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Fabric Defect Detection Using the Sensitive Plant Segmentation Algorithm

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Abstract
Fabric quality control and defect detection are playing a crucial role in the textile industry with the development of high customer demand in the fashion market. This work presents fabric defect detection using a sensitive plant segmentation algorithm (SPSA) which, is developed with the sensitive behaviour of the sensitive plant biologically named "mimosa pudica". This method consists of two stages: The first stage enhances the contrast of the defective fabric image and the second stage segments the fabric defects with the aid of the SPSA. The SPSA proposed was developed for defective pixel identification in non-uniform patterns of fabrics. In this paper, the SPSA was built through checking with devised conditions, correlation and error probability. Every pixel was checked with the algorithm developed to be marked either a defective or non-defective pixel. The SPSA proposed was tested on different types of fabric defect databases, showing a much improved performance over existing methods.

Key words: *external stimulation, fabric pattern, sensitive behaviour, texture.*

Introduction

Fabric is produced from textile fibres of natural materials, like cotton. Defects on the fabric are due to flaws on the surface of the fabric. Defect detection is highly important for fabric quality control. Traditionally, defects are detected by human eyes. However, the efficiency of this manual method is low and the missed rate high because of eye fatigue. Hence, an automatic inspection system is necessary for textile industries.

Method proposed

This work proposes a defect detection model which is developed based on the sensitive behaviour of the sensitive plant biologically named mimosa pudica. First, all images are pre-processed through grey-level transformation to enhance image contrast. The second step involves the segmentation process, developed on the basis of the sensitive behaviour of mimosa pudica, to segment the various patterns of fabrics. The conditions were derived for different patterns of fabric to easily segment and isolate the defects with a higher degree of precision and accuracy.

This plant gives unusual quick responses to stimulation and comes back to normal after several minutes. It droops in a sense to defend itself against herbivores. The leaves of the plant also droop in response to darkness and reopen with the daylight, known as nycastic movement (***Figure 1***).

With this sensitive behaviour, conditions were derived for various patterns of fabric to extract defective pixels. Three different patterns of fabrics: plain, twill and satin, were checked with conditions derived for each to find defective pixels. The texture pattern and pixel formation of the fabric are given in ***Figures 2*** and ***3.***

Generally, Weaving is the process of combining the two set of threads weft and warp together to produce fabric. The thread weft runs horizontally on the loom and weaved in front and behind the warp fabric. In finding defective pixels in every pattern of the fabric, first the pixel is randomly chosen for its intensity checking and its 8 neighborhood pixels are checked with respect to the conditions derived for each pattern. The 8 neighborhood pixel and its places are represented in the ***Figure 4***.

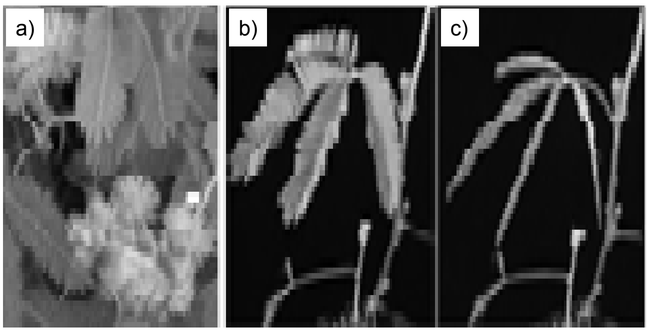

Figure 1. *a) Mimosa pudica plant, b) leaves of the plant in normal condition, c) leaves drooped in response to the external stimuli.*

Segmentation process

The segmentation process was used to detect the sensitiveness of the mimosa pudica plant. The image chosen for detection was in MxN pixels. A random pixel p(x,y) was chosen to check the mimosa plant, and the intensity of the corresponding pixel was denoted as I {(px,y)}. The pixel chosen has to satisfy two conditions derived to detect defects in the plain pattern. The conditions are compared with the normal environmental condition of the mimosa pudica plant. If the pixel chosen (plant) satisfies the conditions, the plant is in a normal state and the fabric is considered as non-defective (also the plant has no droops). If the fabric does not obey the condition, the pixel chosen is considered as defective. (Plant was induced by external stimuli).

Non-uniform pattern

In non-uniform patterned fabric, its structure is woven with different complex patterns, and hence the image of such fabrics have a wide range of pixel intensity. In fabric, defect detection needs the original image i.e. a non-defective image of the sample taken to find defects.

