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Genetic Algorithm Tuned Optimal Gabor Filter and Golden Image Subtraction for Defect Detection in Patterned and Unpatterned Fabric

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Abstract

In this study, Genetic algorithm tuned optimal Gabor filter and golden image subtraction is used in detecting defects in both regular patterned and unpatterned Fabric. Defects in fabric such as shuttle smash, thin bar, hole, empty bar, net-hole, crease mark make the final patterned and unpatterned fabric products faulty. This paper focuses on patterned fabrics with repetitive designs such as an Ankara commonly used in Africa using Genetic Algorithm Tuned Optimal Real Gabor Filter (GAT-ORGF) and Golden Image Subtraction (GIS). A fabric image database comprising of 61 plain, patterned, and irregular patterned (unpatterned) fabrics were created. The images were converted to greyscale and Contrast Limited Adaptive Histogram Equalisation (CLAHE) was used to improve the contrast of the images and features were extracted from the pre-processed images using GAT-ORGF while GIS was used to perform subtractions between golden images from referenced fabric images and test images to get resultant images. These resultant images revealed the presence or absence of defects while the median filter was used for post-processing to enhance the processed images. MATLAB was used to implement the developed system and its performance evaluation was estimated using Sensitivity, Specificity, Detection Success Rate (Accuracy) and Error Rate. The performance evaluation results of the developed system for sensitivity, Specificity, Detection Success Rate (Accuracy) and Error Rate were 93.2, 100.0, 95.1 and 5.0%, respectively.

Keywords: Defects, gabor filter, golden image subtraction, patterned fabrics, unpatterned fabrics, textiles.

INTRODUCTION

1. BACKGROUND OF THE STUDY

Quality assurance and control is a key factor in industrial production in the Textile industry. In the science community, a quality control process comprises observations, tests, and inspections with a view to making valid decisions geared toward performance improvement. Quality control is of necessity in production stages in the textile industry if continuous existence in the highly competitive global market will be guaranteed (Habib *et al*, 2014). Textile product quality is seriously degraded by defects, such that they are responsible for nearly 85% of the defect found in the garment industry (Sengottuvelan and Shanmugam, 2008) and its effect is that manufacturers recover only 45-65% of the profit from second off quality goods (Srinivasan *et al*, 1992). The effects of the inability to detect defects early results in waste of cost time, money and adversely affect consumer satisfaction so as to ensure that the textiles produced are void of defects of any kind.

Detection of defects in the fabric is a quality control process that emphasizes the identification and detection of defects on textiles or fabric. Fabric defect detection is able to precisely locate the defect regions in the fabric for further processing, while it also provides a rough information for fabric products grading. The earlier methods of visual defect detection are through offline and human's discretion, the major drawbacks of these approaches are time-consuming, tiredness, costly, boredom, inattentiveness and lack of accuracy (Malek, 2012). Human errors also extended to the inability to detect fine defects (Shanbhag, Deshmukh, and Suralkar, 2012). Researches have been on-going to replace the manual visual defect detection and inspection with an automated or machine vision-based fabric defect inspection systems of Fabric Defect Detection and Classification (FDDC) systems. There are several techniques published, which discuss the influence of fabric defects on the commercial aspects of the textile industry (Su, 2010; Behera, 2009; Sengottuvelan *et al*., 2008).

Automated or machine vision-based fabric defect inspection system improves fabric quality, reduces labor cost, prevents the risk of delivering an inferior textile products and prevent these defects from reoccurring at shorter production time. Several types of defect in fabric exist, machine malfunctions are known to because of much of them since their orientation is along the pick direction (broken pick yarns or missing pick yarns), which tend to be long and narrow. Causes of other defects are traceable to either faulty yarns or machine spoils. more often than not Slubs appears as point defects, on the other hand, machine oil spoils are often along with the direction along the warp direction, most time they are wide and irregular (Mahajan *et al*, 2009).

