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A Composite Method of Textile Defect Detection using GLCM, LBP, SVD and Wavelet Transform

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ABSTRACT

A spin of material with defects can have a depreciation of 45 to 65% with relevance the primary price. While some commercial solutions exist, automatic fabric defect detection remains alively field of development and research. The goal is to extract the characteristics of the feel of the material to detect defects contained using image processing techniques. To date, there is not any standard method which ensures the detection of texture defects in fabrics with high precision.

In the following work, the utilization of Singular Value Decomposition (SVD), Local Binary Pattern (LBP) and Gray-Level Co-Occurrence Matrix (GLCM) features of images for the identification of defects in textiles is presented, where the applying of techniques for pre-processing is presented, and for the analysis of texture LBP and therefore the GLCM so as to extract features and segmentation is finished using SVD approach. This model makes it possible to induce compact and precise detection of the faulty texture structures. Our method is capable of achieving very precise detection and localization of texture defects within the picture of the Fabric-Defect-Inspection-GLSR database, while ensuring an affordable time interval.

KEYWORDS – GLCM, FDIG, LBP, GLSR, SVD, WT

1. INTRODUCTION

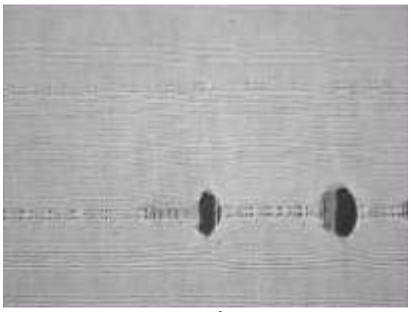
The textile sector has undergone changes throughout the years, due to factors such as: demand, globalization, the high number of producers and changes in fashion, which makes this industry a receptive sector to change and through which the innovation proposes improvements within the various processes. The textile industry is that the arena of the economy dedicated to the assembly of fiber, yarn, cloth, clothing and related products. one all told the fields during which this industry develops is that the weaving process, that is, the conversion of yarn to fabric. the quality control of this product (fabric) is of utmost importance and great economic impact: A roll of fabric with defects can have a depreciation of 45 to 65% compared to the initial price [1].

There are textile companies that perform visual inspections of the merchandise after a serious amount of fabric is produced and stored, however, this finally ends up in just 70% of defects being detected in an exceedingly post-manufacturing inspection of this type even with trained inspectors. it is also common to hunt out companies that use an online visual inspection (while the fabric is being generated by the loom), however, operators recognize but 60% of defects in an exceedingly fabric two meters wide at a speed of 0.5 m / s [1].

In the process that fiber spinning machines do, it's possible that different types of defects may occur that generate tissue failures. Generally, for identification, someone (operator) makes a visual inspection for such defects. Sometimes this type of control is insufficient, because the imperfections are too small and not visible to the oculus, or because the fatigue of the quality inspector prevents identification.

For the automated inspection of defects, within the market we discover different solutions for the textile industry, during which different image processing techniques are implemented to detect defects.

Among the foremost representative we discover [2], [3] and [4] which highlight the capacity of their systems in terms of the width of the fabric examined and thus the speed that it can bear its sensors.[5-7]



(a) Defect

(b) Without defect

Figure 1: Original database images [8]

In any algorithm developed, it is necessary to evaluate the method developed in the intended manner. Generally in the IT sector, any algorithm generated is evaluated by indexes that vary from one context to another. In these standards, we can illustrate the complex design, proper use of resources, and so on. In the field of automated textile inspection, there are no standardized standards for assessing design defects. In fact, in every previously published work, authors use personal criteria to evaluate their methods. Although these criteria seem theoretically feasible, their diversity and variety of adaptations do not permit comparison or deliberate evaluation of these methods. Furthermore, much of the work done has been tested on different image databases, which eliminates the possibility of visual comparison of the results of different algorithms. The third problem is the limited expression of the results of a method. In fact, in many works (such as [9]), we have observed that the data set is limited and there are no references to experimenting in paper or electronic appendices.

