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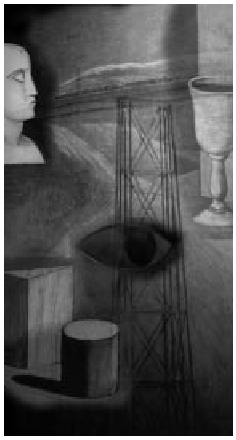

By C. Anagnostopoulos, D. Vergados, E. Kayafas, V. Loumos and G. Stassinopoulos*

Textile manufacturers have to monitor the quality of their products in order to maintain the high-quality standards established for the clothing industry. Thus, textile quality control is a key factor for the increase of competitiveness of their companies. Textile faults have traditionally been detected by human visual inspection. However, human inspection is time consuming and does not achieve a high level of accuracy. Therefore, industrial vision units are of strategic interest for the textile industry as they could form the basis of a system achieving a high degree of accuracy on textile inspection. This work describes the software core of a system designed for fabric inspection on the basis of simple image-processing operations as well as its efficiency on detection of usual textile defects. The prerequisites of the overall system are then discussed analytically, as well as the limitations and the restrictions imposed due to the nature of the problem. The software algorithm and the evaluation of the first results are also presented in details. Copyright © 2001 John Wiley & Sons, Ltd.

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KEY WORDS: textile; quality control; texture segmentation; computer vision; image processing; fabric inspection system

Introduction

Visual inspection is an important part of quality control in the textile industry. Efficient automated product inspection is a key factor for the increase of competitiveness of the textile and clothing industry, since it can enable top quality of final products and reduce total cost, through reduction in inspection labor costs, rework labor and scrap material. The term 'textile defect' covers various types of faults occurring in the fabric resulting from the previous stages of the production. Due to the specific nature of textiles, the defects encountered within textile production must be detected and corrected at early stages of the production process. In spite of using modern weaving technology, fault detection in many industries still continues to create considerable extra cost[1] since textile manufacturers have to monitor continuously the quality of their products in order to maintain the high quality standards established for the textile industry.[2] Regarding the type of fabric to be inspected, there are almost 50 different kinds of flaws. The quality engineers have to deal with an extensive variety of defects either due to mechanical malfunction of the loom, or due to low-quality fibers and spreads. At present, the quality assessment procedures are generally performed manually by expert quality engineers and technicians as indicated in Figure 1. However, the detection and classification of these defects are time-consuming and tiring procedures. Moreover, the low quality control speed when compared to the production speed reveals the bottleneck in the workflow.

Therefore, to increase accuracy, attempts are made to replace the traditional human inspection by automated visual systems, which employ camera nodes and image-processing routines. Image acquisition and automatic evaluation may form the basis for a system that will ensure a very high degree of fabric quality control. The main difficulty with computer-based inspection units in fabrics is the great diversity of their types and defects.

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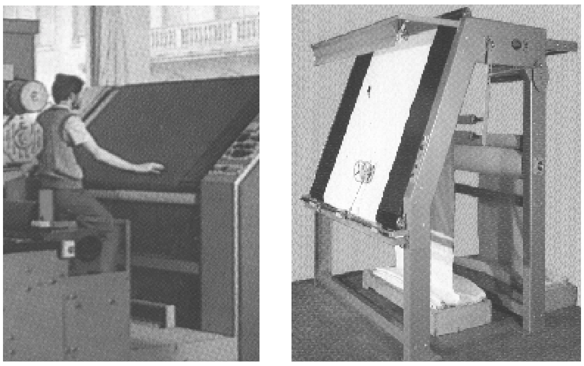

Figure 1. Manual textile inspection.

This paper studies in depth the application of quality control algorithms in the vision systems of the textile companies, by analyzing the quality control processes evaluation of the performance of the vision system and establishing the feasibility analysis of using high-performance computing (HPC)-based machine vision to substitute human operators.

The paper is organized as follows. In the next section visual inspection as an important part of quality control in the textile industry is discussed in detail. In the third section follows a description of the problem. In the fourth section, several software approaches for texture segmentation are presented. In the fifth section a brief description of the vision inspection system is given whereas the proposed algorithms are applied. The sixth section presents in detail the structure of the proposed algorithm as well as the experimental results and the first evaluation and assessment of the system's performance.

Quality Control

As is well known, the quality of a garment has a direct correlation with fabric quality, which is not only a major responsibility of the textile manufacturers, but also a key factor for the textile industry that produces the final product for the consumer. Fabric inspection is mainly effectuated in a textile company through fabric inspection machines, where an operator checks fabric quality.[3] The whole operation is effectuated by using adequate lighting systems. On the other hand, in a garment-manufacturing factory, fabric quality is checked during the spreading and layering process on the cutting table. In this case the operator of the spreading machine is responsible for the visual inspection and detection of fabric defects with the help of a mirror.

However, this method is rather unreliable as the textile is unfolded at a speed of 2 m/s and the operator cannot always locate small defects. All the above systems rely on manual processes and are subject to human error.

