Defects detection and extraction in textile imageries using Mathematical Morphology and geometrical features

Halimi Abdellah*, El kouraychi abdelmajid, Bouzid Abdenabi and Roukhe Ahmed

Received 8 July 2012; Published online 29 September 2012

© The author(s) 2012. Published with open access at uscip.org

Abstract

Defect in textiles are generated in woven fabric due to improper treatments in weaving machines, spinning errors and inadequate preparations of fiber at the spinning stage.

The aim of this work is the detecting of the small surface defects which appear as local anomalies embedded in a homogeneous texture.

The methodology used in this paper is based on the morphological operators contained in toolbox of Mathematical Morphology developed in the software MATLAB. The extraction of the window defect in original image is obtained. A geometric features where calculated in order to identify the textile defect type (size and form). The result obtained show that the combination of the morphological operation and the geometric features approaches can give better results for the identification of the type of defects in homogeneous texture.

Keywords: Quality control, Defects detection, Image processing, Morphological operation, features geometric.

1. Introduction

A new algorithm for defect detection using the geometric feature is presented. Image area measurement is a basic process in image processing and automatic recognition system.

The paper is organized as follows: Sec. I: the image Pre-processing and Image Enhancement Algorithms and filtering(Ralaeal and al 2007).

Sec. II deals with the defect localization and extraction of features based on geometric features. Sec. III contains some typical experimental results and concludes the paper.

*Corresponding author:
Department of physics: Laboratory of optic photonic and application
Moulay Ismail University, Faculty of Science, Meknes, Morocco
E-mail: halimiabdellah@yahoo.fr
2. Pre-processing

We intended to create images that are more suitable to the human visual perception object and target recognition. We used the principles of image processing and Morphological operations on the textile images. Therefore, we get new images that contain the surface defect only to make easier for the detecting process and classification operation via the judgment of the operator.

It becomes difficult, if not uncertain, to detect during the image visualization, the presence of the small defects and to determine accurately their sizes. That is why it is often necessary to start with the pre-processing stage in order to reduce or eliminate the noise enclosing in the image and the small defect and improve its visibility. This procedure permits to obtain an image which would facilitate later the identification of the important connected defects that we can identify.

The first task in image pre-processing is the selection of the region of interest (ROI). This is considered as the parts of the image where the image interpreters suspect the presence of imperfections.

Approach

![Functional block diagram of defect detecting system](image)

Fig. 1: Functional block diagram of defect detecting system
Segmentation is the initial step for any image analysis. There are two different tasks for segmentation of textile images. One is to obtain the locations of defect areas. The other is to classify the abnormalities. Image segmentation has been approached from a wide variety of perspectives. Region-based approaches, morphological operation, multi-scale analysis, fuzzy approaches and stochastic approaches have been used for textile image segmentation but with some limitations. Region-based approach is expensive both in computational time and memory (Ajay Kumar 2008; Mahajan and al 2009). Mathematical morphology requires a priori knowledge of the resolution of calculation and extraction of important defect in order to determine the sizes and shapes of the structure elements (K.L.Mak and al 2009; Canny J.F 1986).

2.1: Morphological operation

As binary images frequently result from segmentation processes on gray level images, the morphological processing of the binary result permits the improvement of the segmentation result. Defects are extracted from the background by thresholding the image and classified according to size and shape parameters. Existing machines commonly detect the following defaults (H.Elbehiery and al 2005; B.Mallick and al 2000).

These images are captured by using a digital camera.

Sec.1

2.1.1 Binarisation of image
a) OTSU method

In computer vision and image processing, **Otsu's method** is used to automatically perform histogram shape-based image thresholding (M. Sezgin and B. Sankur 2003) 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 (Nobuyuki Otsu 1979). 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.

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

\[
\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)
\]

Weights \(\omega_1\) are the probabilities of the two classes separated by a threshold \(t\) and \(\sigma_1^2\) variances of these classes.