In the following, we cite some previous work. In [4], the authors achieve a detection rate of 66%, but the accuracy is low and false alarms are high. Therefore we should note that the criterion taken is related only to defective blocks. Healthy blocks are definitely not found. Therefore, false alarms are ignored because they are damaging the plant as healthy tissue is defective. This will seriously affect the decision of the final product framework. Furthermore, because the data set used in the work is so small (16 images, 8 of them with innocence and 8 with errors), it is not sufficient to evaluate this method.

In [10], the authors expressed a detection rate of 79%, followed by 49% of the work [11]. Further, the evaluation criteria of their algorithms are individualized and shifted from one article to another. In fact, in previous works [10], the authors defined a certain accuracy and the evaluation was expressed in terms of the percentage of this criterion. In other works [11, 12], this criterion no longer exists. On the other hand, the evaluation of these functions depends on the number of blocks that are not exactly found in the set of the global blocks of the image.

Numerous works on detecting texture defects have been proposed over the past two decades. However, there are not enough articles addressing the problem of error detection, especially in the textile sector. In the existing works, the evaluation of the approach is not clear. First, there is no general evaluation criteria between these tasks. Some use detection accuracy [9, 10], while others [11, 12] use the number of errors detected. These expectations are subjective and do not permit new work to be compared to the old. Furthermore, it does not allow comparing them to images of different sets of methods. Although there are no standard evaluation criteria, we can see that each class of approaches has strengths and weaknesses, and combining multiple types of approaches makes the hybrid method able to detect design flaws.

2. PROPOSED METHODOLOGY

The proposed system is developed in three stages: first, various filtering techniques are analyzed to make the surface of the images homogeneous; Second, the spatial methods of texture analysis are studied, and third, the partitioning system that uses SVD for textile separation detection systems. Fig. 2 shows the flow diagram for the proposed approach.

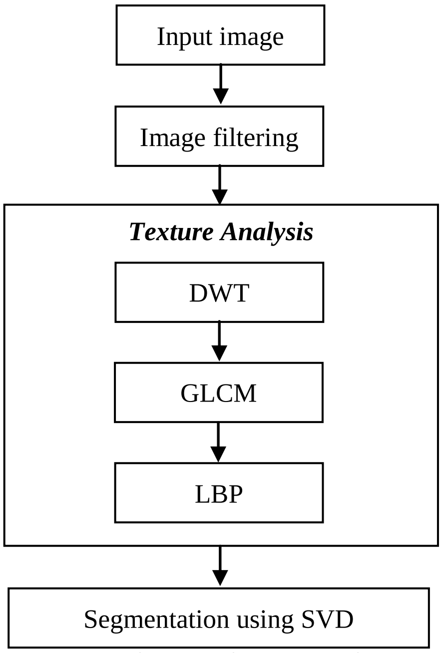


Figure 2: Proposed flow sheet for detection of textile defect

2.1 Image Filtering Technology

In the process of retrieving images from the database, the lighting system used allowed the effect of light from the environment to mimic the industrial environment, as it allows contrasting images and contrasts in brightness. To see these variations, different options are asked to stabilize the gray levels of the image.

2.2 Implemented Texture Analysis Techniques

In common sense, texture refers to the surface characteristics and appearance of a particular object, according to the shape, size, density, arrangement and proportion of structural elements. There are different approaches to extracting information from image textures. In this paper, one of these approaches is explored based on the spatial distribution of image variations and tone variations in a set of resolution pixels. To begin with the texture, four spatial techniques for feature extraction are explored. Below is a brief description of each.

2.3 Filters Based on Wavelet Transformation

The use of a filter based on waveform changes is proposed, which seeks to improve the distribution of gray levels of the surface. The filter is initially used to attach high light levels using the Daubcheese wavelet; In the case of low brightness levels, the harness wavelet is used where the low frequency frequency component is removed to increase the level. Figures 3 (b) and 3 (c) show the surface image of the output image and Figure 3 (a) using this method.