The original image X and sample image Y are expressed as:

$$X = \sum_{M=1}^{x} \sum_{N=1}^{y} P_{x,y}\,, \qquad Y = \sum_{M=1}^{x} \sum_{N=1}^{y} P_{x,y} \tag{1}$$

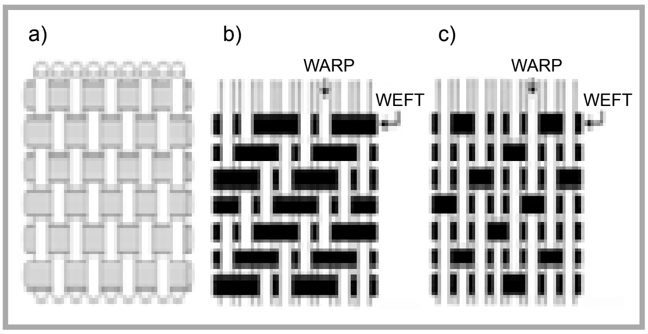

Figure 2. *a) Plain fabric texture, b) twill fabric texture, c) satin fabric texture.*

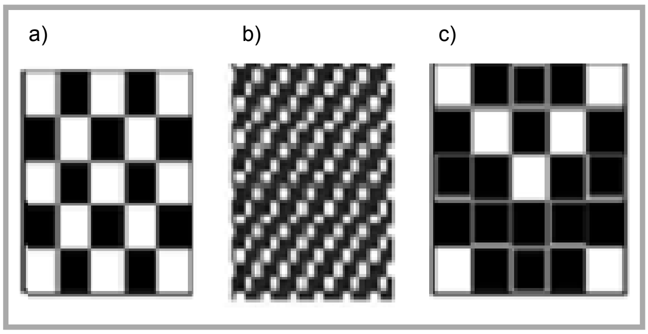

Figure 3. *Pixel formation of fabric patterns a) plain, b) twill, c) satin.*

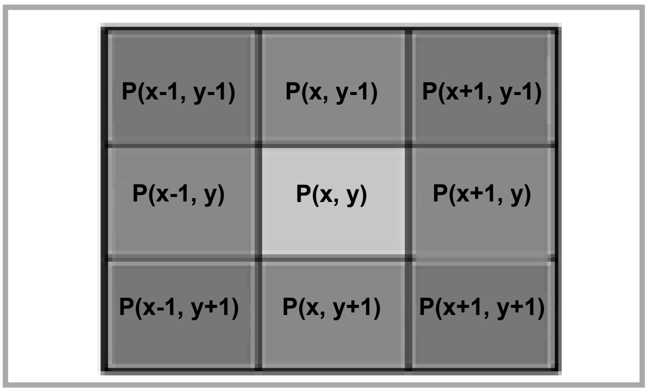

Figure 4. *Pixels shown in green are the four neighborhood pixels of the pixel p(x,y) and pixels shown in brown are diagonal neighbor pixels to the pixel (x,y).*

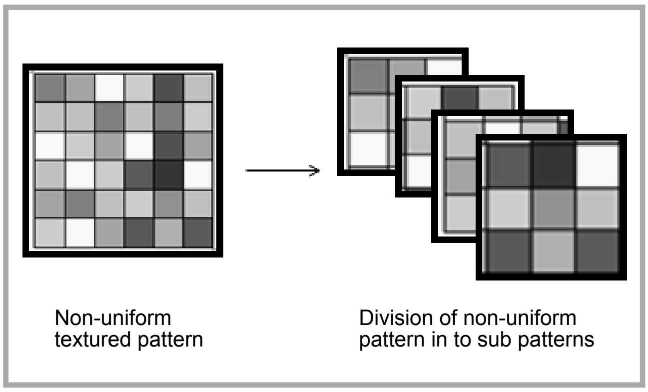

Figure 5. *Process of subpatterns formation.*

The first step in the segmentation process is to divide the original image X and defective image Y of size 'MxN' into sub patterns of size 'm x n'. The number of patterns generated depends on the size of the image, as shown in ***Figure 5***. The patterns generated can be symmetrical or asymmetrical. The 'q' number of patterns generated can be expressed as:

$$X_{sub_{pattern}} = \sum_{t=1}^{q} P_t^{m\times n}\ ; \quad Y_{sub\_pattern} = \sum_{t=1}^{q} P_t^{m\times n} \qquad (2)$$

Where, $\sum_{t=1}^{q} P_t^{m\times n} = \sum_{m=1}^{x}\sum_{n=1}^{y} I(P_{x,y})$ Sub patterns are generated for both images. After that, conditions are generated for each sub patterns X of the image with respect to their 4 neighboring and diagonal pixels.