Methods used for this patterned fabric detection (PFD), must be designed in a way to improve or increase accuracy while reducing complexity, time and cost. Existing approaches for fabric defect detection are mainly for non-patterned fabric, which has achieved over 95% recognition success rate and has been broadly characterized as statistical, spectral, model-based (Ngan, Pang and Yung, 2011) while it has a few methods for regular and irregular patterned fabrics. One of the reasons is repetitive design that provides more underlying information; the other is complicated and varied fabric texture transform. This research was motivated by designing an algorithm that will detect defects in both regular and irregular patterned and non-patterned fabrics using a single designed system

2.0 METHODOLOGY

The input images obtained from the database were first converted into grayscale images for the improvement of both the image processing speed and reduction of space. The converted grayscale images are histogram equalized using Contrast Limited Adaptive Histogram Equalization (CLAHE). Then, for the pre-processed images, the optimal Gabor filtering method was introduced. The Gabor filter parameters (center frequency, orientation, and kernel size) were randomly tuned using Genetic Algorithm (GA) to obtain the minimum energy response on the grayscale image until GA terminated the process to obtain the resultant filtered image. The termination by GA is attained when the average change in the penalty fitness value converges.

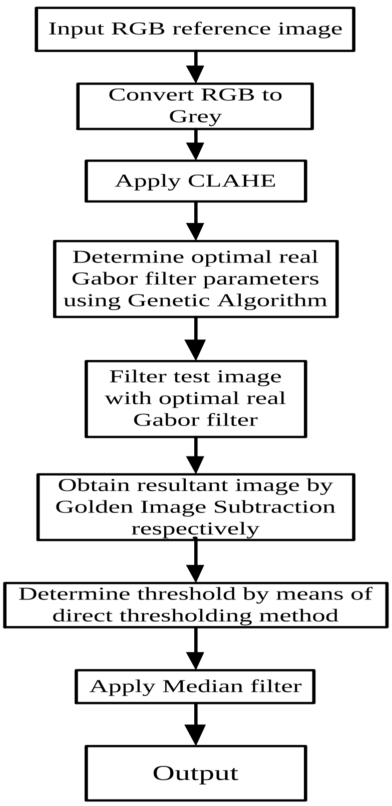


Figure 1 Block Diagram of the proposed Patterned Fabric Defect Detection System

A suitable golden image template G with $m \times n$ pixels of various sizes was subtracted from a non-defective fabric image of size $M \times N$. The resulting image became the energy of the Golden Image Subtraction (GIS). A threshold level was set using direct thresholding (DT) method such that if the value of the resultant image is larger than some pre-determined thresholding, the test sample fabric image was tagged as a defective one. Otherwise, it was categorized as a fabric image free of defect. The basic GIS operation then followed for the filtered fabric image to determine the presence or absence of defects and obtain a resultant image. To obtain better detection results, the white impulse noise level of the various range was introduced to reduce or weaken the noise in the resultant image. The developed system was divided into the Training stage and the Testing stage. In the training stage as highlighted in the block diagram of the fabric defect detection technique in figure 1 and 2

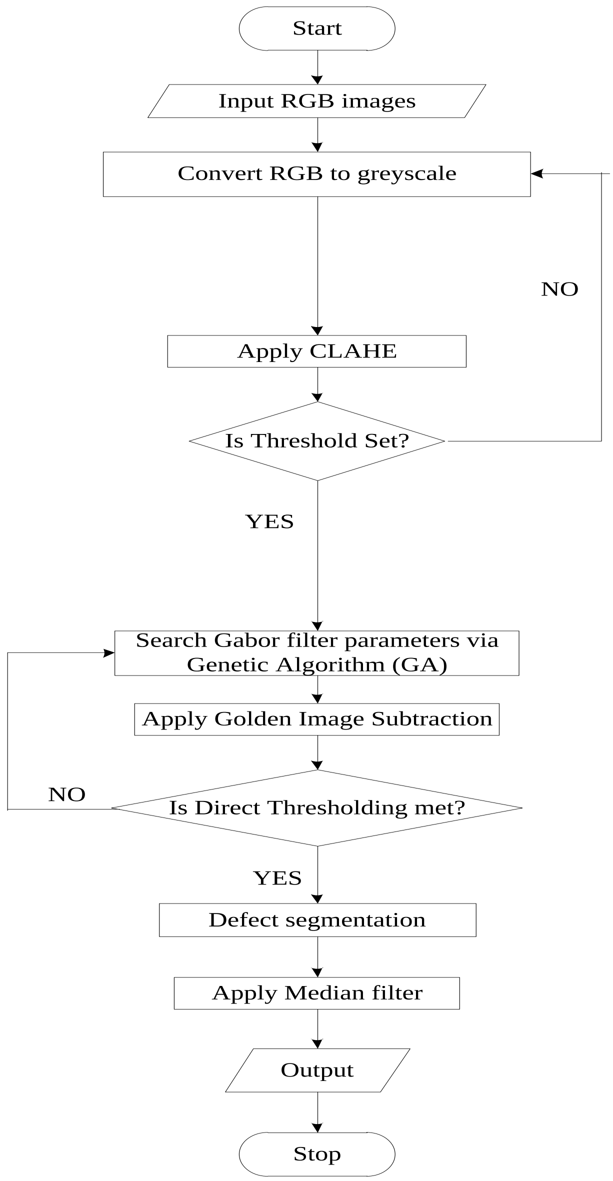


Figure 2: Flowchart of the proposed Patterned Fabric Defect Detection System.

