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Wavelet Analysis to Real-Time Fabric Defects Detection in Weaving Processes

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Abstract

This paper introduces a vision-based on-line fabric inspection methodology of woven textile fabrics. Current procedure for determination of fabric defects in the textile industry is performed by human in the off-line stage. The advantage of the on-line inspection system is not only defect detection and identification, but also quality improvement by a feedback control loop to adjust set-points. The proposed inspection system consists of hardware and software components. The hardware components consist of CCD array cameras, a frame grabber and appropriate illumination. The software routines capitalize upon vertical and horizontal scanning algorithms characteristic of a particular defect. The signal to noise ratio (SNR) calculation based on the results of the wavelet transform is performed to measure any defects. The defect declaration is carried out employing SNR and scanning methods. Test results from different types of defect and different style of fabric demonstrate the effectiveness of the proposed inspection system.

Key words : Defects detection, fabric inspection, wavelet transform, computer vision, process control

I. Introduction

The textile industry, as with any industry today, is very concerned with quality. It is desirable to produce the highest quality goods to meet customer demands and to reduce the costs associated with off-quality in the shortest amount of time [1], [2]. Currently, much of the fabric inspection is done manually after a significant amount of fabric is produced, removed from the weaving machine, batched into large rolls (1000-2000 yards or more) and then sent to an inspection frame. Only about 70% of the defects are being detected in the off-line inspection even with the most highly trained inspectors. Off-quality sections in the rolls must be rerolled to remove them.

An automated defect detection and identification system enhances the product quality. It also provides a robust method to detect weaving defects. Higher production speeds make the timely detection of fabric defects more important than ever. Newer weaving technologies tend to include larger roll sizes and this translates into greater potential for off-quality production before inspection. Computer vision systems do not suffer from some of the limitations of humans while offering the potential for robust defect detection with few false alarms.

In this paper we introduces a computer vision based automatic inspection system that effectively used to detect and identify faults on various kinds of fabrics. The four major textile defects and defects of the different styles are illustrated in Fig. 1 (a) and (b), respectively. Automatic inspection of textile fabrics can be achieved by employing feature analysis algorithms. The feature extraction and identification problem is in fact a problem of classifying features into different categories [3]. It may be viewed as a mapping from the feature space to the decision space. Product characterization is an important application area of these algorithms.

This paper is organized as follows. In Section II, the preprocessing is presented. Wavelet transforms is introduced in Section III. Defect detection process based upon signal-to-noise ratio is presented in Section IV. Experimental results to illustrate the robustness of the proposed approach are shown in Section V. Finally, some conclusions are drawn.

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II. Preprocessing

The proposed inspection system architecture consists of preprocessing, feature extraction and decision support system as shown in Fig. 2.

2.1 Vertical and Horizontal Scan

The preprocessing should actually work together the feature extraction or at least with feature extractor's objective in its own mind. So, the objective of this procedure is to reduce the search space in order to ease the operation of the feature extraction and enhance the real signal to improve the quality of the feature extraction. Since time requirement is critical in the on-line inspection system, reduction of search space appears to be of the first priority in this application.

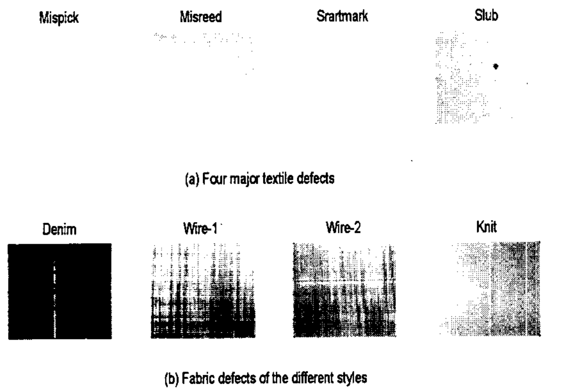

Fig. 1. (a) Four major textile defects (b) Fabric defects of the different styles.

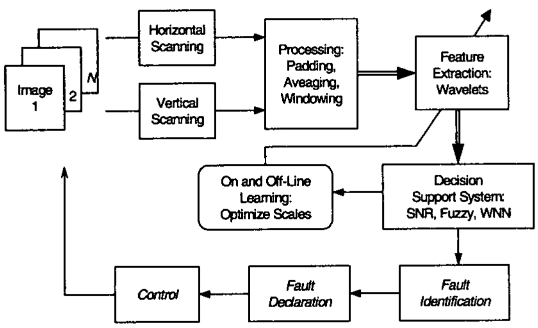

Fig. 2. The inspection system architecture.