Taking into account that the textile industry uses many types of yarns and wave patterns, there are many types of visual defects that affect overall quality. There are several formal systems to evaluate the quality of the fabric, namely the 4-point system, Graniteville,[4] 10-point system etc. The main concept of all these systems is that the operator calculates the numbers of major and minor defects as point values per square meter and then considers the quality of the fabric as 'first' or 'second' quality.[5] Each fabric, either woven or knitted, presents specific defects. The main defects in the woven fabrics are: knots, harness misdraws, open reeds, dropped picks, soiled fillings, thin or thick places (doubling), warp burls, mixed filling, broken picks, loom bars, foreign fibbers, warp and filling floats, defects in printing and color differences etc. As far as knitting fabrics are concerned, main defects are: ends outs, dragging ends, color misdraws, mixed yarns, missing yarns, holes, compactor creases, needle loops, skipped stitches, color differences[6] etc. Each one of the defects stated above has to be analyzed in order to define the best software solution. Software has to be able to detect and to classify automatically all the visual defects of the fabric with high recognition accuracy.

Textile faults that should be detected by an automated system include:

- Color differences: including hue–saturation differences and ability to ensure web quality under different lighting and brightness conditions.
- Slabs and knots up to a threshold scale in order to evaluate web graduations and set penalties in point grading.
- End down: its most common form is the cord effect where the fabric is attained by two color ends weaving plain between each end of 2/ply white; the 2/ply white end also weaves plain with the adjoining color ends.
- Open reed: this defect is the result of a bent reed wire holding the warp ends apart, exposing the filling.
- Slack end: this is the result of an end broken far back on the loom beam being woven into the cloth without tension—this tends to pucker the yarn as it is woven.

- Double end: this defect is the result of an extra end being woven double with a regular end of the fabric.
- End out: this defect is the result of a loom continuing to run after an end is broken; it is similar in appearance to the double end effect.
- Harness breakdown: this is the result of harness straps breaking on a conventional loom; the harness can stay either down or up; on the back of the fabric the warp floats are reversed; that is, they can appear like or vice versa.
- Warp knit end out: this defect is the result of the knitting machine continuing to run with an end missing; in the most favorable case, the end-out is hardly discernible on the face but it is shown on the back of the fabric.
- Dragging end: this is the result of an end being knitted under erratic and extensive tension; this quite often is caused by ends being entangled and/or trapped on the warp beam.
- Straying end out: this is the result of a broken end straying over and being knit irregularly into another area of the fabric.
- Double end: while this appears as a dark end, it is actually caused by two ends of a finer denier being knit together as one.
- Mixed yarn: this happens when a yarn with different dye affinities are mixed during creeling of the warp.
- Coarse yarn: this is the result of one feed of yarn being much coarser than that normal to the fabric.
- Missing yarn: this defect occurs when a machine continues to run with one yarn broken and/or one feed of yarn missing.

Problem Description

This work presents a vision system for textile quality control. The textile and clothing industry has an estimated turnover of 150 billion euros and employs about 2.5 million persons in Europe. The majority of the companies in this sector are small or medium enterprises, which are facing an ever-increasing competition by low-price imports. Automation and technological development are suggested as key factors for the survival of this industrial sector. Another key factor is the production of new top-of-the-range products, which are less sensitive to price competition. Although the clothing industry has benefited from technological innovations, particularly in CAD, it is still a labor-intensive industry.

Due to the specific nature of textiles, the defects encountered within textile production must be detected and corrected at early stages of the production process. Thus, visual defect detection is of utmost importance for the product's overall quality and cost.

Software Approaches

The software core of an automated inspection system for textile defect detection should be based on a robust texture segmentation technique. A lot of texture segmentation techniques are present in the literature. Unfortunately, despite the fact that these algorithms achieve good results, they are computationally complex and are not suitable for on-line applications. Some approaches incorporate texture segmentation using optimal filter parameters.[7–9] The optimal filter design approach concerns the determination of a filter that provides the largest discrimination between two textures. Other approaches with very good performance implement the *gray level co-occurrence matrices* (GLCM),[10] which contain information about the positions of pixels having similar gray level values. Collecting the value for the co-occurrence matrices is not especially difficult; however, it is time consuming. Many texture descriptors are based on GLCM, like homogeneity and entropy.[11] The main drawback for the time being is the fact that the software that actually segments images using GLCM descriptors is very slow. Fractal dimension[12–14] can be used on occasion to discriminate between textures. A wide variety of methods for fractal dimension evaluation have been tested. A major disadvantage is that in many cases these methods are not applicable to many types of textiles. Wavelet transforms were also implemented for texture segmentation.[15] Wavelet transforms are one of the relatively new transforms being explored mainly for image compression applications.

Further techniques implement texture segmentation using the statistical moments mean, standard deviation, skewness and kurtosis.[16] This approach provides statistical information over a region and the values are used for the segmentation of the image. Rather large windows are preferred, so that a statistical sample is gathered. The main drawback of these techniques is the fact that they are affected from non-uniform illumination conditions in the image, which may lead to wrong segmentation. An overview of such techniques reveals the necessity of a pre-processing step for the correction of illumination inhomogeneities[17] in the image. Additionally, the main advantage of the statistically based operations is their computational simplicity.

As the complexity of an algorithm grows, it becomes more and more difficult to execute the image examination in real time. Thus, an algorithm for real-time textile quality control should be specially designed on the basis of fast computational approaches. This paper proposes an algorithmic process based on simple statistical measurements, thresholding and morphological operations.

The Vision Inspection System

A vision inspection system is made up of several different components and modules that are usually installed at separate spots. Some of the system's components are configurable such as cameras and computer system in order to achieve the desired resolution, the archiving system for varying requirements in regard to the following up of inspection results, while others are optional such as light field lighting unit, extra rows of cameras for high web speeds, extra user consoles, and buffered electrical power supply. Also, the vision inspection system where the developed algorithms are applied, includes an inspection bridge, illumination modules, image acquisition technology (CCD cameras, frame grabber, cables etc.) with corresponding peripherals, as well as a high-performance computer, which enables scalability concerning speed and width of material. The system is presented in Figure 2.

