \ldots$ for all *i*. The first order moment $m_1^x = E\{X(k)\}$ is the mean value of $\{X(k)\}$ and the second order moment function $m_2^x(\tau_1) = E\{X(k)X(k+\tau_1)\}$ is the autocorrelation function of $\{X(k)\}$.

The nth order cumulant function of a real, stationary discrete-time signal, $\{X(k)\}$, may be defined as:

$$c_n^x(\tau_1, \tau_2, \ldots \tau_{n-1}) = E\{X'(k), X'(k+\tau_1), \ldots\ldots, X'(k+\tau_{n-1})\} \quad (4)$$

Here, the process *X'(k)* is the zero mean version of the process *X(k)*. If a process is zero mean, its second and third order cumulants are equal to the second and third order moments, respectively. However, for higher order cumulants this relationship is not valid.

The definitions of higher order cumulants for real, stationary random fields are similar to those for real, stationary discrete-time signals. In Eqs. (3) and (4), k, τ variables are scalars for real, stationary discrete-time signals. If they are interpreted as vector variables, $k = [k_1, k_2]^T$ and $\tau = [\tau_1, \tau_2]^T$ then definitions and equations describing higher order statistics of real, stationary random fields are obtained.

2.2 Cumulant Lag Definition For Higher Order Statistics

Signal processing techniques that use second order statistical or power spectral analysis generally depend on a number of autocorrelation lags of the signal. The number of autocorrelation lags that are used in the analysis usually determines the order of complexity of the analysis. From a model based point of view, the number of autocorrelation lags determines the order of complexity of the model process proposed as the generator of the signal. In two-dimensional signal processing, the autocorrelation lags used in the analysis should be defined according to neighborhood relations. Neighborhood relations are defined in terms of distances between pixels of an image. Pixels, which are equidistant from a given pixel A, are labeled with same number. Each label number defines a neighborhood order around pixel A [12].

Markov Random Fields (MRF) are used as model based methods that utilize autocorrelation function. The brightness level at a point in an image is highly dependent on the brightness levels of the neighboring pixels. MRF use an accurate model of this dependence and are able to capture the local (spatial) contextual information in an image. These models assume that the intensity at each pixel in the image depends on the intensities of only the neighboring pixels and use sufficient statistics instead of the autocorrelation lags since the autocorrelation function is an even function of the lags [1]. Neighborhood definition of autocorrelation lags depends on distances between two pixels; and it is not convenient for higher order statistics since they are concerned with more than two pixels. Tsatsanis and Giannakis [10] proposed the third order cumulant lags in the set { $c_3^x([i_1, i_2], [j_1, j_2])$, $i_1 = 0$, $i_2 = 0,1$, $0 \leq j_1, j_2 \leq 3$. But the cumulant lags in this set are asymmetric. In order to prevent this asymmetry, a new neighborhood definition is proposed. The neighborhood definition of autocorrelation lags are generalized to more than two pixels to enable the definition to be used for statistics of all orders: The order of neighborhood of a group of pixels may be defined as the maximum order of neighborhoods of two-pixel combinations in the group [11]. The proposed neighborhood definition places the third order cumulants and MRF under the same frame.

3. TEXTURE DEFECT DETECTION

Texture defect detection can be defined as the process of determining the location and/or extend of a collection of pixels in a textured image with remarkable deviation in their intensity values or spatial arrangement with respect to the background texture.

The main concern of this work is to use the higher order statistics that are defined by the generalized neighborhood relations as the new feature vectors [11]. The aim here is to extend the second order statistical work to higher order statistical domains as the cumulant lag features may carry information that is useful to discriminate defective and nondefective regions of textures. The defect detection performances of the following feature sets of second and higher order statistics are presented:

1. Second order statistics up to second neighborhood (S2)
2. Second order statistics up to fifth neighborhood (S5)
3. Second order statistics up to ninth neighborhood (S9)
4. Third order statistics up to second neighborhood (T2)
5. Third order statistics up to fifth neighborhood (T5),
6. Thirty-one third order statistics proposed by [10] (T31)
7. Fourth order statistics up to second neighborhood (F2)