A projection method is proposed in consideration of uniqueness of fabric defects. It is not difficult to perceive that defects on clothes are sitting most of time either horizontally or vertically. As a matter fact, this is determined by the way in which fabrics are made. Since only line type of information is more important for fabrics, there is no need to tackle time-consuming 2-D identification unless defect details re required to be identified to almost the extreme degree. Thus, we have applied projecting the 2-D image horizontally and vertically into two 1-D signals. Vertical projection is called horizontal scan and produces horizontal signals. This projection is illustrated in Fig. 3. By projection, more specifically we mean that we average all pixel values along a specific direction and use this average value (a point) to represent all the pixels (a line), Mathematically, we can express this kind of projection as below:

$$\begin{aligned} &\text{horizontal signal:} \quad P_h(i) = \sum_{j=1}^{n} A(i,j)/n \\ &\text{vertical signal:} \quad P_v(j) = \sum_{i=1}^{m} A(i,j)/m \end{aligned} \tag{1}$$

where A(i, j) is the scanned image matrix and i=1,···, m, j=1,···, n. These 1-D processing approaches will cater to the feature extractor.

2.2 End Artifact

For the convolution (or transform) with the wavelets, we need to pad at the start and finish end of the 1-D signal. We have tried (1) pad a constant value (2) pad an average value (3) pad a mirrored part of signal (4) pad a repeated part of the signal. We propose to pad a rotated part of signal. An example of the rotational padding is shown in Fig. 3. The benefits of this method are:

- use a part of signal not a man-made one
- create no high frequency area at the ends
- amplify the defect very close to the ends
- align the center of the wavelet with the start of the signal and then slide.

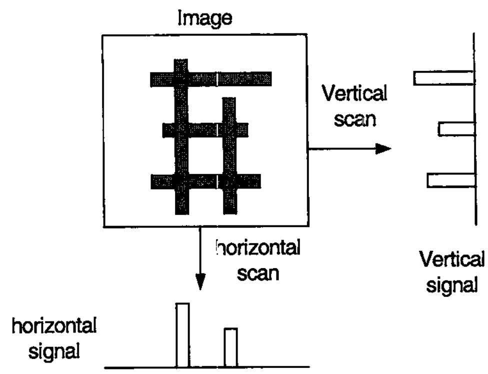

Fig. 3. Projection of 2-D image into two 1-D signals.

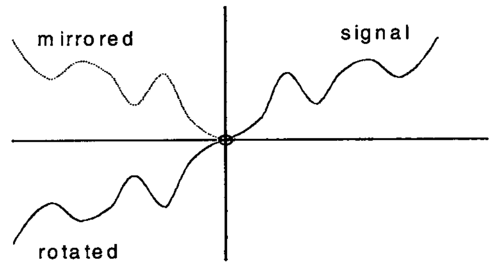

Fig. 4. The rotated and mirrored parts of signal.

III. Feature Extraction

Automatic inspection of textile fabrics can be achieved by employing feature analysis algorithms. The feature extraction and identification problem is in fact a problem of classifying features into different categories. It may be viewed as a mapping from the feature space to the decision space.

The overall block diagram of the proposed method is shown in Fig. 5. The algorithm consists of the wavelet analysis technique, optimization of the wavelets' coefficients, and signal-to noise ration (SNR). These components for feature extraction, detection and identification are discussed in the following sections.

3.1 Wavelet Analysis

The wavelet transform (WT) has been widely described in [4], [5] and consists of the convolution product of a function with an analyzing wavelet. The input signal x(t) is in the form

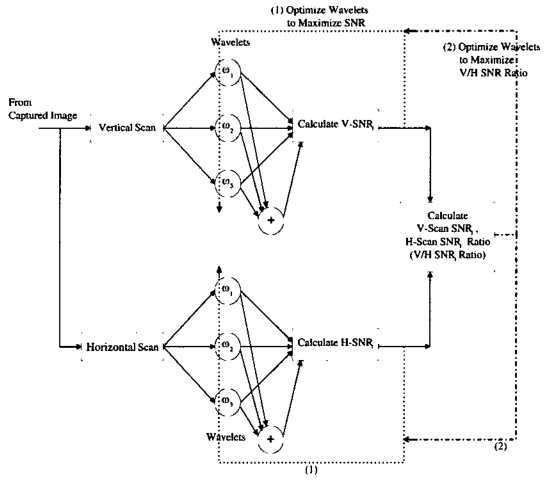

Fig. 5. Feature extraction and optimization using wavelet coefficients.