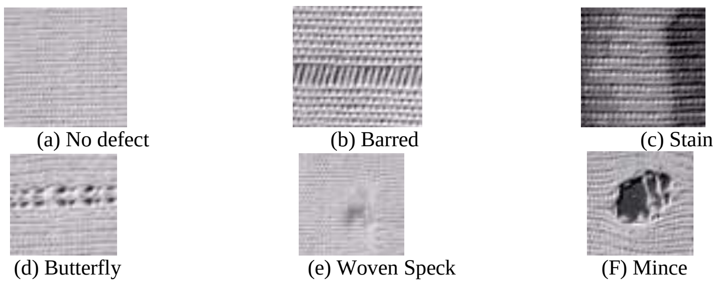


Figure 3: Types of 100×100 images [8]

2.4 Gray Level Co-incidence Matrix (GLCM)

Co-occurring matrix technology analyzes the repetition of the gray level distribution displayed in an image, the pixels of interest and the surrounding pixels are called neighbors; The information gathered in this matrix describes the ratio of pixels to specific texture conditions.

To perform this analysis, the technique can be defined in the following steps:

- The distance to the pixel interest of Neighbor neighbors.
- Angle(Θ) to establish the diagnostic model.
- The depth or number of bits in the image.

- Browse the image to collect information in the matrix.
- Description Use of descriptors.

The inter-pixel spatial distance acts as a reference to the window size; Its values vary from 3 × 3 to 21 × 21 in odd numbers. The angles can be 0o, 45o, 90o and 135o. Changing these values makes it possible to classify different textures or patterns of a particular texture. Figure 4 shows the distribution of angles in a 3 × 3 sale [13].

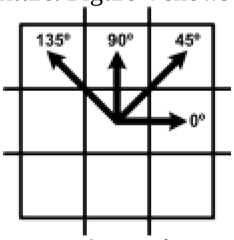


Figure 4: Distribution of GLCM [13]

The level of the GLCM matrix is defined as 2 ^ n, where n depends on the depth of the image (number of bits). Typically, the form is analyzed on gray-level images (8 bits), during this case, the amount of levels is 256. Table 1 shows an example of the distribution of combinations in an exceedingly 5-level structure. GLCM Matrix. Therefore for 256 levels we obtain a 256 × 256 dimensional matrix with information on the spatial distribution at a particular distance and angle. Finally, some shape specifications like energy, entropy, contrast, correlation, and symmetry are used.

Table 1: Co-occurrence matrix

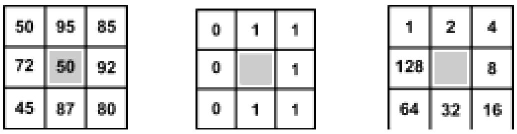
	0	1	2	3	4
0	(0,0)	(0,1)	(0,2)	(0,3)	(0,4)
1	(1,0)	(1,1)	(1,2)	(1,3)	(1,4)
2	(2,0)	(2,1)	(2,2)	(2,3)	(2,4)
3	(3,0)	(3,1)	(3,2)	(3,3)	(3,4)
4	(4,0)	(4,1)	(4,2)	(4,3)	(4,4)

2.5 Local Binary Pattern (LBP)

The LBP texture analysis operator is locally defined as a gray level change measure derived from the general definition of the shape. The original proposal involves comparing the central pixel with its neighbors, where the central pixel is bounded relative to its neighbors. When comparing the central pixel to its neighbors, it is assigned one (1) value if it is greater than or equal to the neighbor; Otherwise, it will be given a zero (0) value. Each threshold result is assigned a weight of 2 ^ n, where n is the position of the neighbor relative to the center pixel. Finally, obtaining the total pixel LBP representation of different weights [14].