$$\sum_{t=1}^{q} P_t^{m\times n} = \mathrm{Cond}\left(\sum_{m=1}^{x}\sum_{n=1}^{y} P_{x,y}\right) \qquad (3)$$

From ***Figure 6***, in the uniform texture pattern segmentation, every pixel is considered as the plant acting normally in it own environmental conditions, which is related to the conditions devised and the degree of correlation calculated for every pixel. If any condition is not matched (if the plant is induced by any external stimuli) with the pixel chosen, then the pixel (plant) is marked (droops) as defective. Then the degree of correlation between the sub patterns of the original image and the sample image is established as the second confirmative parameter for confirming the defective pixel.

$$\mathrm{Corr}\ (X, Y) = \sum_{t=1}^{q} \mathrm{corr}(P_t^{m\times n}, P_{t+1}^{m\times n}) \qquad (4)$$

If the pixel chosen violates the condition, there is the possibility that the pixels surrounding the pixel being checked may be defective. At that time the probability value of the chosen pixel and the surrounding pixel being the defective one. The probability is obtained with the formula:

$$\rho(P_{x,y}) = \frac{1}{8}(\text{No of 4 neighborhood pixel violating conditon} + \text{No of diagonal pixel violating condition}) \qquad (5)$$

probability checked for chosen pixel and condition violating surrounding pixels:

$$\text{Probability} = \rho(P_{x,y}, P_{x+a,y+b}) \qquad (6)$$

With the calculated value of probabilities, the pixel with a higher probability is concluded as defective and marked for defect identification. One or two pixels which are non-defective surrounding the group of defective pixels have the chance to be marked as defective in the case of the complicated situation of diverse pixel variations. However, these changes will not have any great impact on the output accuracy.

Results and discussion

This section consists of a performance evaluation of the proposed fabric defect detection with two databases. The first database is the TILDA database and the second one was scanned from a fabric defect handbook. For these defect classes, 50 images of size 768 × 512 were attained by rotating and relocating the textile samples. All those above the denoted model used in comparison with the model proposed were programmed and simulated using MATLAB. A set of non-defective samples was collected as training data for dividing it into sub patterns and devising conditions for each sub pattern. ***Figure 7*** shows the detection results of fabric defects. The sensitive plant algorithm proposed located and outlined the defective pixels with great precision and accuracy for all types of fabric. The work proposed was compared with existing methods, shown in ***Figure 8***.

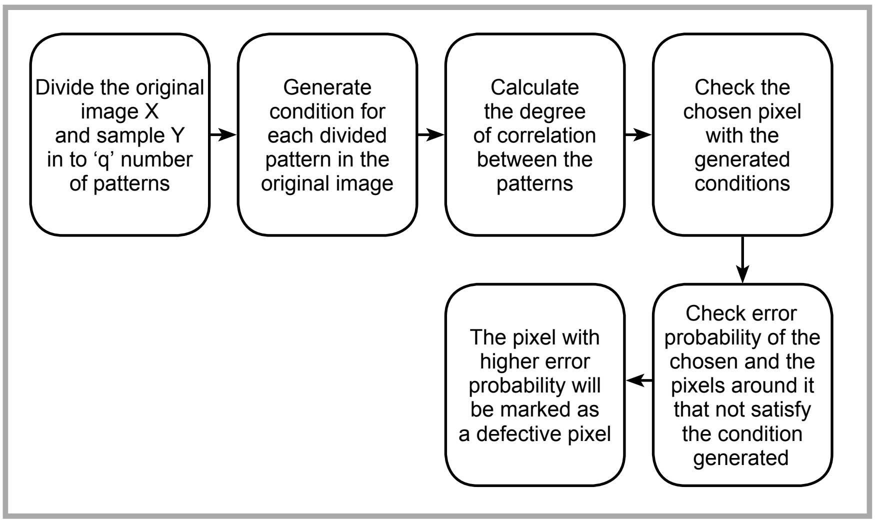

Figure 6. *Process sequence of defective pixel identification in in non uniform pattern.*