The inspection system is typically made up of the following main component [18]:

- the inspection bridge, with cameras and lighting;
- the defect analysis computer system, including a main computer (server) and a workstation per camera;
- the quality control console for production purposes;
- The archive subsystem for the strip and defect databases.
- The cabling of the system including the interface to the operational database.

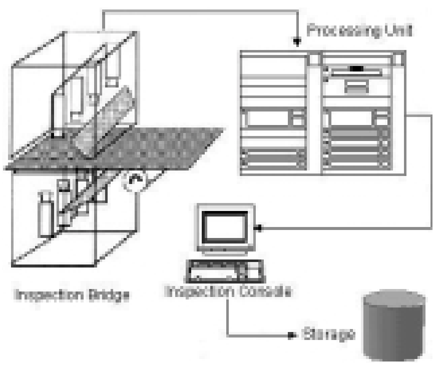

Figure 2. The inspection system.

As the quality and resolution of the images taken of the strip surface have a big influence on the quality of inspection, determination of the acquisition system (camera and illumination) is one of the most important steps. Finally the graphical user interface (GUI) should reflect all the functionality of the system.

The Algorithm

The algorithm consists of three parts. The first one deals with normalization of the image and correction of non-uniform illumination in the image's plane. The second one is the image-processing procedure, which detects irregularities in the normalized image and reveals possible flaws in the textile. The third part identifies the region of interest (RoI) within the image, which is the exact position of the defect. Additionally, it performs geometric measurements on the detected defect, which are useful for flaw assessment.

Normalization

The first part consists of a pre-processing, similar to that proposed in Daul *et al.*,[17] which is used to normalize the image, correcting for inhomogeneous lighting conditions. This allows generalization of the approach, gaining independence from local varying conditions within the image. The goal of this step is the correction of local varying mean gray values and variances. This approach permits a subsequent evaluation of the image without having to adjust the illumination conditions.

The above algorithmic part is presented in the following sequence, consisting of seven steps:

1. Divide the initial image into $N \times N$ non-overlapping block regions (processing blocks).

With this operation the initial image I (Figure 3) is divided into $N \times N$ subimages to be processed. The size of the processing blocks is of great importance and should be determined according to the texture of the inspected fabric. It should be small enough to encapsulate the local variations of mean and variance values but also large enough not to influence the result.

2. Calculate the mean value of each processing block in the initial image I and multiply it by an $N \times N$ block of ones.

This step creates the local mean value image I_1

$$I_1 = \mathrm{mean}(I, [N\ N])$$

Each local mean is then multiplied by a block of ones in order to obtain a local mean gray value image of the same size as the initial image I. Image I_1 is shown in Figure 4.

3. Calculate the standard deviation of each block in the initial image I and multiply it by an $N \times N$ block of ones.

This step creates the standard deviations value image I_2:

$$I_2 = \mathrm{std}(I, [N\ N])$$

Each local standard deviation value is then multiplied by a block of ones in order to obtain a local standard deviation gray value image of the same size as the initial image I. Figure 5 shows the result of this step.

4. Subtract the initial image from the local mean image.

$$I_3 = I - I_1$$

The computed illumination (I_1) is subtracted from the original image for the non-uniformity correction.

5. Divide the difference image block by block by the respective local standard deviation values of the initial image.

Each processing block of the acquired image (I_3) is divided by the respective local standard deviation value in order to normalize the image. Unfortunately, the normalized image is dark (Figure 6).

$$I_4 = I_3 / I_2$$

6. Calculate the variance of the pixel values in image I_4.

$$\text{Variance} = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - x_m)$$

where n = the number of the pixels in the image I_4, x_i = the pixel values of the image I_4, and x_m = the mean pixel value of the image I_4.

Figure 3. The original woven textile image.

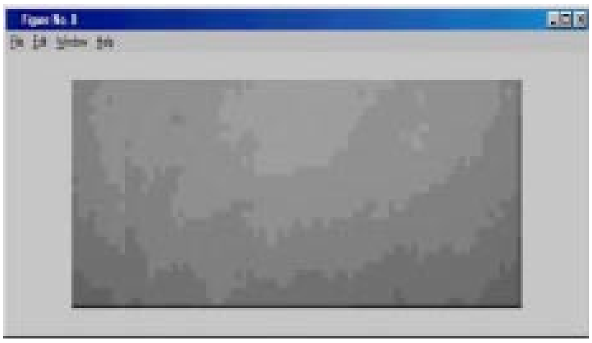

Figure 4. The local mean values image (N=10).

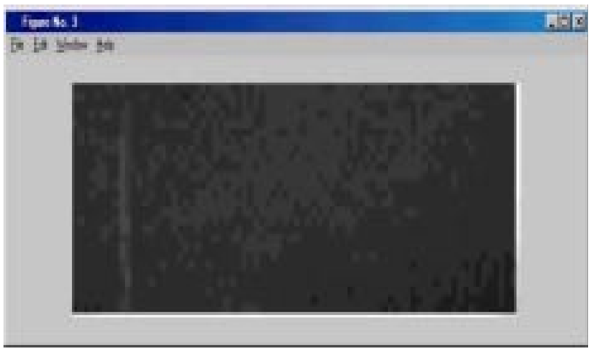

Figure 5. The local standard deviation image (N=10).

