Defect Detection and Classification on Web Textile Fabric using Multiresolution Decomposition and Neural Networks

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ABSTRACT

In this paper a pilot system for defect detection and classification of web textile fabric in real-time is presented. The general hardware and software platform, developed for solving this problem, is presented while a powerful novel method for defect detection after multiresolution decomposition of the fabric images is proposed. This method gives good results in the detection of low contrast defects under real industrial conditions, where many types of noise is present. An artificial neural network, trained by a back-propagation algorithm, performs the defect classification in categories.

1. INTRODUCTION

Product inspection is an important aspect in modern industry manufacturing. The high cost, low accuracy and very slow performance of human visual inspection has enforced the development of on-line machine vision-based systems capable of executing effective inspection tasks [1]. The problem of web inspection, particularly, is very important and complex and the research in this field is widely open [2].

The implementation of an automated visual inspection system for detection and classification of defects in the textile industry is of crucial importance. A typical web material is 1-3m wide and moves with speeds ranging from 20m/min to 2000m/min and good inspection results can be achieved if the horizontal and vertical resolution is less than 1mm. In the best case, a human can detect not more that the 60% of the present defects and he cannot deal with fabric wider than 2 meters and moving faster than 30m/min. On the other hand, in literature, 235 defects and their possible causes are discussed [3]. The correct detection and classification of them is a big problem that requires complex, time-consuming algorithms.

This paper proposes a real-time pilot system for defect detection and classification of web textile fabric based on standard, low price, hardware components and supported by very fast and effective software solutions. A novel method for the defect detection is implemented. It is based on double thresholding, binary filtering, binary labeling, multi-resolution decomposition via the wavelet transform, and statistical texture feature extraction. This results to a reduced number of data information and high processing speed. The method detects effectively fabric defects in real industrial conditions, where the presence of many types of noise is an inevitable phenomenon. It also has good characteristics in detecting small and low-contrast defects. For defect-classification, an artificial neural network is implemented. For the sake of the system's flexibility and functionality the number of defect classes is reduced in its final industrial implementation.

In this paper Section 2 presents a general view of the experimental system, developed in the laboratory, the method for defect detection is described in Section 3, while the classification strategy and the experimental results are presented in Section 4.

2. AN OVERVIEW OF THE WEB INSPECTION SYSTEM

The experimental visual inspection system (Fig.1) that was developed in the laboratory for fabric fault detection consists of the fabric machine, the lighting system, the hardware that performs image processing, and the software. The fabric machine consists of a five degrees freedom base and of a fabric feed mechanism. The freedom base, on which the camera is mounted, enables varying field of view and inspection in difference axes over the web area.

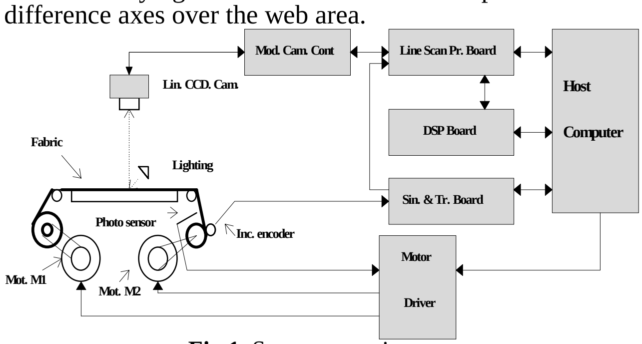


Fig.1. System overview.

The fabric feed mechanism consists of the forward/backward 3HP motors M1 and M2 operatively connected to a rotating mounting where the cloth sample is rolled up. The speed, moment, and direction of the motors are controlled by a frequency-inverter based Motor Driver.

For the implementation of the lighting system, a specular illumination technique is employed. A 2048 element line-scan camera scans the front side of the web. The camera that is used in the specific experimental implementation can operate up to 20MHz-clock rate enabling up to 70000 lines per second line acquisition. The power and timing signals are provided from a modular camera controller.

The line scan processor board that is used for data acquisition supports variable acquisition speed, external or internal trigger for line scanning, several pixel values correction capabilities, adequate maximum and minimum thresholding values for each pixel in the line, two buffer memory for line storage, direct data transfer to target memory and many other capabilities.