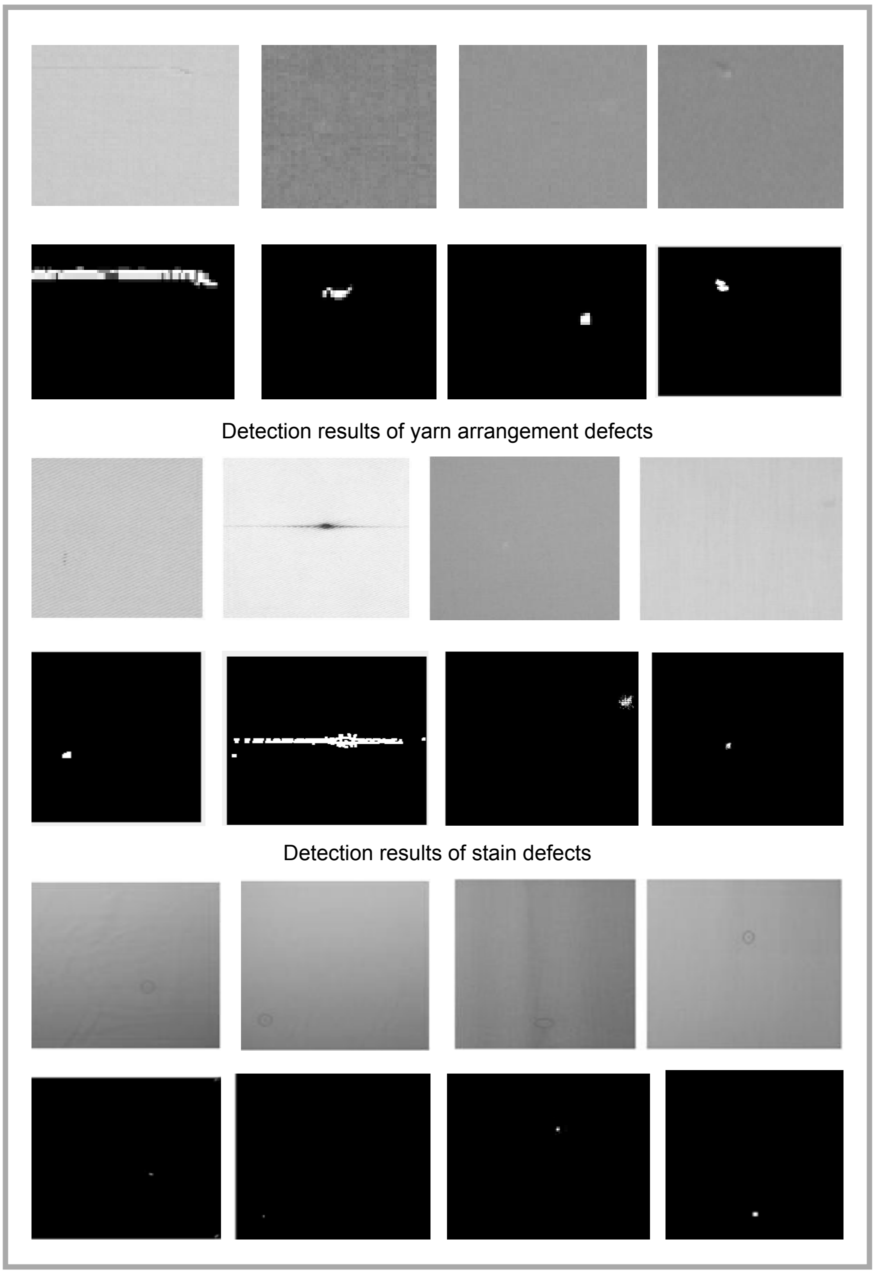

Figure 7. *Detection results of tiny defects.*

Performance metric

The model proposed was compared with traditional methods to shows its efficiency. Its performance compared with the four defect detection models depends on the metrics: precision, sensitivity, specificity and accuracy. Four basic and important performance metrics were used in evaluating the performance of the detection model, shown in the ***Figure 9***, namely:

$$\text{Precision} = TA/TA + FA \quad (7)$$

$$\text{Sensitivity} = TA/TA + FN \quad (8)$$

$$\text{Specificity} = TA/TN + FA \quad (9)$$

$$\text{Accuracy} = TA/TA + TN + F\,A + FN \quad (10)$$

Conclusions

In this work, a fabric defect detection algorithm was developed based on the sensitive behaviour of the sensitive plant algorithm. Detection was performed in two processes: (i) contrast enhancement & (ii) segmentation. The algorithm was developed in such a way as to detect defects in both uniform and non-uniform texture patterns. Sample images with various types of defects were used for defect detection. the results of which were all compared with past researches. The work proposed can detect most types of defects. even if they are tiny and with uneven illumination. It also achieved a much higher percentage of precision, sensitivity and accuracy – 96% than other works, with a higher detection rate of true positive pixels and lower false-alarm pixels. In the future, the method could be implemented in devices mounted on a loom.