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

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

Which is expressed in terms of class probabilities \(\omega_1\) and class means \(\mu_1\), which in turn can be updated iteratively. This idea yields an effective algorithm.

b) Algorithm

1. Compute histogram and probabilities of each intensity level
2. Set up initial \(\omega_1(0)\) and \(\mu_1(0)\)
3. Step through all possible thresholds \(t=1,...,\) maximum intensity
   1. Update \(\omega_1\) and \(\mu_1(0)\)
   2. Compute \(\sigma_b^2(t)\)
4. Desired threshold corresponds to the maximum \(\sigma_b^2(t)\)

![Fig. 4: (a) the original image for the textile defect (b) isolated textile defect binary image procured after Thresholding implementation.](image-url)
Fig. 4: (a) and (b) show the defective tile image containing textile defect and the isolated textile defect tile image using Image processing and Morphology operations textile defect detection.

In the binary output image local defects appear segmented from the background.

The features computed were area, perimeter and compactness (percentage occupied by the surface of defect on the total image in the window) (J.R.Parker 1997). But we can determine the geometric parameters for a given defect, namely the classification; so why it is necessary to remove small defects and the noise that can negatively influence us the location of default.

To clarify, the more we determine the contour of the region related (canny method) [Fig 5].

**c) Edge detection**

Edge detection is a fundamental tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness changes sharply, or more formally, has discontinuities.

There are many methods for edge detection, but most of them can be grouped into two categories: search-based and zero-crossing based.

**d) Canny edge detection method**

John Canny considered the mathematical problem of deriving an optimal smoothing filter given the criteria of detection, localization and minimizing multiple responses to a single edge (Alper Pahsa 2006). He showed that the optimal filter given these assumptions is a sum of four exponential terms. He also showed that this filter can be well approximated by first-order derivatives of Gaussians.

A subsequent filtering stage is compulsory in order to reduce the false defects introduced by the previous stages. At the same time, the factory requirement indicates that some little objects should not be considered as faults. Then, several shape and size filters are applied which eliminates those objects accomplishing the following conditions:

![Two Small defects and noise](image)

**Fig. 5**: Two small defects and noise.

The image after edge detection clearly shows the two small flaws that we can disrupt, by using morphological filters (K.L .Mak and al 2009).

**e) Reduction of Binary Noise**
In the binary image of Fig. 4, there are a number of very small objects contributing to the total area defect. However, most of these objects are too small to correspond to real important defect and it is more likely that they are residual noise that should be removed.

Different Mathematical Morphological Operators

Mathematical Morphology is one of the most productive areas in image processing (Alper Pahsa 2006; Beaut Kaur and al 2011; K.L.Mak and al 2009). The content of mathematical morphology is based on a 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:

Morphological operation

The language of mathematical morphology is a set theory. Sets in mathematical morphology represent objects in an image. In binary images, the sets in question are members of the 2-D integer space $\mathbb{Z}^2$ 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 $\mathbb{Z}^2$ for binary images, defining the reflection of set $B$, denoted by $\hat{B}$ as:
$$\hat{B} = \{W / W = -b, \text{for } b \in B \}$$
And the translation of set $A$ by point $z = (z_1, z_2)$ denoted by $(A)_z$; as $(A)_z = \{C / C = a + z, \text{for } a \in A \}$, the four fundamental morphological operations are as follows:
(a) The dilatation of $A$ by $B$:
$$A \oplus B = \{Z / (\hat{B})_z \cap A \neq \emptyset \}$$
(b) The erosion of $A$ by $B$:
$$A \ominus B = \{Z / (\hat{B})_z \subseteq A \}$$
(c) The opening of set $A$ by structuring element $B$:
$$A \oslash B = (A \oplus B) \ominus B.$$ 
(d) The closing of set $A$ by structuring element $B$:
$$A \oslash B = (A \ominus B) \oplus B.$$ 

Not that dilatation and erosion on binary images can be viewed as a form of convolution over a Boolean algebra of operations (NOT, AND, R, XOR). Which are defined between pixels of corresponding locations in two images of equal dimensions (I.T.Young and al 1998).
Furthermore, opening and closing are two higher order operations built on dilatation and erosion due to the connection with Boolean operations. The erosion and dilatation can turn black pixels white, and white pixels black when certain conditions are met.
In our case, the structuring elements are disks, and as it is exemplified (see Fig.5) this gives really interesting results in terms of vision process.