Median filtering was then introduced to smoothen the threshold image, reduce the impact of the noise, preserve the edge sharpening and obtain a better defect detection result.

2.1 DATABASE

A new database was created containing 17 defect-free (plain twill, patterned and irregular colored patterned) images and 44 (plain twill, patterned and irregular colored patterned) defective images were obtained from textile industries. These were used to create a new database that contained different types of fabrics (patterned, irregular patterned, rhombus patterned, curved edge rectangular patterned, checked colored patterned). To create the database, samples of patterned colored, rhombus patterned defect-free and defective fabric images were obtained using HP LaserJet M1132 scanned at 100dpi. This contained several defect sample types commonly reported in the industries such as Barre, Broken Hole, Shuttle Smash, Net-Hole, Empty Bar and Colour contamination.

2.2 IMAGE PRE-PROCESSING STAGE

The image acquisition stage involved acquiring the fabric images (weave, rhombus patterned, colored, irregular patterned) from different textile companies. The test sample images were first pre-processed and converted from RGB to grayscale to reduce image complexity, reduce storage space and improve processing speed. Then, Contrast Limited Adaptive Histogram Equalisation (CLAHE) was performed for the enhancement of the low contrasted grayscale non-defective reference sample images

2.3 OPTIMAL REAL GABOR FILTERING PARAMETER TUNING STAGE

Optimal Gabor filter parameters such as direction or orientation θ, frequency μ_0 or ϕ, and kernel size played an important role in searching for the real optimal Gabor filter parameter to obtain a minimum energy response of the grayscale image samples. The tuning of these parameters to acquire the minimum energy response (fitness function) was done and determined using the Genetic Algorithm (GA). In the training stage, to choose the Gabor Filter Parameters, the energy response of the gray image samples was convolved with the Gabor filter in such a way that it is near to zero minimum for a detect free sample of the input image. At the testing phase, based on the energy response, an unknown image is either marked as defective or defect-free at every unknown image sample. GA not only randomly searched the optimal Gabor filter parameters, but it also eliminated the manual experimental repetition of selecting the parameters of the optimal Gabor filter as this was done by Genetic Algorithm to obtain an optimized filtered result of the non-defective Reference grayscale image. To improve this, the Gabor filter parameters were selected to obtain the minimum energy response, which was terminated using the Genetic Algorithm (GA) optimization technique.

2.4 IMAGE SUBTRACTION STAGE

The basic Golden Image Subtraction (GIS) was adopted to perform subtractions between golden images from referenced fabric images and test images to get resultant images. Genetic Algorithm was employed in tuning the resultant images.

2.5 DIRECT THRESHOLDING STAGE

Thresholding was obtained by training defect-free fabric samples to segment defects from fabric background using a direct thresholding method. A noise level range of 1%, 5%, and 10% was introduced to play an important role in determining the threshold value.

2.6 FINAL FILTERING STAGE

A median filter was then used to smoothen the threshold image for lessening the various white impulse noises and enhancing the image for defects on the threshold image. The steps involved in the algorithm are:

a. Input image.
b. Convert the image from RGB color space to greyscale.
c. Apply CLAHE on the resultant image
d. Apply optimal real Gabor filter parameters through Genetic Algorithm (GA)
e. Apply Golden Image Subtraction (GIS) to obtain resultant images (R)
f. Apply thresholding on the result in (e)
g. Apply Median filtering
h. Output result.

