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Defect Detection and Identification in Textile Fabric by SVM Method

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ABSTRACT: *In this paper we use a support vector machine (SVM) for defects identification in textile. This new approach serves in the fast detection and extraction of fabric defects from the images of textile fabric based on geometrical analysis of the textile pattern images. Actually, most defects arising in the production process of textile material are still detected by human inspection [1] and the work of inspectors is very tedious and time consuming. They have to detect small details that can be located; the identification rate is about 70%. In addition, the effectiveness of visual inspection decreases quickly with fatigue. For these reasons, an algorithm has been proposed for the defect identification and classification. So, the images analyzed came from an artificial vision system that we used to acquire and memorize those images under jpeg format. The vision system is composed of a camera with a sensor 512X512 Pixels. The classifier SVM was manipulated to classify all defects in the defected fabric.*

KEYWORDS*: textile defect's identification; features extraction; vision system; SVM*

I. INTRODUCTION

The Automated visual inspection of industrial goods for quality control plays an ever-increasing role in the production process as the global market pressures put higher and higher demand on quality. In most cases, the quality of inspections through visual inspection is still carried out by humans. However, the reliability of manual inspection is limited by ensuing fatigue and inattentiveness. For example: in textile industry, the most highly trained inspectors can only detect about 70% of the defects [2]. Therefore, the automation of visual inspection process is required to maintain high quality of products at a high-speed production. The analysis of images in an artificial vision system is an expensive process. SVM was applied to many problems, and has demonstrated its excellence over traditional methods. The methodology used in this investigation follows the pattern recognition schema: image segmentation, feature extraction and classification. The segmentation process is oriented towards the detection of edges and suspecting the area (defect). This technique seeks changes in the gray values of the image (edges) and then identifying zones delimited as suspect defect. However, only some of them are defects and the others are false alarms. Subsequently, the feature extraction is centered principally on the measurement of properties of the regions. Finally, classification orders segmented regions.

II. PRE-PROCESSING

The aim is to eliminate the probable noises of images, the following pre-processing procedures are carried out on the images prior to feature extraction step.

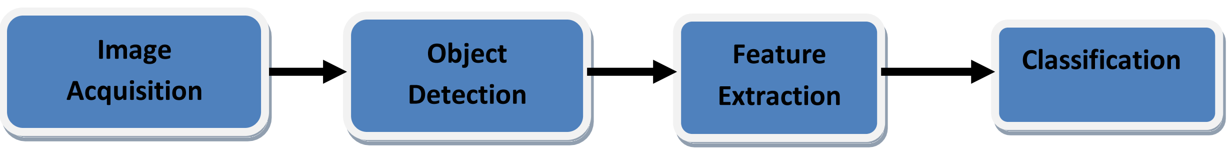


Figure 1: Computer vision system

The acquired RGB image is converted to gray image, then; the gray level image is enhanced by using the histogram equalization method. A sharp contrasted image is obtained. The first step in processing and sorting the image, is to detect the defect or to determine the location and borders of the defect. This operation is considered as an image segmentation process while the image is segmented in to two classes: abject and background. After the detection of the defect, the area of the defect is analyzed. Features are extracted from detected regions. For example size and shape of the defect are extracted to determine the type of defect. The final step is a trained classifier, which gives the decision. The next section presents the image segmentation and classification.

III. METHODOLOGY FOR DEFECT DETECTION

The system of digital image processing may be presented schematically as shown below.