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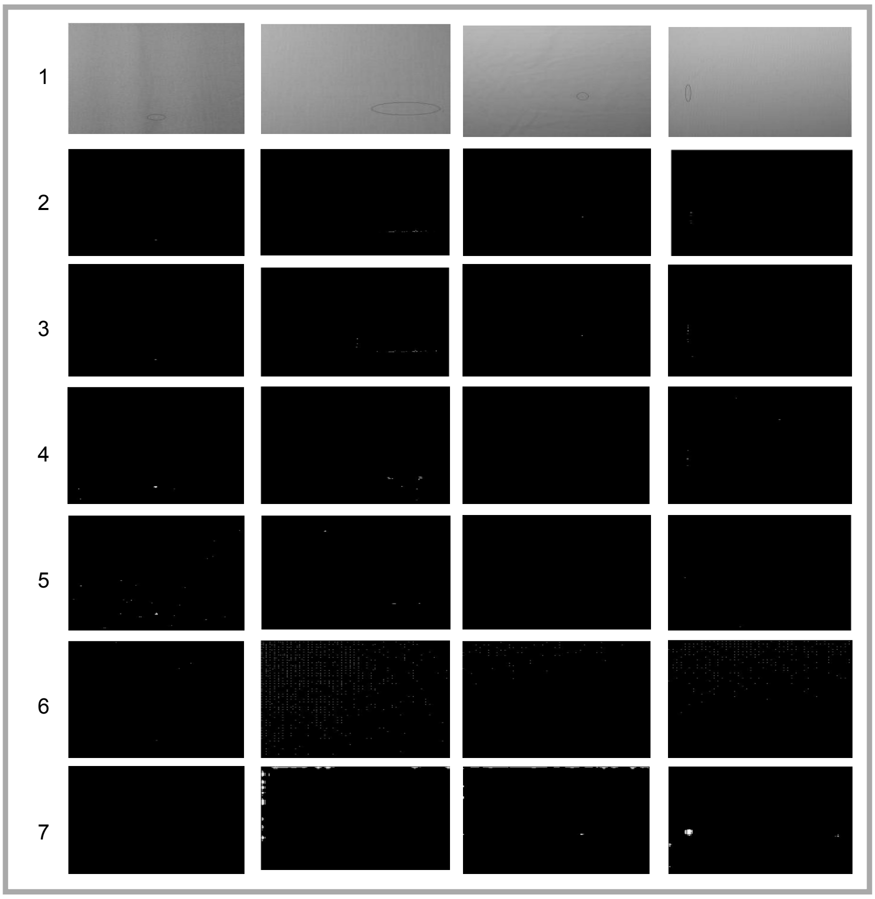

Figure 8. *First row – input images, second row – proposed method, third row – non local sparse representation based detection model, fourth row – differential evolution based optimal gabor filter model , fifth row – gabor filter bank model, sixth row – adaptive sparse representation model, seventh row – fourier and wavelet shrinkage method.*

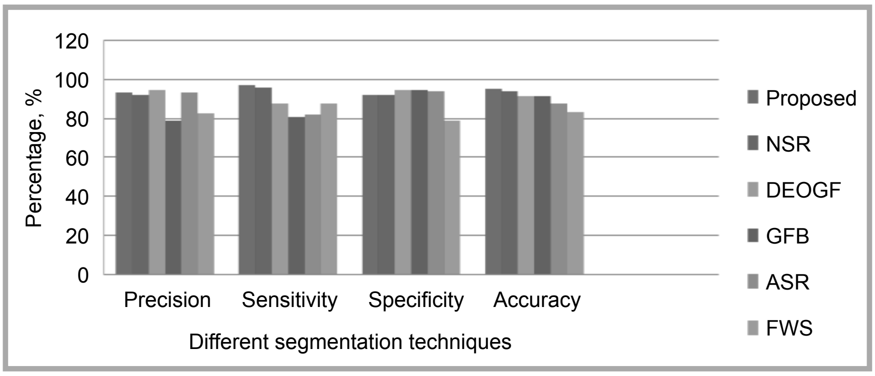

Figure 9. *Performance comparison of different segmentation techniques.*

Table 1. *Performance comparison table of proposed and conventional work.*

Metrics	Proposed	NSR [10]	DEOGF [20]	GFB [19]	ASR [21]	FWS [18]
Precision	93.6	92.5	94.7	79.3	93.3	82.7
Sensitivity	97.2	96.1	88.2	81.2	82.3	88.2
specificity	92.2	92.2	95.1	95.1	94.1	79.1
Accuracy	95.8	94.1	91.7	91.7	88.2	83.5

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