8. Second and third order statistics up to second neighborhood (S2T2)
9. Second order statistics up to fifth neighborhood and third order statistics up to second neighborhood (S5T2),
10. Second order statistics up to ninth neighborhood and third order statistics up to second neighborhood (S9T2),
11. Second, third and fourth order statistics up to second neighborhood (S2T2F2)

The first three feature vectors consists of only second order statistics. The next four feature vectors consists of various higher order statistics. Three of these are generated using the concepts of neighborhood developed in this study [11]; other is feature vector that consists of the cumulant set $\{c_3^x([i_1, i_2], [j_1, j_2]),\ i_1 = 0,\ i_2 = 0,1,\ 0 \leq j_1, j_2 \leq 3\}$ proposed by Tsatsanis and Giannakis [10]. The last four feature vectors are the hybrid feature vectors formed by second and higher order statistics.

The proposed defect detection system consists of two stages [11]: (a) The feature extraction part which extracts statistical features and (b) the detection part which is a mahalanobis distance classifier being trained by defect-free samples. The algorithms for each are provided below:

(a) Feature extraction

(i) An image I(n,m) of size N x N is subdivided into M nonoverlapping subwindows (S_i) of size p x p.

(ii) For each subwindow, second and higher order statistics are computed and the 11 feature vectors defined above are formed.

(iii) Steps (i) and (ii) are repeated for all subwindows S_i.

(b) Detection part

The detection part of the system consists of a learning phase and a classification phase. These phases will be elaborated in the subsequent parts:

Learning Phase

(i) Given k defect-free N x N images, the feature vectors for each subwindow of the image are calculated using the feature extraction scheme given above. These vectors are considered as the true feature vectors and are labeled as $\mathbf{t}_i$ ($1 \leq i \leq Mk$).

(ii) The mean vector $\mathbf{m}$ and the covariance matrix $\mathbf{K}$ are computed for the feature vectors $\mathbf{t}_i$.

Classification phase

(i) Given a test image, the feature vectors $\mathbf{x}_i$'s are calculated using the feature extraction scheme given above.

(ii) The mahalanobis distance d_i between each feature vector $\mathbf{x}_i$ and the mean vector $\mathbf{m}$ is calculated.

$$d_i = (\mathbf{x}_i - \mathbf{m})^T \mathbf{K}^{-1} (\mathbf{x}_i - \mathbf{m}) \qquad (5)$$

Vector $\mathbf{m}$ and matrix $\mathbf{K}$ are determined in the learning phase.

(iii) A subwindow S_i for which di exceeds a threshold value α is labeled as defective, else it is identified as nondefective. i.e.,

$$S_i = \begin{cases} \text{defective} & \text{if} \quad d_i > \alpha \\ \text{nondefective} & \text{otherwise} \end{cases}$$

The threshold value α is determined in terms of the sample median D_m and the upper quartile D_q of the order statistics D_i obtained by arranging distances d_i in ascending order as follows:

$$\alpha = D_m + \eta\,(D_q - D_m) \qquad (6)$$

Here η is a constant determined experimentally. The second term of summation in Eq. (6) is the confidence interval. For an N x N sized image partitioned into M subwindows, $D_m = (D_{M/2} + D_{M/2+1})/2$ and $D_q = (D_{M-M/4} + D_{M-M/4+1})/2$. In calculating the threshold for an image, the median of the distances of subwindows from the learned sample instead of mean is used since the mean will not be a reliable measure when there are errors.

Intuitively, what the classifier does is to label subwindows with considerable difference from the rest as defective.

The basic steps of the defect detection scheme are summarized in Figure 1.