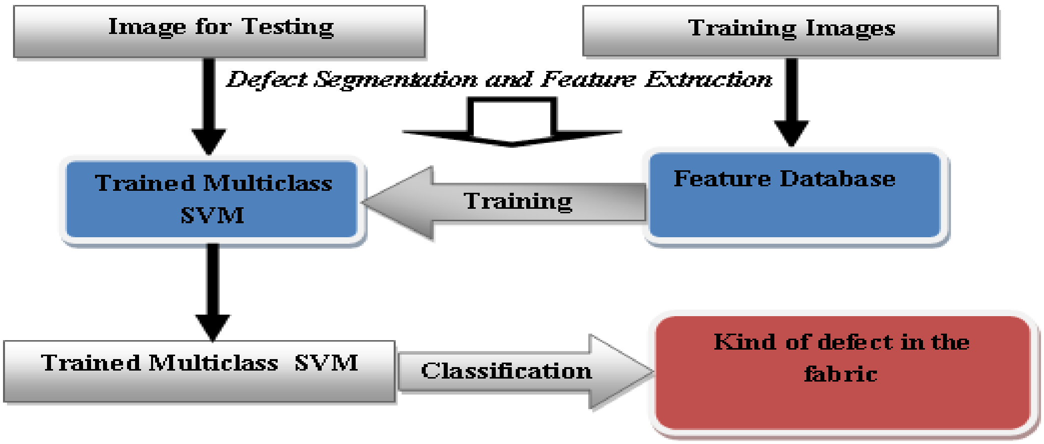


Figure 2: Proposed Approach for the Fabric Defect Identification

The starting point of our algorithm is an image which contains the defect of the textile. The detection phase has been performed by using a simple method based on the segmentation methods and a geometric feature was extracted from the segmented image.

The following operations are carried out during image quality improvement:

- Image Acquisition
- RGB to Gray Color Conversion
- Image Enhancement and segmentation
- Defect Identification and classification.

We are giving an example of different types of fabric defects:

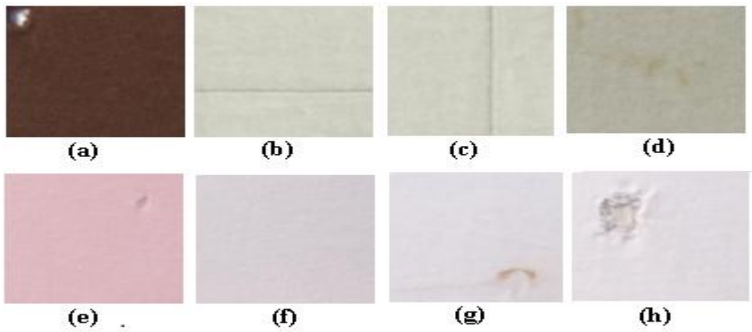


Figure 3: Example of fabric defects (a) Hole,(b) Horizontal Missing Yarn

(c) Vertical Missing Yarn ,(d)Spot ,(e) Hole,(f) Defect-Free ,(g) spot,(h) Hole.

Image Acquisition: the high definition camera was used to capture the images from the fabric

IV. IMAGE SEGMENTATION

Image segmentation refers to the process of dividing image into regions with characteristics, extracting the targets of interest and deleting the useless part. Inspection of textile webs using the segmentation of defects in the inspection images is most common and is described in Refs. [3–5, 6, 7, 8–10, 19]. The segmentation of defects provides an accurate localization of size and location of defects. Otsu algorithm is used for thresholding of the gray image. It has been observed that Otsu algorithm works good in case of fabric image and a fairly binary image is obtained [2][11-13]. Otsu's method proposed by Japanese Nobuyuki Otsu is also called maximizing inter-class variance method. The algorithm assumes that fabric image as threshold contains two classes of pixels or bi-modal histogram (e.g. foreground and background) then optimum threshold separated into two classes is calculated so that inter-class variance is maximal [14]. Otsu algorithm proposed has got an extensive attention for its efficiency; see (Figure 3-b).

OTSU method: In computer vision and image processing, Otsu's method is used to automatically perform histogram shape-based image thresholding [15] or, the reduction of a gray level image to a binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal[16].The extension of the original method to multi-level thresholding is referred to as the Multi Otsu method. Otsu's method is named after Nobuyuki Otsu[22].

In Otsu's method we exhaustively searched for the threshold that minimizes the intra-class variance, defined as a weighted sum of variances of the two classes:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

Weights ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2 variances of these classes.

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance

$$\sigma_b^2(t) = \sigma^2 - \partial_w^2(t) = \omega_1(t)\omega_2(t)[\mu_1(t) - \mu_2(t)]2$$

Which is expressed in terms of class probabilities ω_i and class means μ_i which in turn can be updated iteratively. This idea yields an effective algorithm.