A DSP board containing the AT&T 32C processor is used for carrying out the low level image processing in the defect detection process and for implementing the classification algorithms in order to increase the system's performance.

An FPGA based synchronization trigger board and an incremental encoder enables the synchronization between the web speed and the line acquisition rate. A Pentium-based machine is used as a host computer for the high-level image processing and defect classification and for control and coordination of the vision system boards and the feed mechanism. For the programming and control of the board a PC bus is used, while a serial port controls the motor driver.

The software is developed under the Windows95 environment and consists of four parts:

- the system initialization, setup and calibration functions,
- the software interface,
- the line and image processing algorithms and
- the defect detection and classification algorithms.

The system initialization, setup and calibration routines enable the programming of the corresponding board registers the definition of timing signals, look up tables (LUT) and registers, the signal correction and calibration, low level image processing, data flow between boards and host, interrupt initialization etc. The software interface helps the industry operator to create adequate reports and statistics of defects, which are important for the production process, and protects the system from a non-legal use. Algorithms for line and image processing and defect detection in the booth boards and in the host are defined as part of the software. For the classification of the defects an artificial neural network, trained under back-propagation algorithm, is used. In the next sections the proposed methods for defect detection and classification are described in details.

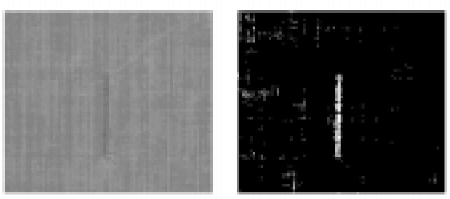
3. THE DEFECT DETECTION METHOD

The processing time is the most restricting factor in the final choice of algorithms for automated visual inspection of textile fabric. Consider a 1m wide textile material moving at a 2m/s speed and containing defects of 1*mm* x 1*mm* size. If a defect must be represented by a minimum of 2 pixels in both directions (i.e. spatial resolution of 0.5mm/pixel) it is necessary, in real-time data acquisition, to realize a data flow of 4MB/s for a line-scan camera of 2048 pixels. For applications that demand full data processing, defect detection and classification must be also considered.

Very fast hardware and software solutions must be implemented to achieve this task. Towards this aim, in the evolution process of inspection, many possible approaches are examined on an adequate experimental setup. The method presented is selected as the optimal solution. Simple and fast thresholding and filtering algorithms set apart the possible defect regions that comprise the input to a classifier that declares the type of defect that was detected.

3.1 Thresholding

The first processing step that is applied to the incoming data from the line camera is implemented by thresholding algorithm. It is a standard double thresholding algorithm with two threshold values T1 and T2. The hardware capabilities of the line-scan board permit to apply the thresholding process to the input line signal in real time, after the signal digitization on the line-scan board. The values T1 and T2 are experimentally determined during the calibration procedure.



a) b)

Fig. 2. a) A gray-level fabric image with one defect b) A binary image, procured after thresholding implementation

Fig. 2 (a) presents the input gray-level image $f(i,j)$ while Fig. 2 (b) presents a binary image $B(i,j)$ ($0 \le i \le M, 0 \le j \le N$) which is produced after applying the thresholding operator χ on the input image $f(i,j)$:

$$B(i,j) = \chi(f(i,j)) = \begin{cases} 0; T_1 \le f(i,j) \le T_2 \\ 1; otherwise \end{cases}.$$

3.2. Image filtering

A filter based on the sum of neighboring convolutions $CONE_\tau$ in a sliding window W of size m**x**n pixels is applied on the thresholded image $B(i,j)$. It is used in order to eliminate the presence of noise in the image. The $CONE_\tau$ function is computed in sequential positions, each time moving the sliding window with step τ.

$$CONE_\tau(p,q) = \sum_m \sum_n B(i,j)[B(i-1,j)B(i,j-1)B(i-1,j-1)]$$

A reduced size binary image $B_{CONE}(p,q)$ ($0 \le p \le M/m, 0 \le q \le N/(n-\tau)$) is produced after thresholding the function $CONE_\tau(p,q)$ with a value of T_{CONE}:

$$B_{CONE}(p,q) = \begin{cases} 1; CONE_\tau(p,q) \ge T_{CONE} \\ 0; otherwise \end{cases}$$