The operation of the original operator is presented in Fig. 5, where the window of the size 3 × 3 and in this case the relationship of the central pixel with its 8 neighbors is analyzed. The LBP equivalent to the values in Figure 4 (b) is presented in Equation (1).

$$LBP = (0*1) + (1*2) + (1*4) + (1*8) + (2)(1*16) + (0.32) + (0.64) + (1*128) = 158 \quad (1)$$

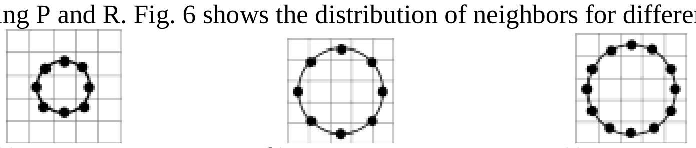


(a) Sample (b) Pattern (c) Weights

Figure 5: Operation of the LBP operator [15]

Next, a new source is taken from the LBP operator, which is the pixel of window size and neighbor number. For this derivative a parameter called R and P is defined, where R corresponds to the distance (radius) from the pixel to the source, and P is used to calculate the number of neighbors LBP.

The distances and distributions of neighboring P are evenly distributed over the symmetric circumference formed by the value of R> 0 and R. 1. The different shape dimensions of the area of interest can be obtained by modifying P and R. Fig. 6 shows the distribution of neighbors for different values of R and P.



(a) R = 1, P = 8 (b) R = 2, P = 8 (c) R = 2, P = 12

Figure 6: Operation of the LBP operator [15]

The circular distribution of the neighboring pixels is done using Equation (2), resulting in a basic approximation of the neighboring position, for which it is replaced by the interpolation process to define the coordinates (x, y). There is a need to do. From neighbors:

$$x = R\ \sin\left(\frac{2\pi p}{P}\right), y = R\ \cos\left(\frac{2\pi p}{P}\right) \quad (2)$$

Finally, the derivation of the LBP operator for an picture is defined in equation (3).

$$LBP_{PR}(x_c, y_c) = \sum_{p=0}^{P-1} s(x_c - y_c)2^P \quad (3)$$

2.6 Partitioning using Singal Value Decomposition

For some class matrices, we have seen decomposition as indigenous:

A = XDX ^ (- 1)

Where D is the diagonal matrix of eigenvalues and X is the inverse matrix of eigenvectors. When we give the matrix vector product Ax = (XDX ^ (- 1)) x, we take x, we express it on the basis given by eigenvectors (X ^ (- 1) x), multiplying this vector of elements. We repeat the inverse basis change by multiplying eigenvalues D, and x, one by one. If we have a linear system Ax = b, we can change x X = X ^ (- 1) x, bˆ= X ^ (- 1) b, and we get the system Dx b = b. Limitations: To make this change, the matrix A must be square and diagonal [16].

The idea of decomposition into singular values is similar to decomposition in antigen, but the magnitude of any matrix A works for m × n: a factor A is produced into three matrices [16]:

$$A = U \sum V^* \quad (4)$$

With U a unitary matrix $m \times m$ a unitary matrix V of size $n \times n$ and $\sum$ a diagonal matrix of size $m \times n$ with real and positive coefficients.