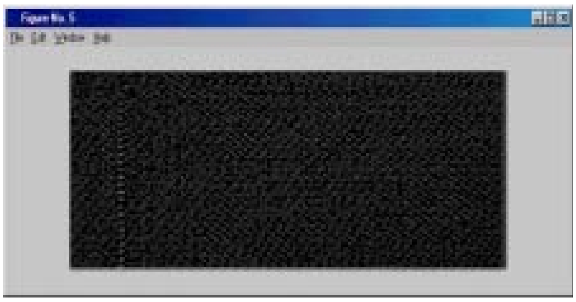

Figure 6. The initial normalized image.

7. 7. Divide the pixel values of image I_4 by the square root of the above variance:

$$I_5 = \frac{I_4}{\sqrt{\text{Variance}}}$$

This operation leads to an image with unit – variance. The resulting image is the final normalized one (Figure 7).

The method implemented to compute mean and variance images, respectively, is based on the fact that for a fabric without defects or anomalies the local mean and the local variance gray values vary smoothly across the image plane. Thus, significant changes do not occur in the local mean and standard deviation images.

Defect Detection in the Normalized Image

After image normalization, evaluation for the presence of possible defects in the fabric follows. Defects are usually displayed either as irregularities in the texture of the image, or as 'black' or 'white' regions in case of mechanical defects in the fabric such as 'holes'. In any case, abrupt changes in the local characteristics of the normalized image indicate the presence of a possible defect. On the other hand, it can be assumed that in a normalized image without irregularities or changes in the local regions no defect should be detected.

On the basis of this observation a simple operation was developed in order to describe the 'local' regularity of the underlying fabric. This operation was motivated by the fact that the standard deviation value of a processing block should not vary with those in the neighboring blocks.

Hence, the standard deviation difference between neighboring blocks should be near zero, or at least should vary smoothly across the texture plane. In contrast, the presence of a defect modifies the 'local' standard deviation of the fabric.

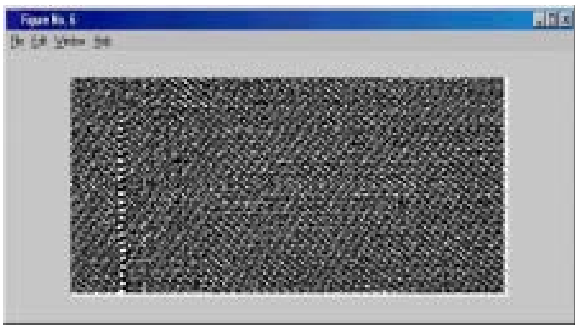

Figure 7. The final normalized image.

The steps of the above algorithmic operation are the following:

1. Divide the normalized image into non-overlapping blocks of size $N \times N$ pixels, where N was defined in the previous operation.
2. Calculate the standard deviation of each block. The resulting image is I_6.
3. Divide the normalized image into non-overlapping blocks of size $M \times M$ pixels, where $M = 2{*}N$.
4. Calculate the standard deviation of each block. The resulting image is I_7.

The processing block $M \times M$ in I_7 is four times larger than that in the previous step ($N \times N$). Therefore it encapsulates the standard deviation values in a wider region, which is the neighboring region of the $N \times N$ block.

5. Perform a mean filtering operation using the following simple mask in both images I_6 and I_7. The mask is a 3×3 matrix of ones.

1	1	1
1	1	1
1	1	1

The mean filter operation smoothes the image plane and eliminates small effects that occur due to block processing. It is a filtering method, which retains image details, since it does not depend on values that are significantly different from typical values in the neighborhood.[19] The resulting images are I_8 and I_9.

$$I_8 = \text{median}\ (I_6)$$

$$I_9 = \text{median}\ (I_7)$$

6. Interpolate the images I_3 and I_4 to images of the same size, using the bicubic interpolation method.

Using the bicubic interpolation method the images I_8 and I_9 are transformed to images with the same dimension. More specifically, they are interpolated to the dimension of the original image (760×260). The resulting images are I_{10} and I_{11}:

$$I_{10} = \text{bicubic interpolation}\ (I_8)$$

$$I_{11} = \text{bicubic interpolation}\ (I_9)$$

7. Subtract the interpolated images I_{10} and I_{11}.

The result will reveal the irregularities between the N-sized processing blocks and the M-sized ones.

Hence, possible fabric flaws correspond to deviations between images I_{10} and I_{11} and the degree of this deviation reveals the severity of the defect. The resulting image is image I_{12} and it is presented in Figure 8.