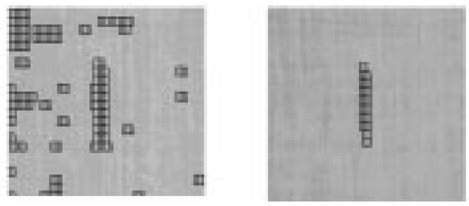
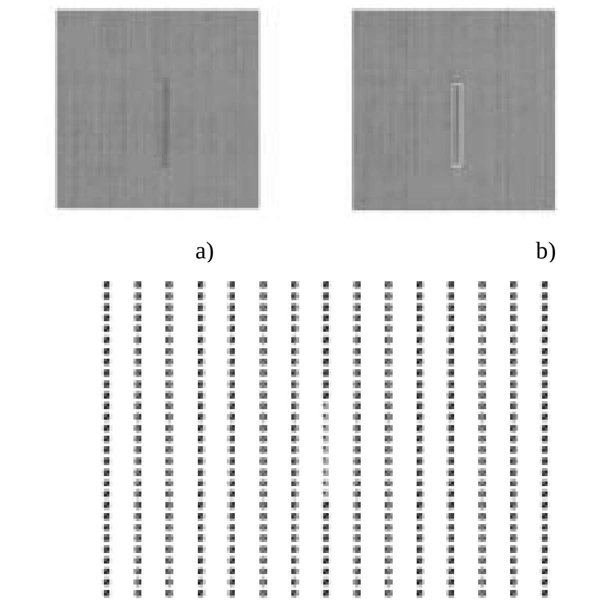


Fig.3. Filtering of input image *B(i, j)*:
a) T_{CONE}= 1 and b) T_{CONE} = 30

Results of the filtered process, for τ=4, are presented in Fig. 3. The labeled rectangles show the regions detected after applying the filtering process

3.3. Defect region extraction and wrinkle rejection

After filtering the binary image $B(i,j)$, the number of picture elements in the resulting image $B_{CONE}(p,q)$ is reduced by a factor that is a function of the window size W and the overlapping constant τ. In the binary image $B_{CONE}(p,q)$ a logical "one" is in the position where the $CONE_\tau(p,q)$ value is over the threshold and a logical "zero" anywhere else. If the threshold has been properly selected, there is a high probability that possible defects appear as is that possible defects are separated objects in the binary image. The goal of this step of the algorithm is to find adequate objects and determine their coordinates. On the other hand, some specific defects such as "wrinkle" errors can be rejected following this procedure considering them as objects with binary parameters, such as area or length, are outside the usual values. The algorithm consists of two steps. The first step is a modified sequentially labeling algorithm [6] and the second step is an algorithm for calculating the coordinates of the extracted defects and their length. Results of the algorithm are presented in Fig.4. The labeled image in Fig.4 (c) is produced from Fig.4. (b).



a) b)

c)

Fig.4. Applied defect extraction algorithm:
a)A gray-level image with vertical error b)The same image with extracted defect region. c) A labeled image

4. CLASSIFICATION OF FABRIC

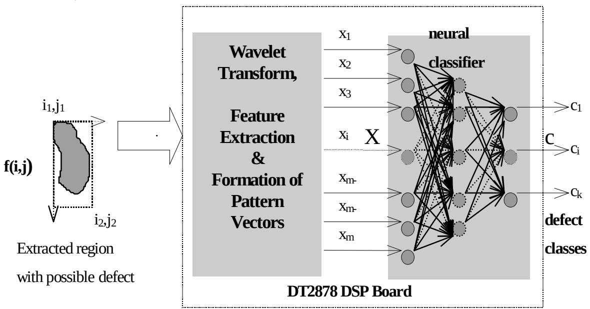


Fig. 5. The feature extraction and classification section

The fabric area that may contain a possible defect $f(x)$ is a rectangular area of variable size with coordinates (i_1,j_1,i_2,j_2). It is located by the inspection system and it is imported to the DSP board, where the classification procedure is performed (Fig. 5). The software installed on the DSP board can be easily divided into three parts:

In the first part, a one-stage wavelet transform [7] is applied to the rectangular area with coordinates (i_1,j_1,i_2,j_2). This way, it is decomposed to four sub-images each one of them containing different parts of the image's frequencies

The pattern vectors are extracted from the sub-images area after implementing specific algorithms from the field of texture analysis (GLDM) [8].