2.7 PERFORMANCE EVALUATION METRICS

To evaluate the performance of the defect detection algorithm, four parameters namely, detection success rate (accuracy), specificity, sensitivity and Error rate were used.

$$\textbf{Detection Success Rate} = \frac{\text{Number of Defective Samples Correctly Detected}}{\text{Total Number of Defective Samples}} \tag{1}$$

Specificity: this is the correct detection of defect-free samples

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{2}$$

Sensitivity: this is the correct detection of defective samples

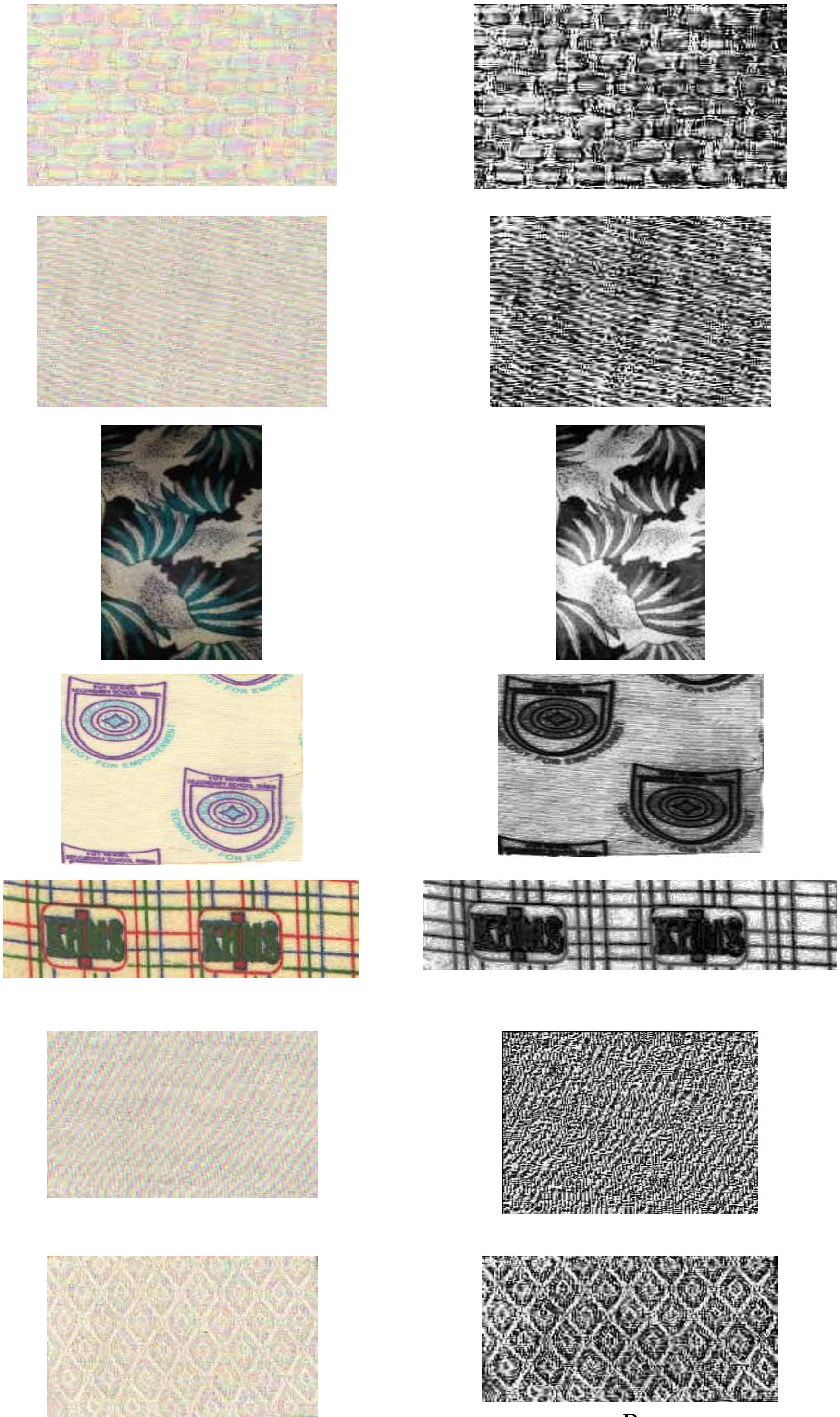
$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{3}$$

Where TP = True Positive, FP = False Positive, TN = True Negative, FN = False Negative