$$I_{12} = I_{10} - I_{11}$$

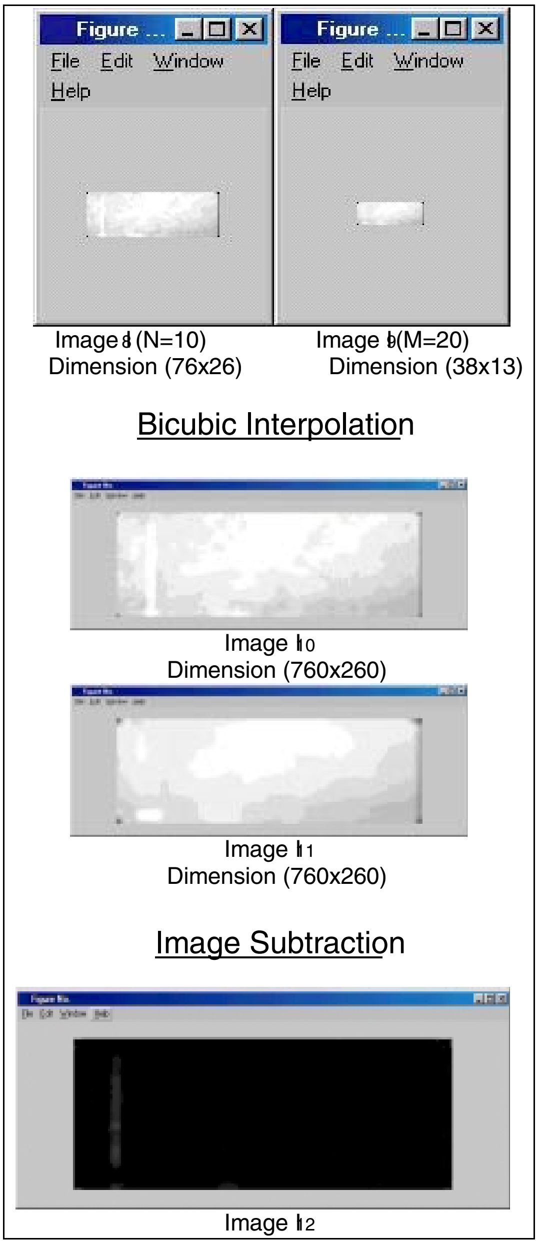

Figure 8. Bicubic interpolation of the standard deviation images I_{10} and I_{11} up to the same size (760 × 260). Then follows the image subtraction.

Visualization of the Results

Inspection results should be efficiently presented to the user and possible defects or irregularities should appear in different colors for easy identification and assessment using a specific colormap.

In the resulting image I_{12} a histogram modification is applied, in order to increase contrast, and thus image I_{13} is obtained.

$$I_{13} = \left[\frac{I_{12} - I_{12\mathrm{MIN}}}{I_{12\mathrm{MAX}} - I_{12\mathrm{MIN}}}\right][\mathrm{MAX} - \mathrm{MIN}] + \mathrm{MIN}$$

where $I_{12\mathrm{MAX}}$ is the largest value in the image I_{12}, $I_{12\mathrm{MIN}}$ is the lowest value in the image I_{12}, MAX = 0.4 and MIN = 0. This is a procedure where the image's histogram is stretched. Figure 9 depicts the above operation.

The process continues with the transformation of the resulting image (I_{13}) in a specific colormap where regions without flaws are presented in red color. In contrast with the above, defects are mapped in different colors according to the degree of the irregularity in the image. Figure 10 presents the defect

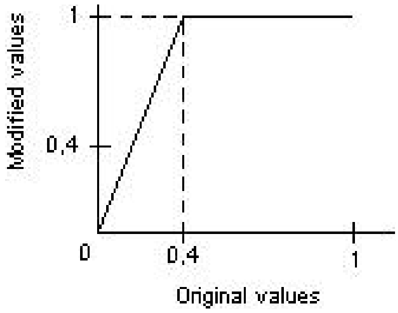

Figure 9. Histogram modification. The horizontal axis corresponds to the original values of image I_{12} and the vertical axis to the modified ones.

Figure 10. Color representation of the textile quality evaluation. Red color indicates flawless regions, while the defects are mapped in blue and green color.

detection in the inspected sample and flaw assessment in green color (severe flaw). Table 1 presents the scale of the fabric quality evaluation. Hence, regions with high variations manifest themselves in green color, while moderate ones are presented in yellow, following the scale that is shown in Table 1.

Image I_{13} difference	Assessment	Color
0–0.05	Flawless	Red
0.05–0.08	Slight	Yellow
0.08–0.15	Moderate	Blue
>0.15	Severe	Green

Table 1. Scale used for defect assessment

Regions of Interest (RoI)

During the third stage, pixels suspected for defect are clustered to form the RoI, roughly describing the shape of detected defects (Figure 11). This operation of the algorithm merges objects, which belong to one defect performing a simple dilation with a structural element, which is a 5×5 matrix of ones. With this technique pixels belonging to the same defect are merged in one region. Besides that, some features like the bounding box coordinates, width, length and orientation are calculated.

Classification

A future development of the algorithm will perform further measurements of the features in the respective regions, in addition to classification systems properly trained for textile defect detection.

Textile flaws could be classified according to their shape and additional criteria into macro classes. It

Figure 11. Region of Interest (RoI) of the defect.

must be noted that the classification into micro classes. It must be noted that the classification into micro classes requires further specific knowledge provided by texture features and second-order statistics.

Several approaches have been proposed for textile flaw classifiers, such as neural networks[20] or rule-based calculation methods.[17] Nevertheless, building a classifier is a complex process, which demands the deep knowledge of expert textile engineers. Flaws in the textile have a wide variety of features and their classification is based on numerous aspects. Therefore the implementation of such techniques is restricted for the time being.

Experimental Results

The algorithm was tested with several gray-level images of size 760×260 using free-running CCD cameras and a frame grabber. The distance between the camera and the inspected fabric was set to 600 mm. The processing block dimension varied between $N=8$ and $N=14$ according the type of fabric. However, for the majority of the inspected images it was set to $N=10$.