Algorithm

- Compute histogram and probabilities of each intensity level
- Set up initial $\omega_i(0)$ and $\mu_i(0)$
- Step through all possible thresholds t=1…. maximum intensity
- Update ω_i and $\mu_i(0)$
- Compute $\sigma_b^2(t)$
- Desired threshold corresponds to the maximum $\sigma_b^2(t)$

IMAGE FILTRING: Noise and small objects are removed by the noise removal program and filtrated by using Mathematic morphology see (figure 4-d) [12][17].

Morphology Mathematics: Morphology is based on set theory. A structuring element is a special mask filter that enhances an input image. It can be of different sizes and of different shapes (square, diamond, and circle). Following are the main mathematical morphological operators [12] Three morphological operations, closing, region filling and area opening, were used in order to identify the region of interest: Fundamental morphological operations are as follows:

The language of mathematical morphology is set theory. Sets in mathematical morphology represent objects in an image. In binary images, the sets in question are members of the 2-Dinteger space Z^2 where each element of a set is a 2-D vector whose coordinates are the (x,y) coordinates of black or white pixel in the image.

Let A and B be sets in Z^2 .for binary images, defining the reflection of set B, denoted by $\hat{B}$ as:

$$\hat{B} = \{{}^{W}/_{W} = -b, for \;\; b \in B\}$$

And the translation of set A by point

$z = (z_1, z_2)$, denoted by $(A)_z$;

As $(A)_z = \{C/C = a + z, for\ a \in A\}$, the four fundamental morphological operations are as follows:

The dilatation of A by B:

$$A \oplus B = \{Z/(\hat{B})_z \cap A \neq \emptyset\}$$

The erosion of A by B:

$$A \ominus B = \{\frac{Z}{(\hat{B})_z} \subseteq A\}$$

The opening of set A by structuring element B:

$$A \circledcirc B = (A \oplus B) \ominus B.$$

The closing of set A by structuring element B:

$$A \odot B = (A \oplus B) \ominus B$$

The aim of area opening is to eliminate small area blemishes that can be ignored by our processes. The algorithms are based on several steps:

- Definition of the connected components;
- Calculation of the area of each connected component;
- Elimination of small areas with is less than the threshold T experimentally predefined.

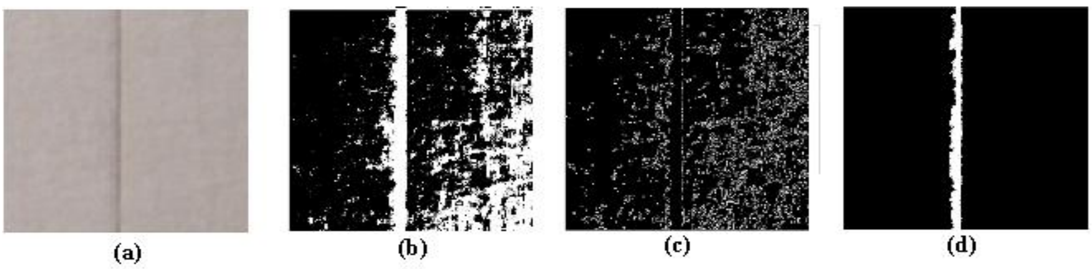


Figure 4: (a) Inspected image, (b) Segmented image, (c) edge detection (canny), (d) Noise-removed image

V. DEFECT IDENTIFICATION AND EXTRACTION

The suspect defect was identified and extracted [3][11][12][16-18].

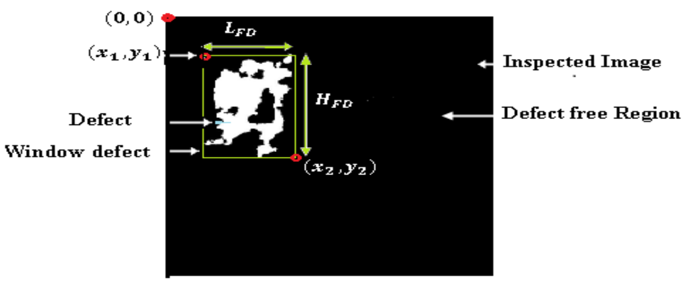


Figure 5: Examples of defect detection and extraction

L_{FD}: Width of Defect Window

H_{FD}: Height of Defect Window

(x_1, y_1) and (x_2, y_2) are the coordinates of the two pixel start and end of the defect window on the image. The following step is the determination of the size of the defect. The calculation of the characteristics can be performed on the pixels of the defect, without having to scan a large amount of data. The set of features is determined by scanning line by line and pixel by pixel of the rectangular defected region limited by (x_1, y_1) and (x_2, y_2).