4. IMPLEMENTATION AND RESULTS

The defect detection scheme elaborated in the previous section is used to detect defects in the textile products. For this reason, 8-bit gray level images of dimension 256 x 256 taken by a Sony CCD Iris SSC-M370CE camera in a laboratory environment are tested. Front lighting was used during the acquisition of the images, that is the camera and the light source were placed on the same side of the fabrics. Each of the acquired 256 gray level images corresponds to 8.53 cm x 8.53 cm fabric with the resolution of 3.33 pixels/mm, which is the same resolution that is required in the factory environment. The texture image sample set on which the experiments are performed contains images of eight different texture types. Set of first texture type consists of 35 images. 19 of the images of first texture type contain defects and 16 of them are defect free (clean). Each of the remaining seven sets of texture types contains four images. For each set, two images contain defects and two images are clean. In the experiments, the system is trained by 30 clean images and 33 defected texture images are used as the test images. Effort is made to include various textures and different types of defects that most frequently occur during production (Figure 2). In the experiments, the highest performance is obtained by using 32x32 sized nonoverlapping subwindows. Window size chosen, in scanning the images depends both on the resolution of the camera used for image acquisition and the textural properties of the fabrics as well as how localized the defects are. The correct detection rates for all the feature vectors are illustrated in Fig.3. The detection rates are calculated by comparing the results of the automated system with real locations of defected regions

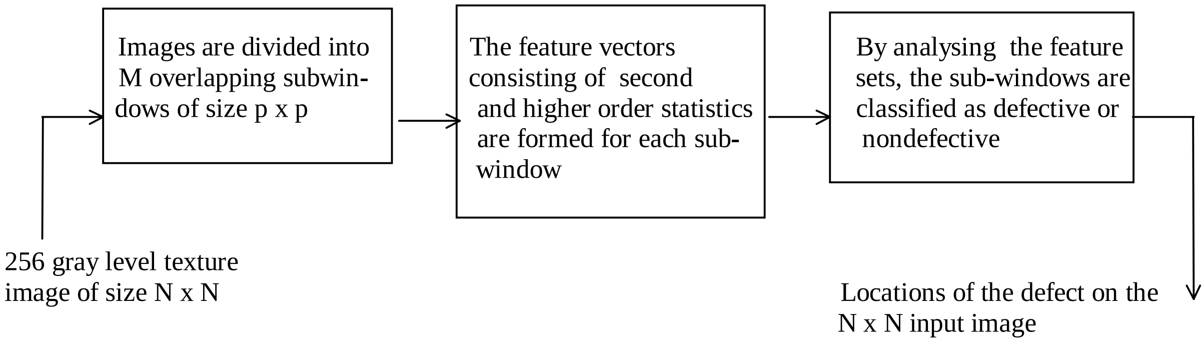
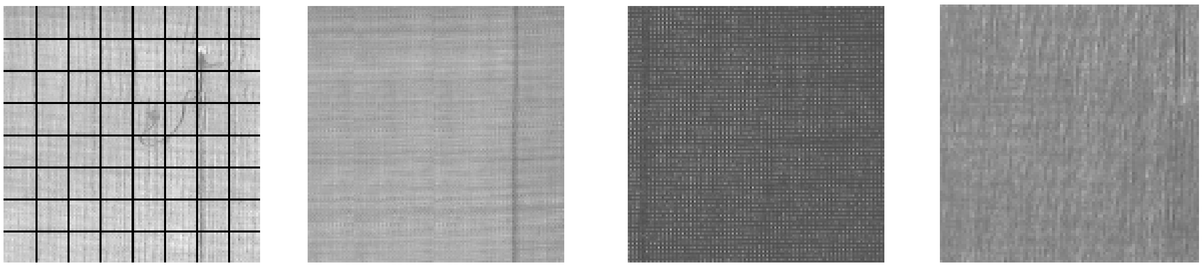


Figure 1. Basic steps of the texture defect detection scheme.



(a) (b) (c) (d)

Figure 2. 256 gray level texture images of size 256x256, having different type of defects**. a)** Texture Type 1 is divided into subwindows of size 32x32 (S_i :i=1,…,64); **b)** Texture type 1; **c)** Texture type 2; **d)** Texture type 3.

labeled by a trained quality inspector. Before each defected image is processed by the automated system, a trained quality inspector marked the defected regions of the images. Then, the results obtained by the automated system are compared with the locations of the defected regions labeled by the inspector. If n_s denotes the total number of analyzed subwindows, n_{dd} denotes the number of defected subwindows which are also found to be defected by the automated system and n_{cc} denotes the number of nondefective (clean) subwindows which are also found to be nondefective (clean) by the automated system, the detection rate (DR) is calculated by the following formula. The formula handles also the number of false alarms, namely the number of nondefective subwindows which are found to be defective:

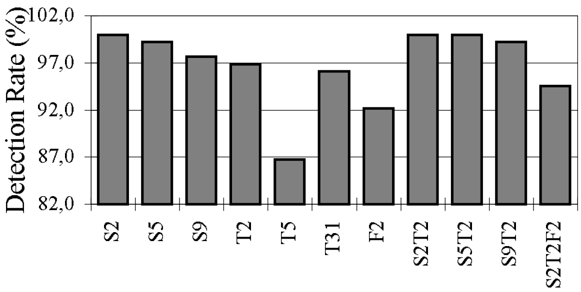
$$DR = ((n_{dd} + n_{cc}) / n_s) * 100 \tag{7}$$

The results obtained can be summarized as follows: The defect detection scheme has been tested over a set of eight different textile textures having various defects on them. Only for two textures of this set, the autocorrelation based feature vectors (S9) have given the best results. The feature vectors that consist of only third order statistics, namely T2, T5, T31, have performed satisfactorily for texture types 2 and 3, however for other types of texture and defects they have not performed as good as other feature sets. However, when third order statistics and second order statistics are used together, in other words for hybrid feature vectors, the results were very good for five texture images. For one image both second order statistics (S2) and the hybrid (S2T2, S5T2) feature sets gave 100% detection rate (Fig. 3a). Figure 3 illustrates the performance of different feature sets for texture types1, 2 and 3.

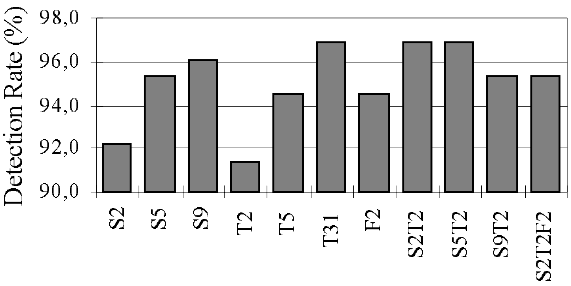
It is observed that the hybrid feature vectors obtained by using second and third order statistics have increased the defect detection rate. However the arithmetical complexity encountered in the calculation of the hybrid feature vectors are much greater than that of second order statistics. Table 1 illustrates the arithmetical complexity for computing different feature vectors.

5. CONCLUSIONS

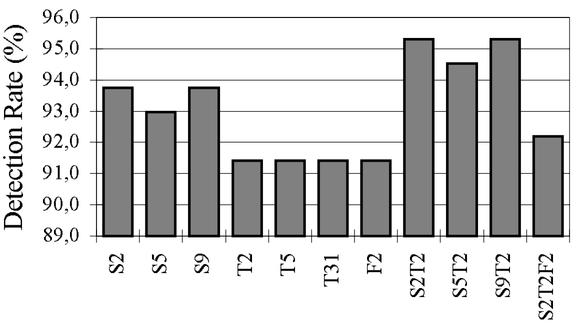
In this study, the possibility of using higher order statistics for defect detection of textile images has been investigated. Higher order statistics based methods may be used to model textures for which second order statistics are insufficient. As expected, for some texture types, hybrid features that combine second and higher order statistics have shown better performance. However, due to the fact that the computational complexity of higher order statistics is very high, the hybrid feature vectors are also computationally complex. A study on the reduction of computation complexity of higher order statistical analysis is necessary to enable their application to texture analysis and image processing.



(a)



(b)



(c)

Figure 3. Performances of different feature sets over **a)** texture type 1; **b)** texture type 2; **c)** texture type 3

TABLE 1

Computational complexity of different feature sets

Feature Sets	Additions ($x10^6$)	Multiplications ($x10^6$)
S2	0.66	0.33
S5	1.72	0.87
S9	3.32	1.64
T2	4.27	4.28
T5	24.26	24.31
F2	20.49	29.05
S2T2	4.93	4.62
S5T2	6.01	5.17
S9T2	7.63	6.01
S2T2F2	25.49	33.73
T31	10.22	10.24

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