3.0 RESULTS AND DISCUSSION

3.1 IMAGE PREPROCESSING STAGE

Plate 1 shows the result of the converted grayscale images for the various fabric sample patterns used in the developed system. The 61 fabric samples images were preprocessed by first converting the RGB sample images to greyscale. Histogram equalization by Contrast Limited Adaptive Histogram Equalization (CLAHE) was done to prevent the overamplification of noise and for improving the image contrast in the converted images. The converted images were filtered using the GA-tuned optimal Gabor filter. The tuning of these parameters to acquire the minimum energy response (fitness function) was done and determined using the Genetic Algorithm (GA). Convergence or Termination condition was accomplished when the best penalty fitness value of one individual (a sample grayscale image) is zero or a maximum number of iterations has been reached



A B

Plate 1: RGB images and greyscale images during preprocessing

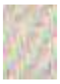
(a) original RGB images

(b) the greyscale image after conversion

3.2 GOLDEN IMAGE SUBTRACTION

Plate 2 shows a suitable golden template extracted with a size $m \times n$ pixels and obtained from the non-defective fabric images (filtered image F) of size $M \times N$. The image was used in training the fabric defect detection system. The size of the golden image template was crucial for the Golden Image Subtraction method because, for different fabric textures, a corresponding golden template image sizes ($2 \times 2, 4 \times 4, 7 \times 7, 26 \times 16$) were chosen and experimented with in order to obtain the best defect detection results. The Golden template sizes were kept constant and the noise level varied proportionately so that there is no mass generation of noises which would have reduced the recognition rate.

(a)



(b)

(c)

Plate 2: (a) Reference Image (b) The Golden Image size (c) The extracted Golden Image size.

Table 1: Values of the Gabor filter parameters after selection at the end of the individual generation

Fabric Sample	Frequency	Orientation	Kernel Size	Mean Fitness Penalty Value	Best Fitness Penalty Value
Plain Twill pattern	47	32	5	151.55	14.1794
Rounded-edge Rectangular pattern	48	122	5	86.1136	37.2798
Rhombus Weave pattern	47	32	5	134.181	20.0045
Coloured Regular pattern	43	84	5	2442.1	1976.82
Coloured Irregular pattern	46	82	5	5.01131	0.316553

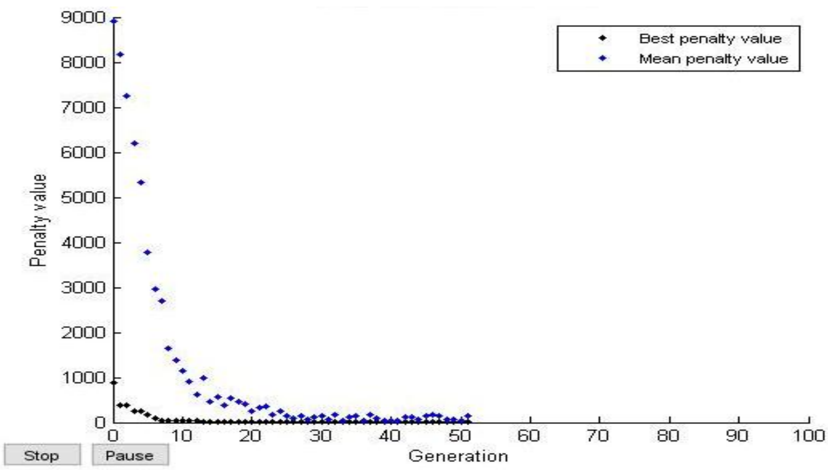


Figure 3: GA Convergence curve for the energy response the or termination for a plain twill pattern

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3.3 POST PROCESSING USING MEDIAN FILTERING

Median filtering was then applied to smooth the threshold segmentation image. It also removed various types of noise, preserved edge sharpening of the defect area.

3.4 RESULT OF THE TESTING STAGE

The performance evaluation results of the developed system as presented in Table 2 shows detection success rate (accuracy of the system), Detection Success Rate (Accuracy), Specificity, Sensitivity and Error Rate of 95.1%, 100%, 93.2%, and 5% respectively. Table 3 compares the accuracy of the proposed fabric defect detection with existing fabric defect detection methods