This algorithmic approach was tested with textile images containing various textile defects such as slacks, droppings, cuttings, pickings, slabs and knots, holes, color differences, end outs, open reeds, missing yarn and other flaw types, as referred to in detail previously.

The algorithm had a very good performance in the majority of the defected images and identified correctly the regions of the flaws as presented in Table 2. However, some segmentation errors have been presented in images containing pickings and cuttings.

Kind of flaw	Success ratio	(%)
Slacks	5/5	100%
Droppings	5/5	100%
Cuttings	3/5	60%
Pickings	3/5	60%
Slabs and knots	5/5	100%
Holes	5/5	100%
Color differences	5/5	100%
End outs	4/5	80%
Open reeds	4/5	80%
Missing yarn	3/5	60%
Total	42/50	84%

Table 2. System's performance in each defect type

This is due to the fact that these kinds of defects are quite thin and don't differentiate significantly the statistical features in the neighboring region.

In these cases the algorithm identified a slight (yellow value) or moderate (blue value) irregularity on a rather severe defect. Improvements have been achieved by decreasing the dimension N of the processing blocks, which yields an increase in processing time.

The algorithm was tested in a total sample of 50 images. This sample consists of five representative images for each type of the 10 kinds of flaws that are usually met during the textile production line and were described above.

The overall results are summarized in Table 2.

System Performance

Some examples of the defect segmentation ability of the proposed algorithmic procedure follow.

In Figure 12 the results of the algorithm are presented, when a woolen image with 'knots' defect was introduced. These types of defect, which evaluate graduations to textile surface and set anomalies in point grading, is called knots or slabs. The flaw is properly segmented and evaluated with a green color (green RoI), while in the remaining textile surface no other defects were detected.

In Figure 13, the proper segmentation of two flaws of different kinds is depicted, namely cutting (horizontal RoI) and slab (vertical RoI). In spite the fact that the

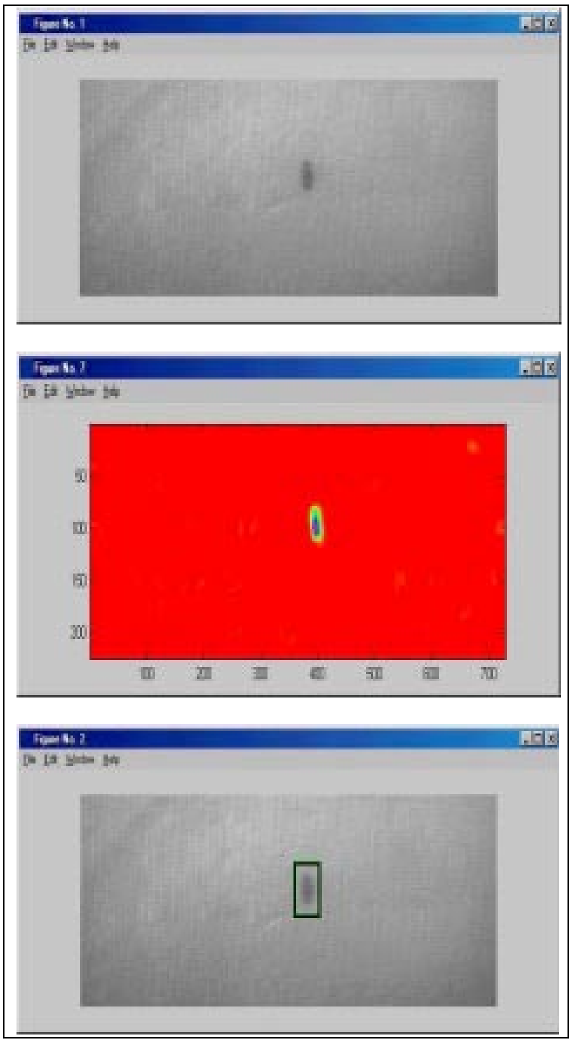

Figure 12. 'Knots' defect on woven fabric (N=10).

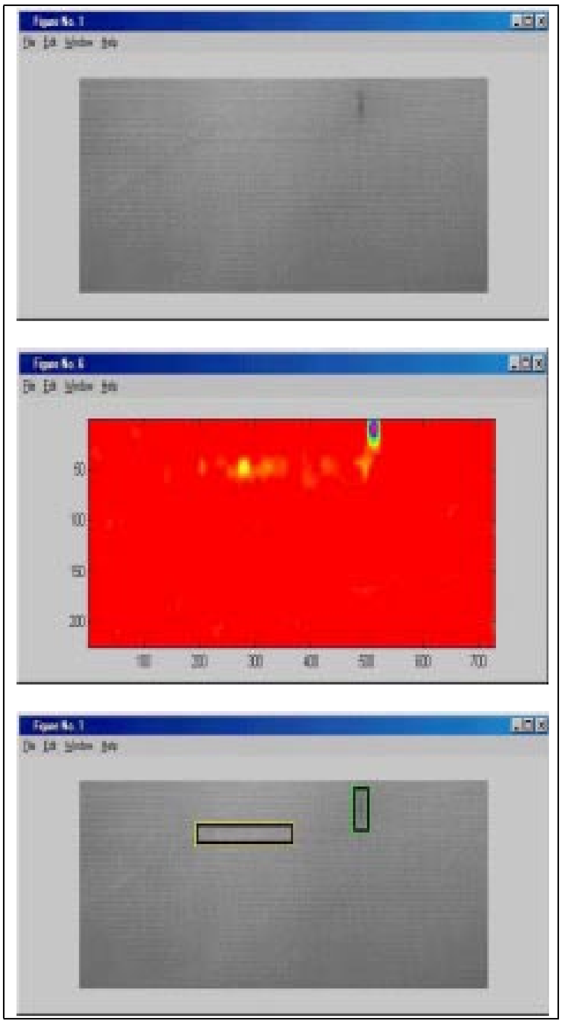

Figure 13. 'Cutting' and 'slab' defects on woven fabric (N=10).