3. SIMULATION RESULTS

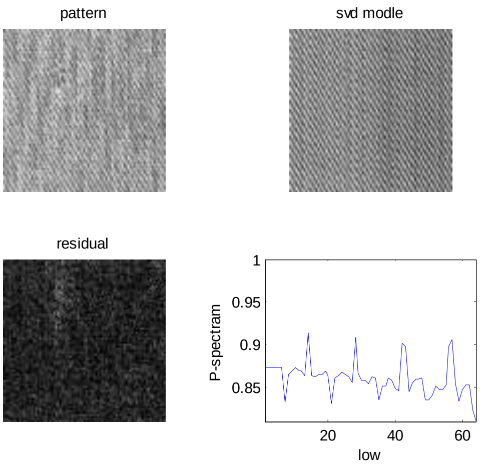


Figure 7: SVD implementation of textile fault model for Dataset-1

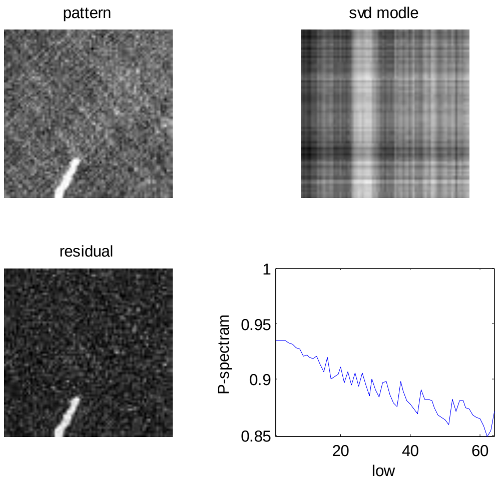


Figure 8:SVD implementation of textile fault model for Dataset-2

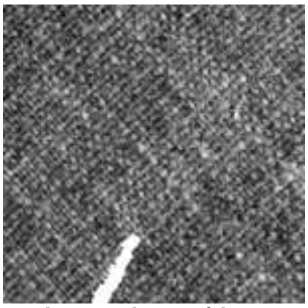


Figure 9: The original input of the wrong image

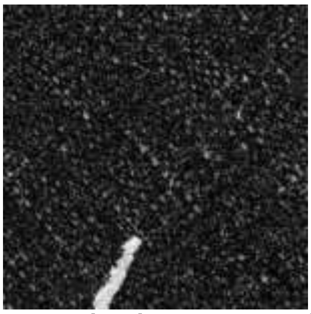


Figure 11: Fault analysis using LBP method

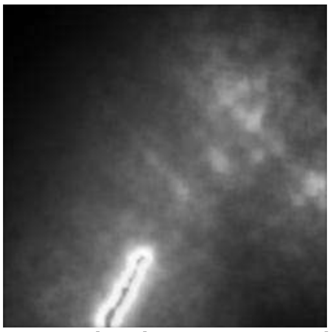


Figure 10: Fault analysis using DWT method

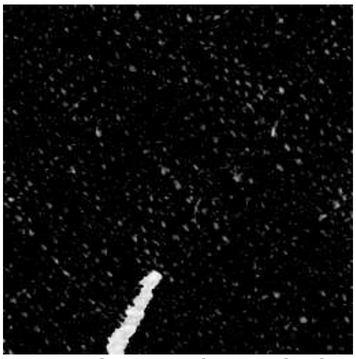


Figure 12: Error analysis using the generalized BP method

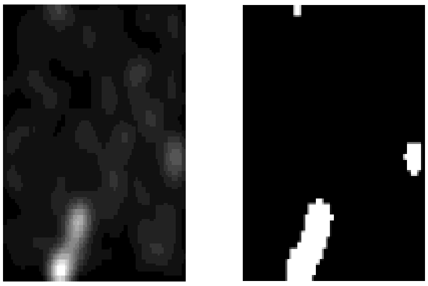


Figure 13: Post-processing using morphological operation in DWT method

Table 2: Tabular comparison of results

Method	Standard Deviation	Entropy
DWT	9.3	0.9
LBP	10.1	0.8
SVD	9.7	0.9

Table 2 clearly shows that the proposed LBP-based method outperforms other approaches based on low entropy and high standard deviation.

4. CONCLUSION

The development of an automatic defect detection tool has become a necessity for the textile industry. The proposed approach improve the success rate of the feel analysis techniques. For the local binary patterns and within the co-occurrence matrix, the wavelet filter, increased the proportion of success in identifying the defects within the fabric. For the co-occurrence matrix, different alternatives were explored to boost the proportion of success, among which the one that showed the simplest classification results was the mixture of the four components of GLCM 0o, 45o, 90o, 135o. the initial derivation of the LBP operator wasn't efficient for the identification of defects in textiles because the knowledge collected could be a general description of the feel, and also the characteristics of the study images present a similarity that can't be established with this method. On the opposite hand, the extensions derived from normalized LBP presented better percentages of the fault analysis with the employment of morphological operation together with DWT, where it clothed to be the technique with the simplest leads to the identification of defects in textiles, since it seeks to characterize uniform textures present within the image.

5. REFERENCES

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