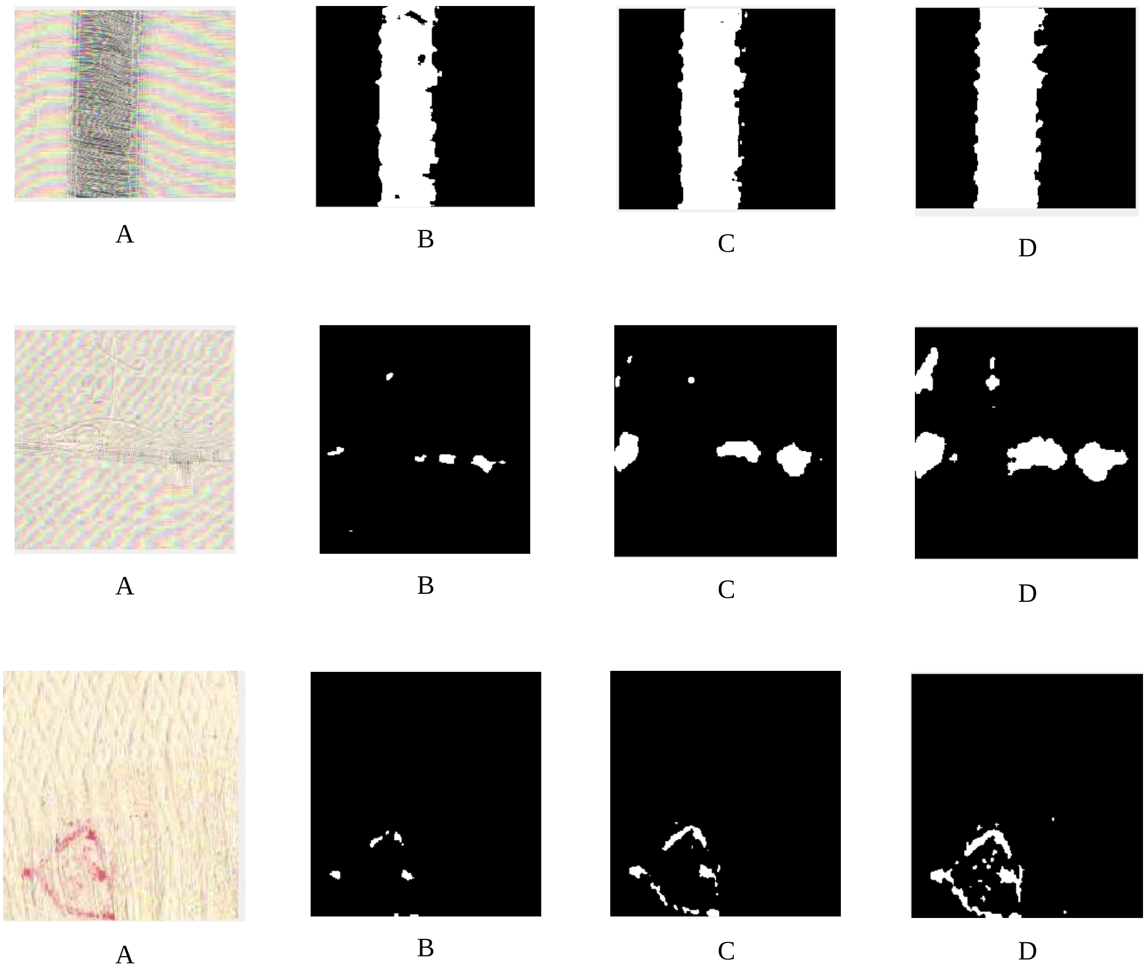

Plate 3: Effect of the noise level on the threshold filtered image;

(A) Defective fabric image

(B) Defect detection result with 1% noise level

(C) Defect detection result with 5% noise level

(D) Defect detection results with a 10% noise level.