Sec .II

3. Defect localization and extraction

3.1: Defect localization

![Diagram of defect localization](image)

**Fig.8:** Area textile defect and space localization in defect textile
The first step is a modified sequentially labeling algorithm and the second step is an algorithm for calculating the coordinates of the extracted defects and their length:

\[(x_1, y_1)\text{ and } (x_2, y_2)\] where the coordinate of pixels board window of defect.

Geometry shape is very important for pattern recognition and image analysis. And the defect area is one of the most important and most common use feature parameters in the geometry shape. Many areas calculation algorithms have been used in image and pattern recognition, and each of these methods has their own characters and special application field (Weihia and al 2009).

3.2 Examples of differences defects localised and extracted in textile image

The input gray-scale texture images of size 640X480.
Fig. 10: Example of a defect which occupies a squares area window:

(a) Gray scale image of textile.
(b) Windows defect extraction from gray scale image of textile.
(c) Windows defect extraction from binary image of textile.

Fig. 11: Example of Vertical textile defect extraction.

(a) Gray scale image of textile.
(b) Windows defect extraction from gray scale image of textile.
(c) Windows defect extraction from binary image of textile.
Fig. 12: Example of Horizontal textile defect extraction:

(a): Gray scale image of textile.
(b): Windows defect extraction from gray scale image of textile.
(c): Windows defect extraction from binary image of textile.

4. Geometric measures (GEO)

We are interested only to one category of defects, which appears in several ways, according to the form and the surface occupied by that last, longitudinal, horizontal, transverse or other forms, compact, important area or not, these parameters will determine the importance of defect, or not, according to the criteria to be imposed by the operator.

4.1 Feature Extraction
The basic idea in data classification is to recognize the form of defect based on features. In detection of defect we used three features which is derived from the contour of our defect.

\[
\text{area} = \sum_{x=1}^{n} \sum_{y=1}^{m} B(x,y)
\]

\[
\text{Perimeter} = \sum_{x=1}^{n} \sum_{y=1}^{m} P(x,y)
\]

\[
\text{Compactness} = \frac{p^2}{A}
\]

Where \( B(x,y) \) : is image pixel of area,

\( P(x,y) \) : is image pixel of perimeter.
The area is the number of pixels in the contour. The perimeter is lengths of the contour. It is sum of pixel separating region from background. $P$ and $A$ are the figure’s perimeter and area. Compactness is shape of circle. A circle is the most compact figure (i.e., has the smallest compactness value) according to this measure. And finely we can extract others parameters as:

- $D_x, D_y$: area of windows occupied by defect
- $D_x/D_y$: The report $D_x$ and $D_y$
- $Areamax$: Surface of the biggest defect in the window.
- $Areamax/D_xD_y$: report of $Areamax$ and $D_xD_y$

$D_x$ and $D_y$ are the lengths of window occupied by the defect.

- Percentage of the area window occupied by the defect by report the size of original image textile.

Sec. III

5. Typical experimental results
Fig. 13: Some examples of textile defects in homogeneous texture.

All the features are computed and then plotted. From the plots we can identify some characteristics of different defect. Here follows the plots (Tab. 1).