In the third part, the fabric parameters, the pattern vectors, are used as an input to the artificial neural network that classifies the fault detected in the fabric area under check to certain categories.

4.1. The Wavelet Transform

For the wavelet transform [8] a scaling function $\varphi(x)$ is first determined in order to construct the mother wavelet. This wavelet satisfies the equation $\varphi(x)=\sqrt{2}\sum_k h(k)\ (2x-k)$. Using this relation the mother wavelet $\psi(x)$ can be constructed as $\psi(x)=\sqrt{2}\sum_k g(k)\ (2x-k)$, where $g(k)=(-1)^k h(1-k)$.

Using the wavelet transform a signal $f(x)$ is decomposed with a family of real orthogonal bases $\psi_{m,n}(x)$ obtained through the translation and dilation of the mother wavelet $\psi_{m,n}(x)=2^{-m/2}\psi\left(2^{-m}x-n\right)$, where m and n are integers.

The coefficients $h(k)$ and $g(k)$ must satisfy certain conditions in order to produce unique, orthonormal and with a certain degree of regularity basis wavelet functions from the mother wavelet. They also play a crucial role in the discrete wavelet transform because they are sufficient to implement the signal decomposition. A. J-level wavelet decomposition can be written as

$$f(x)=\sum_k\left(c_{J+1,k}\quad_{J+1,k}(x)+\sum_{j=0}^{J}d_{j+1,k}\psi_{j+1,k}(x)\right),$$

where the coefficients $c_{j+1,n}$ and $d_{j+1,n}$ at scale j+1 are related to the coefficients $c_{j,n}$ at scale j via $c_{j+1,n}=\sum_k c_{j,k}h(k-2n)$ and $d_{j+1,n}=\sum_k c_{j,k}g(k-2n)$, where $0\leq j\leq J$ and the coefficients $c_{0,n}$ are given.

Using a similar approach a recursive function synthesis algorithm can be derived based on the wavelet coefficients $d_{j,n}$, $1\leq j\leq J$ and $c_{J,n}$,

$$c_{j,k}=\sum_n c_{j+1,k}h(k-2n)+\sum_n d_{j+1,k}g(k-2n).$$

In this specific application the 16-tap Daubechies wavelet is used.

In order to decompose an image $f(x,y)$ a scaling function $\varphi^1(x,y)$ is introduced such that $\varphi^1(x,y)=\varphi(x)\varphi(y)$ and the three two-dimensional wavelets are defined as $\psi^2(x,y)=\varphi(x)\psi(y)$, $\psi^3(x,y)=\psi(x)\varphi(y)$, $\psi^4(x,y)=\psi(x)\psi(y)$. In terms of the two-dimensional wavelets, at each stage, an image $f(x,y)$ is decomposed into four quarter-size images

$$f^1(m,n)=\left\langle f(x,j),\varphi^1(x-2m,y-2n)\right\rangle,$$

$$f^2(m,n)=\left\langle f(x,j),\psi^2(x-2m,y-2n)\right\rangle,$$

$$f^3(m,n)=\left\langle f(x,j),\psi^3(x-2m,y-2n)\right\rangle,$$

$$f^4(m,n)=\left\langle f(x,j),\psi^4(x-2m,y-2n)\right\rangle.$$

This decomposition provides sub-images corresponding to different resolution levels and orientations.