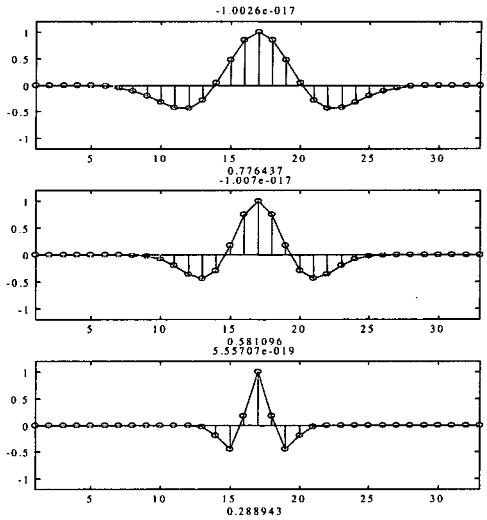

Fig. 6. The optimized wavelets.

of a stream of 1-D data. This data undergoes preprocessing in order to reduce its noise content and increase its usability.

The WT, with different wavelet functions, to extract features from the signal as shown in Fig. 5. The WT provides an alternative to the classical Short Time Fourier Transform (STFT) and the Gabor Transform [6] for non-stationary signal analysis. The basic difference is that, in contrast to STFT which uses a single analysis window, the WT employs short windows at high frequencies and a long window at low frequencies [7]. Basis functions, called wavelets, constitute the underlying element of the wavelet analysis. They are obtained from a single prototype wavelet via compression and shifting operations. The prototype is often called the mother wavelet. The notion of scale is introduced as an alternative to the frequency, leading to the so-called time-scale representation.

Let $x(t) \in L2(R)$ be the signal to be analyzed. Let $\alpha, \beta \in R$, where α is a scaling factor and β is a translation in time. A family of signals is chosen, called wavelets, $\{\psi_{\alpha,\beta}\} \in L2(R)$, for different values of α and β, given by

$$\Psi_{\alpha,\beta} \equiv |\alpha|^{-\frac{1}{2}}\psi\left(\frac{t-\beta}{\alpha}\right) \quad \forall \alpha, \beta \in R \qquad (2)$$
$$\int_{-\infty}^{\infty}\psi(t)dt = 0$$

where $\psi(t)$ is called the mother wavelet.

The coefficients of the WT, for some α and β, are defined as the inner product in L2(R) of x(t) and $\psi_{\alpha,\beta}(t)$ as

$$c_{\alpha,\beta} = \langle x, \psi_{\alpha,\beta}\rangle = \int_{-\infty}^{\infty} x(t)\,\psi_{\alpha,\beta}(t)dt \qquad (3)$$

For the discrete case, the wavelet coefficients are obtained as:

$$c_{\alpha,\beta} = \sum_{j=0}^{N} x(j)\,\psi_{\alpha,\beta}(j) \qquad (4)$$

where N is the number of samples for which $\psi_{\alpha,\beta}(j) \neq 0$.

By choosing a wavelet which is the second derivative of a smoothing function, the wavelet coefficients become proportional to the second derivative of the smoothed signal. The Mexican hat transform involves the wavelet:

$$\psi(x;\alpha,\beta) = \left[1-\left(\frac{x-\beta}{\alpha}\right)^2\right]\exp\left[\frac{-(x-\beta)^2}{2\alpha^2}\right] \qquad (5)$$

The transformation applied to the wavelet coefficients at the different scales includes segmentation, generation of windows, and multiresolution recombination using a coarse-to-fine approach. We use three wavelets with different scales in Equation 5. The wavelet coefficients are optimized based on the SNR defined in the next section. As an optimization method, the flexible polyhedron search [8] is employed. The objective function is defined as:

$$J = \text{maximize}\left[\min_i\left(\max_j\left(SNR_j^i\right)\right)\right]$$

where i is the number of sampled images and j is the results of 1-D signals. The optimized three wavelets with scale factors α=0.29, 0.58, and 0.78 are shown in Fig. 6.

3.2 Signal-to-Noise Ratio

The maximum and the average of the waveform can be used to calculate SNR. The SNR is then max(waveform) /average(waveform). This method sometimes give us good results. But in some cases, this method did not work well. The reason is that the average of the waveform includes the signal (or feature). Thus, SNR becomes smaller for large signals.

The new method is proposed to separate the signal from the noise. A window is applied to the waveform to pick up the signal. The SNR is calculate as F(signal)/F(noise) where F is a function that could be Max, Area, or Energy (power).