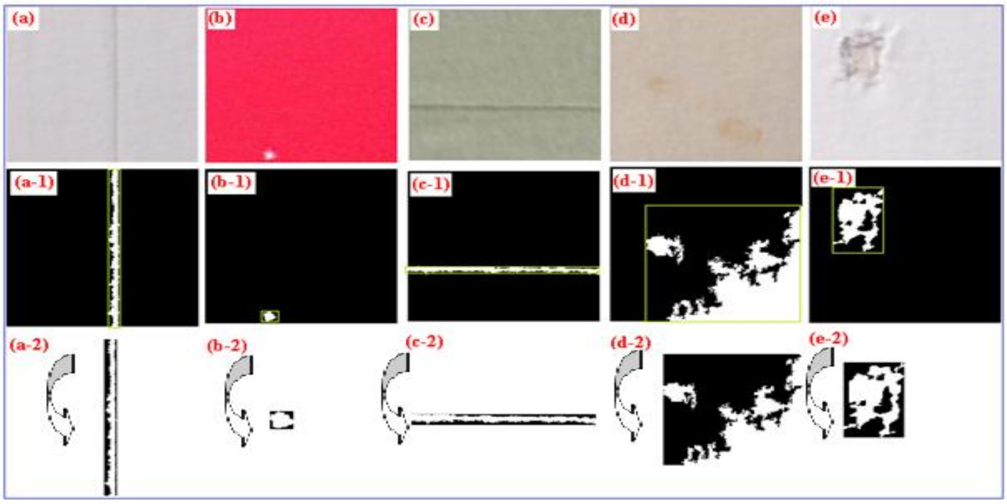


Figure 6: Example of type of defects: (a) $H_{WD} = 30$ pixels , $L_{WD} = \mathbf{550}$ pixels .(b) $H_{WD} = 30$ pixels , $L_{WD} = \mathbf{35}$ pixels .(c) $H_{WD} = 33$ pixels , $L_{WD} = \mathbf{635}$ pixels. (d) $H_{WD} = 445$ pixels , $L_{WD} = \mathbf{511}$ pixels. (e) $H_{WD} = 223$ pixels, $L_{WD} = \mathbf{135}$ pixels (a-1), (1-b), (c-1), (1-d), (e, 1) are the binary image of the images (a), (b) , (c), (d). ((a-2), (b-2), (c-2), (d-2), (e-2)): Image defects previews.

VI. FEATURES EXTRACTION

- Total Area of Defective Regions:

$$S_{RD_k} = \sum_{p=0}^{r} \sum_{q=0}^{s} (B(p,q) = L_k) \quad \text{For defect number K.}$$

$$TS_{RD} = \sum_{1}^{N_{RD}} S_{RD} \quad \text{Is total Area occupied by defect in the Image.}$$

- Total Area by report of Window size occupied by defects:

$$RT_{SRD} = \frac{TS_{RD}}{S_{WD}} = \frac{\sum_{1}^{N_{RD}} S_{RD}}{H_{WD} X L_{WD}}$$

With $S_{WD} = H_{WD} X L_{WD}$: is size of window occupied by defects.

- Compacity of defective parts:

This is a measure of the complexity of the contour vis-à-vis the area

$$Com = \frac{4\pi TS_{RD}}{P^2}$$

Where P is the perimeter of the object and TS_{RD} is the area in pixels.

- Centroid of defective parts

We can define the center of gravity, as well as the moment of inertia about specified points or lines. In fact, it has two characteristics X and Y is a geometric point from the center of defect, the coordinates of this point were calculated using the following formulas: The coordinates of the center region.

$$X = \frac{1}{S_{RD}} \sum_{p=0}^{r} \sum_{q=0}^{s} qB(p,q) \quad , \quad Y = \frac{1}{S_{RD}} \sum_{p=0}^{r} \sum_{q=0}^{s} p.B(p,q)$$

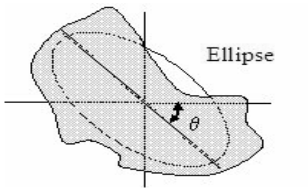
where p and q are the coordinate of a pixel in the image, and the total S_{RD} defect area. According to the variations in the shape and size of the defect, there should be some variation in the center of gravity of defects for all types of defect regions.