4.2. The forming of the pattern vectors.

One-stage wavelet decomposition is applied on the original image $f(i,j)$ producing four quarter-size images $f^k(i,j)$, where $1\leq k\leq 4$. From each produced sub-image $f^k(i,j)$ a pattern vector $X_k=\{x_{k1},x_{k2},\ldots,x_{km}\}$ of statistical texture features is formed [4]. If Λ is the operator for statistical texture features extraction based on the Gray Level Difference Method GLDM [7, 8] then $X_k = \Lambda(f^k(i,j))$. The coordinates $x_{k1}, x_{k2}, \ldots, x_{km}$ of the vector X_k can be some of the following texture features:

Contrast: $CON = \sum_{i=0}^{Ng-1} i^2 p(i,\delta)$,

Angular Second Moment: $ASM = \sum_{i=0}^{Ng-1} [p(i,\delta)]^2$,

Mean value: $MEAN = \sum_{i=0}^{Ng-1} i p(i,\delta)$,

where $p(i,\delta)$ is the estimated probability function $p(i,\delta) = \frac{1}{A} \sum_{m=i}^{m=i_2} \sum_{n=j_1}^{n=j_2} (g_\delta(m,n) = i)$, associated with the possible values $\delta = (\Delta m, \Delta n)$ where A is a normalization factor which is associated with δ, and $g_\delta(m,n) = \left| f(m, n - f(m + \Delta m, n + \Delta n)) \right|$.

In the experiments performed in this paper the values $\delta = (0,1)$ and $\delta = (1,0)$ are used. For these defects the features *CON*, *ASM*, *MEAN* as well as the rectangular area that contains the defect region are computed in the four sub-images that are produced with the wavelet transform.

4.3. The Artificial Neural Network

The above features are computed and, together with the dimension of fabric area are capable of classifying the errors in the eight classes c_i $(1 \le i \le 8)$ that are presented in Table 1. The network is trained off-line prior the fabric detection procedure, using the mentioned experimental platform. Several areas with and without errors are scanned from the moving fabric and the appropriate parameters are extracted after performing the wavelet transform and by using the *GLDM* method. These parameters, together with the size of the scanned fabric area, consist the input to the neural network. They are divided into eight classes (Table 1) depending on the type of fault they contained

Error Number	Error Type
1	No Error
2	Black Vertical Error
3	White Vertical Error
4	Wrinkle
5	Black Horizontal Error
6	White Horizontal Error
7	Black Spot
8	White Spot

Table 1. Classes of fabric defects

The training is performed in a Pentium 133 MHz PC in less than 2 minutes. Fifty samples from each one of the eight categories are used. The adaptive gradient learning rule, using back-propagated gradient information for guiding an iterative line search algorithm, is used in the network's learning procedure. The data are treated as noisy. A comprehensive data transformation, variable selection and network search is performed. The performance of the network model is evaluated by using the average classification rate, i.e. the average of the class dependent fractions of correct classifications over all fault categories. A small neural network with 5 hidden units is created, relative entropy equal to 0, 214 and accuracy (20%) equal to 0, 49.

5. RESULTS AND DISCUSSION

The proposed approach to defect detection was tested on the experimental platform. The results are summarized in Table 2.

Parameter	Value
Number of defects	8
Classification accuracy with present of noise	85%
Classification accuracy without noise	94%
Max. inspection speed	120m/min
Width of testing fabric	1m
Space inspection resolution	$1mm^2$

Table 2. Results obtained using experimental platform

The results obtained in testing procedures indicate that a reliable automatic visual inspection system for moving web textiles can be created. The accuracy of the classification cannot be 100% at the required speed if simple, commercial hardware components are used. On the other hand, the number of defects must be reduced to the reasonable number; otherwise a complex and slow expert system for classification of defects must be incorporated in the final system. In this case the major problems are hardware support and economical justification.

6. CONCLUSIONS

The problem of replacing the off-line destructive inspection of textile fabrics by an automated visual system is a very difficult and still not fully solved problem. It is not easy to create the necessary image analysis and pattern recognition methods to quickly and accurately locate, identify, and determine the classes of the defects in the fabric. In this paper a real-time pilot system for defect detection and classification has been proposed and demonstrated. The results obtained using the proposed methods indicate that a reliable visual inspection system for industrial requirements can be created. The use of the wavelet transform as a mean for decomposing the original image to sub-images of different spatial frequencies improves the classification results.

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