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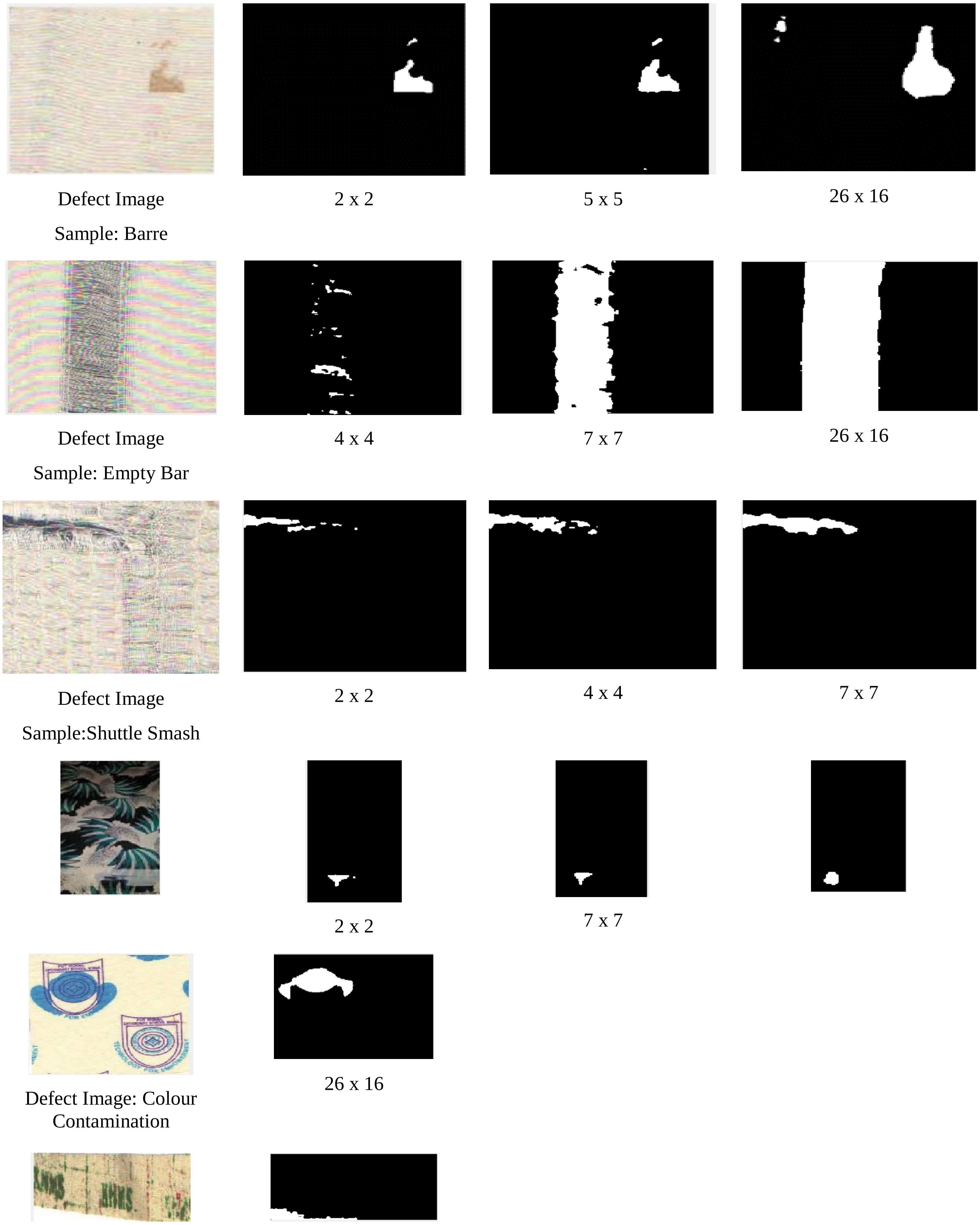

Plate 4: Effect of the size of the golden image template on defect detection results at a noise level of 5%.

Table 2. Performance Evaluation of the Proposed System

Performance Evaluation Metric	Result (%)
Detection Success Rate (Accuracy)	95.1
Specificity	100
Sensitivity	93.2
Error Rate	5

Table 3: Comparison of the proposed Fabric Defection System and Existing methods

METHODS	FABRIC TYPE	AUTHORS	PERFORMANCE (%)
GLCM + PNN	Knitted, yarn and woven	Kulkarni and Patil (2012)	91.1%
Adaptive median filtering + BPN	Woven	Nasira & Banumathi (2014)	93%
GA + Gabor Filter + Regular Band	Printed Pattern	Kang, Yang, Jing (2015)	93%
CLAHE + GA + Gabor Filter + GIS	Plain Twill, Rounded-edge, Rectangular pattern Rhombus Weave pattern, Coloured Regular pattern Coloured Irregular pattern		95.1%

4.0 DISCUSSION

The preprocessing stage involved the creation of the database, conversion of the fabric samples in RGB to greyscale, Histogram Equalisation and obtaining the resultant fabric images part.