'cutting' is a rather serious defect, it was evaluated as a yellow scale defect. In addition, the 'slab' was successfully located and assessed as a green scale flaw.

In Figure 14, the high performance of the proposed algorithm is confirmed, when an image containing a rather serious but hardly distinguishable defect, such as the 'broken pick' flaw, is evaluated. This flaw is the result of the knitting machine continuing to run with an end missing. In the most favorable case, the end out is hardly discernible on the top, but it is shown clearly on the back of the fabric. As shown in Figure 14, there are horizontal defect lines as a result of the previously mentioned mechanical problem in the fabric production. Despite the fact that the specific flaw is not quite visible, the algorithm's processing blocks have distinguished properly the irregularities in the fabric's texture.

Finally, in Figure 15 the successful identification of 'droppings' into a woven textile sample is presented and in Figure 16 some sample images are presented.

Limitations of Defect Detection

The defect detection algorithm sets the system limitations according to the requirements of the user and the type of textile. Therefore, the algorithm can be configured to fit the requirements of the user, by simply changing its parameters. The smallest defect to be identified is determined by the resolution of the camera as well as the algorithm parameters within the image-processing procedure. Nevertheless, the restrictions imposed for the flaw detection could be summarized as follows:

- Defects that are smaller than the resolution capabilities of the algorithm. In this case, the resolution should be adjusted accordingly by the user.
- Homogeneous defects that are extended over the entire image plane. However, this is a rather unusual and exceptional case.
- Some thin and elegant flaws, which don't alternate

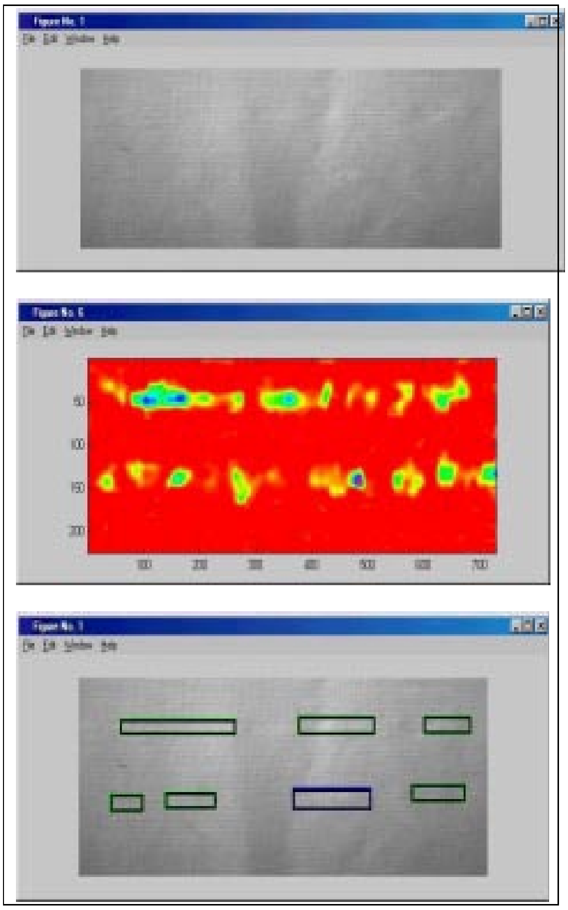

Figure 14. 'Broken pick' defect (N=10).

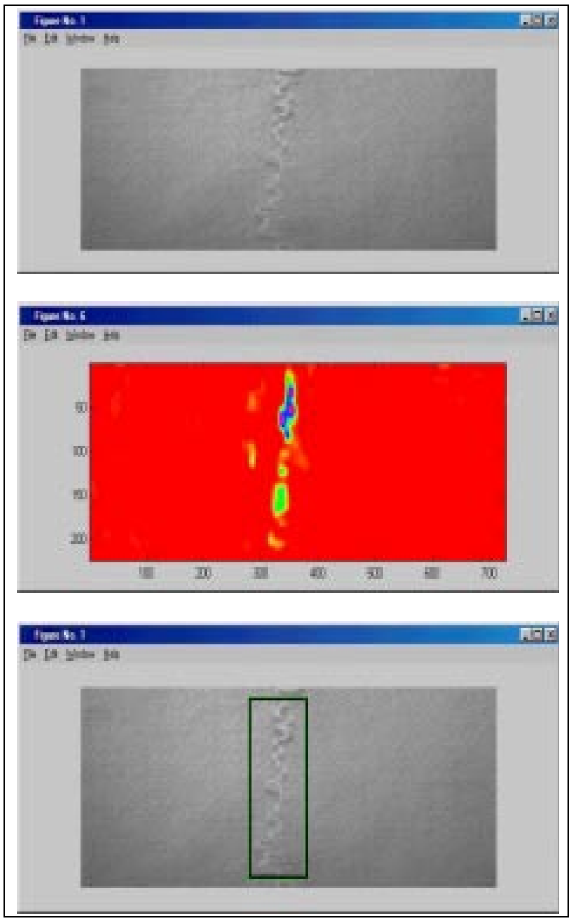

Figure 15. 'Dropping' defect (N=12).