<table>
<thead>
<tr>
<th></th>
<th>$D_\text{x}$</th>
<th>$D_\text{y}$</th>
<th>Area max</th>
<th>Perimeter</th>
<th>$\frac{\text{Area}}{D_\text{x} D_\text{y}}$</th>
<th>$D_\text{x}$ $D_\text{y}$ 640x480</th>
<th>perimeter</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>13.0345</td>
<td>10962</td>
<td>2380</td>
<td>347.5635</td>
<td>21.71%</td>
<td>3.568%</td>
<td>50.75</td>
</tr>
<tr>
<td>D2</td>
<td>2.7879</td>
<td>12144</td>
<td>3651</td>
<td>579.2275</td>
<td>30.66%</td>
<td>3.953%</td>
<td>91.89</td>
</tr>
<tr>
<td>D3</td>
<td>0.6739</td>
<td>5704</td>
<td>3458</td>
<td>271.1787</td>
<td>60.62%</td>
<td>1.8567%</td>
<td>21.26</td>
</tr>
<tr>
<td>D4</td>
<td>0.4404</td>
<td>5232</td>
<td>2538</td>
<td>326.0488</td>
<td>48.50%</td>
<td>1.7031%</td>
<td>41.88</td>
</tr>
<tr>
<td>D5</td>
<td>4.7013</td>
<td>27874</td>
<td>4436</td>
<td>753.8549</td>
<td>15.91%</td>
<td>9.0735%</td>
<td>128.11</td>
</tr>
<tr>
<td>D6</td>
<td>1.6341</td>
<td>10988</td>
<td>6756</td>
<td>387.7473</td>
<td>61.48%</td>
<td>3.5768%</td>
<td>22.25</td>
</tr>
<tr>
<td>D7</td>
<td>1.1548</td>
<td>8148</td>
<td>1639</td>
<td>273.6224</td>
<td>20.11%</td>
<td>2.6523%</td>
<td>45.67</td>
</tr>
<tr>
<td>D8</td>
<td>0.0985</td>
<td>16240</td>
<td>2698</td>
<td>368.0071</td>
<td>16.61%</td>
<td>5.2865%</td>
<td>50.19</td>
</tr>
</tbody>
</table>

Fig. 14: The report (relationship) $D_\text{x}$ and $D_\text{y}$

This relation gives us information about the form of window defect. The separation values of classes are experimentally determined as constant, for example:
If \( \frac{D_x}{D_y} \gg 2 \): the defect is considered vertical.

If \( \frac{D_x}{D_y} \ll \frac{1}{2} \): the defect is considered horizontal.

If \( \frac{1}{2} < \frac{D_x}{D_y} < 2 \): the defect is considered occupying a square window form.

**Fig.15**: Size of windows occupied by defect (Dx.Dy).

\( D_x, D_y \) Give information about size of window occupied by the defect.

**Fig.16**: Area of the defect in textile image.

**Area**: give information about the size of defect in image. For example:

If Area > 1000 the defect is considered as important defect.

If Area<1000 the defect is considered as negligible defect (small defect).
Fig. 17: the Perimeter of defect

Perimeter: give information about the perimeter of defect.

Fig. 18: report of Areamax and $D_x \cdot D_y$

\[
\frac{\text{Areamax}}{D_x \cdot D_y}
\]

give information about area occupied by defect in the window $(D_x \cdot D_y)$.

Fig. 19: Percentage of the area window occupied by the defect by report the size of original image textile.
\frac{D_xD_y}{640 \times 480}

: give information about the importance of window occupied by defect in the total of the image.
If the percentage presents a value greater than a fixed value experimentally determined the defect is considered a great defect.

![Compactness of defect in the image](image.png)

**Fig.20**: compactness of defect in the image

Compactness gives information about the capacity of defect in the window image and repartition of defect.

**Conclusion**

The method proposed for local-defect detection has been shown to be useful for inspecting industrial materials.

This paper is concerned with the problem of detection of the surface defects included on the textile (homogeneous textured surfaces) using image processing and morphology operations. The geometric features used to calculate inform us about the type and the shape of the defect.

By using this technique we can develop the sorting system in the textile industries from depending on the human, which detects the defects manually upon his experience and skills, which varies from one to one, to the automated system depending on the computer vision. We had success in isolating different types of defect in textile images.

When a piece of textile fabric with defects leaves the production line, the locations, the shapes and the sizes of the defects normally can be determined.

We have tested the proposed method on a wide variety of defective fabric samples, obtaining in general, very good results. We have presented several representative cases where different shapes, structures, sizes, etc. of defects and textured background have been correctly segmented.

It has been demonstrated that a combination of morphological and geometric features contribute to better information about the type of the defect in homogenous texture image.

We are aiming to eventually put into effect the classification of defects detected by SVM (support vector machine).
References


[http://dx.doi.org/10.1109/TPAMI.1986.4767851]
Pmid:21869365


[http://dx.doi.org/10.1177/004051750007000902]

[http://dx.doi.org/10.1016/j.imavis.2009.03.007]


[http://dx.doi.org/10.1117/1.1631315]


[http://dx.doi.org/10.1177/004051759506500101]