For an image described by the function I (i, j) the spatial moments are defined by:

$$m_{p,q} = \sum_{i} \sum_{j} i^p j^q \, I(i,j)$$

P , q defines the order of the moment

Major and minor axis of ellipse covered the defect [21]



The ellipse having considered the same moment that the object (defect) to be studied is defined by the major axis (a), the minor axis (b) and the angle of rotation of the object relative to the horizontal different parameters are computed in the manner below:

$$a = \sqrt{\frac{2[m_{20} + m_{02} + \sqrt{(m_{20} - m_{02})^2 + 4m_{11}^2}]}{m_{00}}}$$

$$b = \sqrt{\frac{2[m_{20} + m_{02} - \sqrt{(m_{20} - m_{02})^2 + 4m_{11}^2}]}{m_{00}}}$$

$$élongation = \frac{axe_{majeur}}{axe_{mineur}}$$

An indication of the elongation (between 0 and 1 for a disk to a line segment) and the angle θ between the major-axis of the ellipse and the minor axis-gives the horizontal orientation.

$$E = \frac{\left(m_{2,0} - m_{0,2}\right)^2 - 4m^2{}_{1,1}}{(m_{2,0} + m_{0,2})^2}$$

$$\theta = \frac{1}{2} arctan \frac{2m_{1,1}}{m_{2,0} - m_{0,2}}$$

After the extraction of parameters, it will form a database for the classification step.

Tab 1. Examples of the result of the same geometric features of the four types of defects

Image	Area	Perimetr	HWD	LWD	TSRD	Compacity	N°of Defect	Centre de gravité
Horizontal Missing Yarn	11080	1.86E+03	635	33	0.052	0,040225691	1	(299,2199;370,6931)
Vertical Missing Yarn	37857	3.39E+03	45	557	4.8	0.041374851	1	(222,378 ; 267,6437)
Hole	5014	434	77	93	1.2078	0.726636369	1	(40,494 ; 50,4388)
Spot	49797	1.99E+03	203	366	0.5546	3.17164E-6	12	(393,988 ; 467,86)

VII . CLASSIFICATION

The first step of the analysis is meant to evaluate the efficiency of both the descriptors and learning procedure in the task of classifying procedure by PCA. The use of the cross validation is essential to evaluate the performance of the learning procedure. Without it, our performance would be too optimistic because of potential over-fitting.