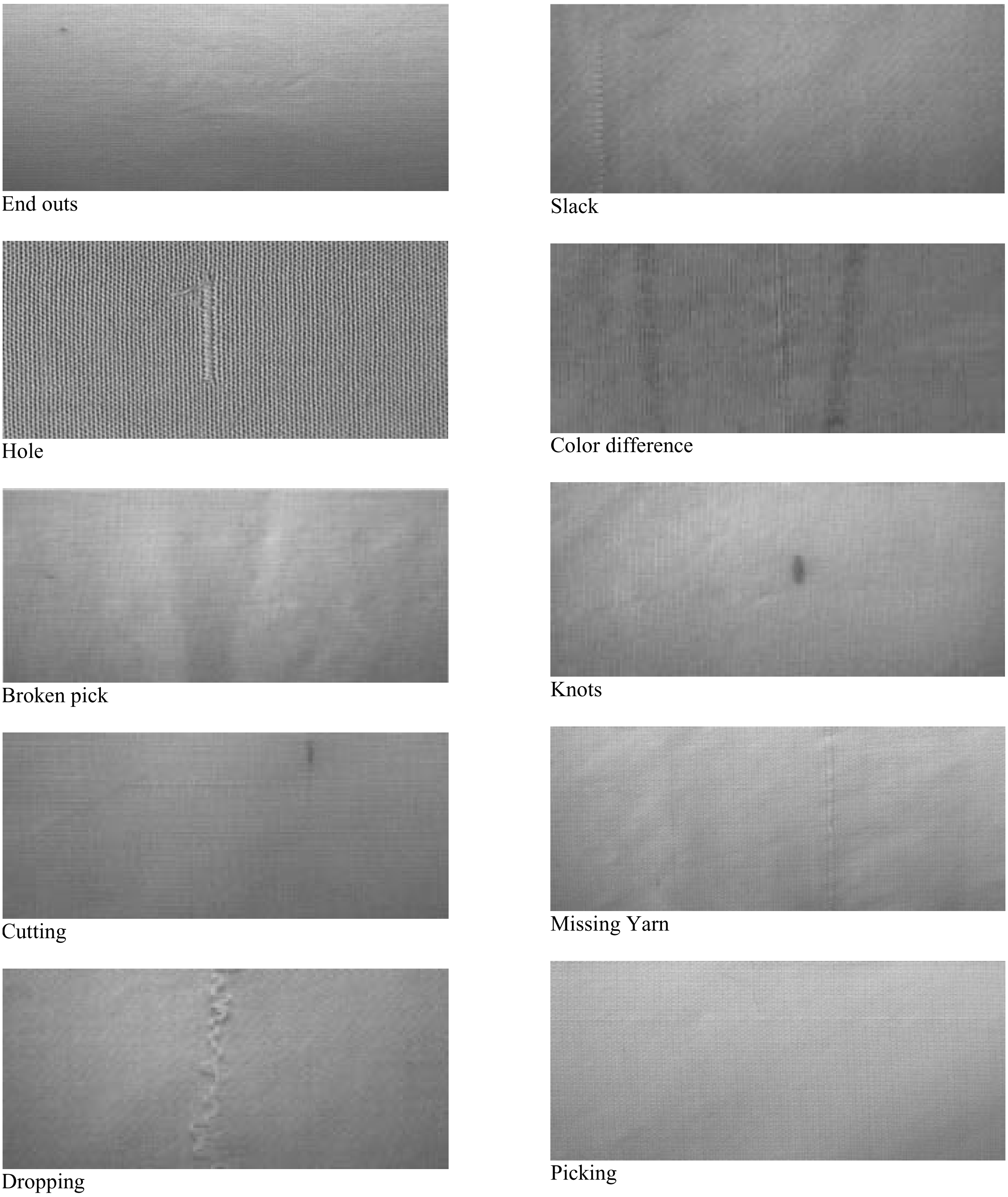

Figure 16. Sample images.

the statistical nature of the textile as mentioned before in the experimental results.

Conclusions

The objective of this paper is to perform and evaluate the quality control results based on the algorithms developed and applied in the textile vision inspection system.

Specifically, this paper constitutes a performance analysis of the quality control algorithms of the vision system, modeling the quality control processes. The developed and applied algorithms are described analytically, showing the effectiveness for the small and medium-sized textile industry.

The algorithm applied consists of three parts. The first part deals with normalization of the image and correction of non-uniform illumination in the image's plane. The second part deals with the image-processing procedure, which detects possible irregularities in the normalized image. Finally, in the third part the RoI is identified within the image, which is the exact position of the defect. Additionally, geometric measurements were performed on the detected defect, which are useful for assessment of the flaw. Finally the algorithm was tested with textile images containing various textile defects, and the forthcoming results evaluated showed in most cases a high performance and behavior of the textile vision inspection system.

Also, these results have shown that the applied algorithms offer an increased accuracy, as many difficulties such as the great diversity of fabric types and defects are overcome. At the present time, where industries like textiles are in constant need of modernization, it is also apparent that the textile industry's presence in the high-technology area of high-performance computing-based inspection is of strategic interest and the replacement of the traditional human inspection by automated visual systems is now more than a necessity.

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