IMAGE PREPROCESSING STAGE

Plate 1 shows the result of the converted grayscale images for the various fabric sample patterns used in the developed system. The 61 fabric samples images were preprocessed by first converting the RGB sample images to greyscale. Histogram equalization by Contrast Limited Adaptive Histogram Equalization (CLAHE) was done to prevent the overamplification of noise and for improving the image contrast in the converted images. The converted images were filtered using the GA-tuned optimal Gabor filter. The tuning of these parameters to acquire the minimum energy response (fitness function) was done and determined using the Genetic Algorithm (GA). Convergence or Termination condition was accomplished when the best penalty fitness value of one individual (a sample grayscale image) is zero or a maximum number of iterations has been reached. Table 4.3 shows the values of the Gabor filter parameters after selection at the end of the individual generation with respect to the best and mean fitness penalty values. Table 4.3 also shows the GA parameters after selection and mutation at the end of the first-generation and sorted population with respect to the fitness value. These parameters form the initial population to the next generation. Figure 4.1 represents the GA Convergence curve for the energy response minimization, which was always completed after tuning the Gabor filter parameters (frequency, orientation, and kernel size) of the grayscale image independent of each fabric sample image.

The detection results obtained showed that 17 defect-free fabric images out of 17 defect-free images and 41 defective images out of 44 defective images were detected after they have been filtered over various golden image template sizes. It was also observed that the color stain patch in the irregular colored patterned fabric was not completely detected. This is due to the fact that there can be a complication, variance or misalignment between the design background and the defect in such fabric texture which led to difficulty in distinguishing them.

4.1 EFFECT DUE TO NOISE LEVELS IN THE SEGMENTATION THRESHOLD IMAGES

There is an amount of noise in the thresholded image. The noise must be kept at a moderate level to give the best result from defect detection. Plate 3 shows that a 5% noise level was the most appropriate level for all test samples. It was observed that if the noise level was adjusted to be too low, such as 1%, pixel to pixel comparison between the test image and reference image around the defect location generated less result from defect detection. It was also observed that when the noise level was adjusted to 10%, the output was not satisfactory because the threshold image would be in white color since the threshold value might reach the middle level of hills and valleys of the resultant image. Thus, the white noise was seen as defective

Table 3 compares the accuracy of the proposed fabric defect detection with existing fabric defect detection methods.

4.2 EFFECT DUE TO THE SIZE OF THE GOLDEN IMAGE

Choosing a golden image is a key step for the basic GIS method. If the size is not bigger than or equal to a repetitive pattern, the detection would not succeed. Although, if the size of the golden image is comparatively bigger than a repetitive pattern, the results appear similar to those only approximately the same size as one repetitive pattern. Plates 2 and 4 show that varying the golden image template sizes affect the number of pixels that are correctly detected in each test sample depending on the sample pattern and defect type. From the different golden template image sizes used ($2 \times 2, 4 \times 4, 7 \times 7, 26 \times 16$), golden template size 7×7 was observed to be the most suitable size at which output obtained the best detection result for plain-twill pattern, Rounded-edge Rectangular pattern and Rhombus Weave pattern. However, for the best detection result in color regular and irregular pattern samples, a golden image size of 26×16 was used to obtain detection results.

This research has improved on the range of fabric (in both patterned and unpatterned) and defects shapes that can be detected fabric these include Plain Twill, Rounded-edge, Rectangular pattern Rhombus Weave pattern, Coloured Regular pattern Coloured Irregular pattern on like Kulkarni and Patil (2012) which detected in knitted, yam and woven fabric, Nasira & Banumathi (2014) only applied to woven fabric and Kang, Yang, Jing (2015) which was only applied to printed pattern only as shown in Table 3. In contrast to this research Zhang et al (2018) worked on patterned textiles using binary features and rule-based classification approach, analysis was done on individual patterns which included dot, box, star-patterned fabrics with great accuracies but their analysis was not done on unpatterned fabrics. Jing, J., Liu, S., Li, P., and Zhang, L. (2016) used a 2-D Gabor filter and CIE L*a*b* color space in fabric defect detection Instead of conversion to greyscale, this method converted the RGB color of a given fabric image to CIE L*a*b color space for feature representation. The positional distance between similar patches and the color dissimilarity was jointly used to measure the defective values, the major difference between the research is the used 2-dimensional Gabor filter and the conversion from RGB color coding directly to CIE L*a*b color space

5.0 CONCLUSION

A system to detect defects in fabrics based on the pixel to pixel comparison in different kinds of fabric textures with different patterns and defects using a common database has been developed. The use of the Contrast Limited Adaptive Histogram Equalization (CLAHE) proved to be successful for the enhancement of the low contrast fabric images and noise reduction. The method located various ranges of defects in various defect categories in fabric samples with patterned and irregular patterned fabric with a higher precision rate

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