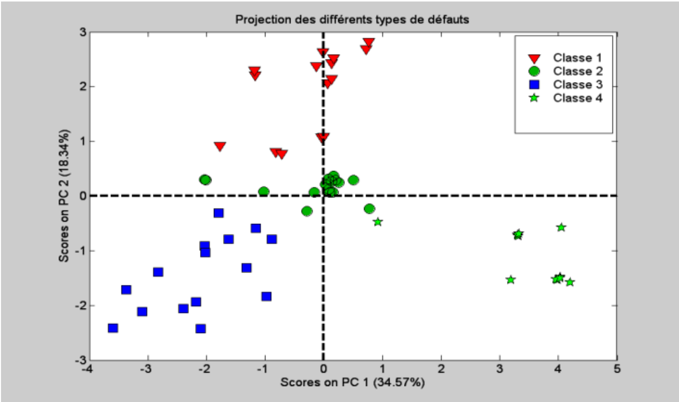


Figure 7: projection of different types of defects on PC1 plan PC2

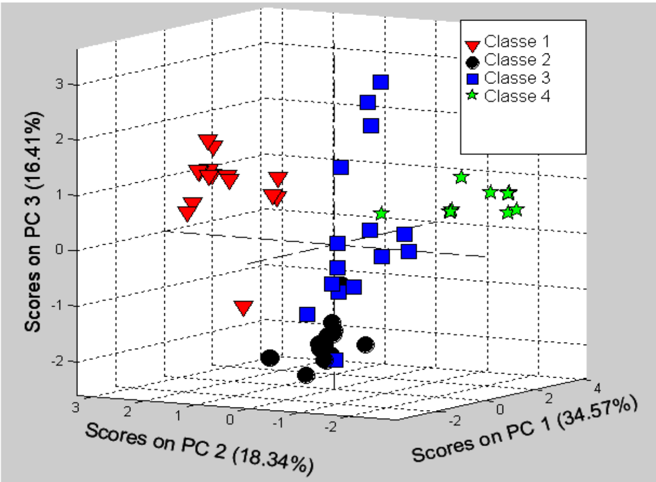


Figure 8: 3D Projection of different types of defects

The dispersion of Class N° 3 with blue color is due to the non-uniformity defects spot. The spot takes different forms and different distributions on the surface of the fabric. The three main components collectively represent 69.32% of the variability in the data from the data matrix and these are the ones that allow you to view the best organizing people.

VIII. DEFECT CLASSIFICATION BY SVM (SUPPORT VECTOR MACHINES)

The features extracted from the previous stage are organized in a feature vector, and are used to train the support Vector Machines (SVM).Among the kernel methods, inspired from statistical learning theory Vladimir Vapnik, SVM is the most known form. SVM is a binary classification method by supervised learning. The goal is to find a classifier that separates the training data and to maximize the distance between two classes. In a space of n attributes (dimensions) of the data, the desired separating hyper-plane is called [19].

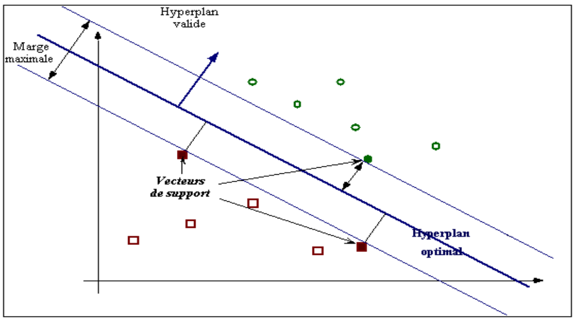


Figure 9: Example of an optimal hyper-plane in R²

A SVM-based multi-class pattern recognition system has been developed for inspecting commonly occurring fabric defects. A one-leave-out cross validation technique is applied to assess the accuracy of the SVM classifier in classifying fabric defects. We have deployed a method SVM algorithm in order to classify the defects. We have found very promising results. The features discussed below contain so much distinguishing information; we look to combine it to a statistical feature in order to perform our method.

Table 2. Frequency of each defect class.

Numéro	Classe	Fréquence
Classe N°1	Vertical Missing Yarn	16
Classe N°2	Horizontal Missing Yarn	16
Classe N°3	Spot	11
Classe N°4	Hole	15
Classe N°5	Sainte	20

Tab3: Matrix of confusion SVM analysis of different types of tissue defects.

Number of Samples	Class	C1	C2	C3	C4	C5
16	C1	15	1	0	0	0
16	C2	0	16	0	0	0
15	C3	1	1	13	0	0
11	C4	0	0	0	11	0
20	C5	0	0	0	0	20

According to the classification result of the 78 testing samples, it can be discovered that there are 3 uncorrected classified samples. The research findings reported in result have mentioned the achievement of 96.15% textile defect detection accuracy. The false classified samples are of a non-uniformity of oil stains. The geometric feature of the hole and oil stains is similar.

IX. CONCLUSION

In this paper, a proposed method was developed. Different types of defect were identified and classified based on geometric features. In this paper a SVM approach for defects identification in textile has been proposed. The SVM classifier is trained by the acquired defect samples. And , penalty factor and kernel parameter are searched by the genetic algorithm for acquired the optimal SVM classifier in the condition of limited samples information. Finally, the performance of the classifier is tested through the unknown defect samples.

We have presented a possibly appropriate feature set in order to solve the fabric defect classification problem and we have found that the geometric features are sufficient to successfully classify the defects. The fabric Defect detection, location and identification in the normal fabrics define the faults by this method. This method classifies 94.84% of defect in fabric. This work is in progress to use a subset or all of the features combined with texture statistical features in order to successfully classify the defects for a sample of a very large number of high-quality images.

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