Energy consideration allows us to use more information in the signal. Hence, the resulting gap between the SNR with signal and SNR with no signal could be relatively greater than that resulted from the first method. This wider SNR gap eases thresholding and thus increases the detectability. The SNR used in this paper is as follows:

$$SNR = \frac{\max(|s_i|)}{\left(\sum_{i=1}^{m}|s_i| - \sum_{i=1}^{n}|p_i|\right)/(m-n)}$$

$$p_j : s_{k-\frac{n-1}{2}} \leq p_j \leq s_{k+\frac{n-1}{2}}$$
$$p_{\max} = \max_i (|s_i|) \quad \text{at } i = k \tag{6}$$

Ⅳ. Experimental Results

The captured images are tested with the optimized three wavelets that help to detect low, medium, and high frequency defects. The images include different defects. Also we test the different styles of fabric. The analyzed results show that defects are detected in the different defect types and styles of fabric. For example, the horizontal defect in Fig. 7 is detected from the vertical scan in the high frequency SNR, 16.56. The vertical defect in Fig. 8 is detected from the horizontal scan in the medium frequency SNR, 7.62. These results show the robustness of the proposed method. The decision support system for identification is performed by these vertical and horizontal SNRs information. As shown in the Table 1, about 99% of the defects that are practically generated are detected by the analysis of sequential captured images (frames).

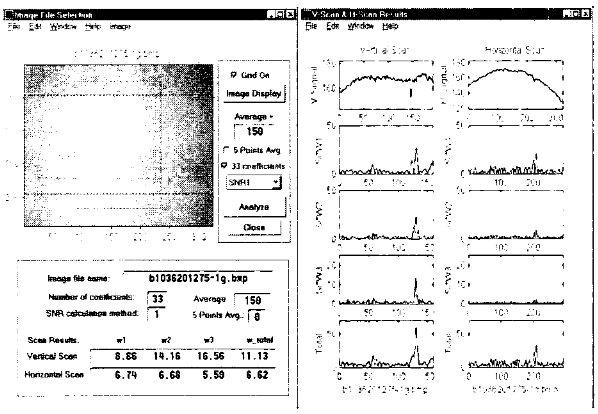

Fig. 7. Analysis results: Broken Pick (Courtesy: Greenwood).

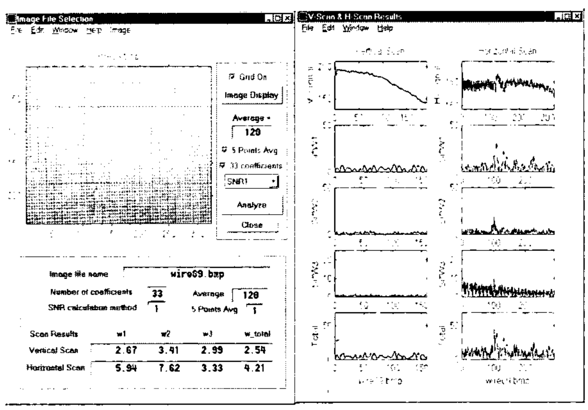

Fig. 8. Analysis results: Warp End (Courtesy: Phifer Wire).

Table 1. Results of test run.

	Defects	% of Frames	Correct	Total	% Detection*
Warp	Endout	93.02%	200	215	99+
	Misreed	42.55%	40	94	99+
	Slack End	100.00%	1	1	99+
	Misdraw	33.33%	4	12	99+
	Double End	90.82%	178	196	99+
Filling	Mispick	53.85%	7	13	99+
	Thin Place	100.00%	5	5	99+
	Thick Place	100.00%	4	4	99+
	Start Mark	100.00%	8	8	99+
	Slubby Filling	80.00%	4	5	99+
	Broken Pick	100.00%	3	3	99+
Area	Oil Spot	100.00%	2	2	99+
	Grease Spot	100.00%	1	1	99+
	Woven-InWaste	100.00%	2	2	99+
	No Defects	89.47%	569	636	99+

** Detection rate using summary logic.*

Ⅴ. Conclusions

This paper introduces a vision-based on-line fabric inspection methodology of woven textile fabrics. Due to the inherent periodicity, variability, and noise of textile fabrics, the traditional frequency techniques are not easy to perform adequate analysis. The proposed inspection system consists of the following modules: capturing images, vertical and horizontal scanning algorithms, wavelet transform to extract features, SNR calculation, and defect declaration routines. The optimization process attempts to choose the best wavelet scales for a given mother wavelet. The test results from different types of defect and different styles of fabric demonstrate the effectiveness of the proposed inspection system.

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