REAL-TIME FABRIC DEFECT DETECTION AND CONTROL IN WEAVING PROCESSES

Project No. G94-2

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Abstract
Project No. G94-2 titled "Real-time Fabric Defect Detection & Control In Weaving Processes" was initiated on March 1, 1994. This brief progress report covers the period from August 15, 1994 to July 15, 1995 and details the major accomplishments during this reporting period. This collaborative research between Georgia Tech and N.C. State addresses the monitoring requirements for performance assessment of a weaving machine under on-line real-time conditions and control of the machine parameters to minimize fabric defects. Novel ideas for fault detection and identification of woven textile structures are introduced and implemented. A survey of major textile defects has been conducted as well as the associated tangible and intangible costs identified. Fractal scanning, a new technique, is developed to scan the digitized image of textile fabrics. A fuzzified wavelet transform algorithm with adaptive noise rejection and on-line learning is used to extract features and a knowledge based inference engine is called upon to declare the defect categories. Off-line learning is introduced to maximize the detectability and identifiability measures. The viability of this technique is shown by test results of major textile fabric defects.

1. Introduction
The textile industry, as with any industry today, is very concerned with quality. It is desirable to produce the highest quality goods in the shortest amount of time possible. Fabric faults, or defects, are responsible for nearly 85% of the defects found by the garment industry. Manufacturers recover only 45 to 65 % of their profits from seconds or off-quality goods. It is imperative, therefore, to detect, to identify, and to prevent these defects from reoccurring. Currently, much of the fabric inspection is done manually, and even with the most highly trained inspectors, only about 70% of the defects arc being detected There is a growing realization and need for an automated woven fabric inspection system in the textile industry.

An automated defect detection and identification system enhances the product quality and results in improved productivity to meet both customer demands and to reduce the costs associated with off-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 also tend to include larger roll sizes and this translates into greater potential for off-quality production before inspection. Many segments of the industry are working towards just-in-time delivery and a poor quality production run can be disastrous. Presently, the inspection is done manually after a significant amount of fabric is produced, removed from the weaving machine, batched into large rolls (1000-2000 yds or more) and then sent to an inspection frame. An optimal solution would be to automatically inspect fabric as it is being produced and to alert maintenance personnel when the machine needs attention to prevent production of defects or to change process parameters automatically to improve product quality. Reducing the number of defects produced by timely maintenance or control would result in obvious savings. Also if inspection is accomplished on the machine. the need for 100% manual inspection is eliminated. Costs to inspect fabric manually range from 1.0 to 1.5 cents/yard. The cost to inspect the annual production of a machine would be $1250 to $1900. Other tangible and intangible benefits could be factored into the savings equation. Computer vision systems do not suffer from some of the limitations of humans (such as exhaustion) while offering the potential for robust defect detection with few false alarms.

A Computer vision based automatic inspection system has been effectively used to detect and identify faults on various kinds of fabrics. Various image analysis techniques, such as Sobel edge operator and Fourier analysis, have been carefully evaluated. Based upon the limitations of these approaches, a new methodology using Fractal analysis and wavelets has been used to detect and identify the defects. A laboratory prototype has been made and implemented successfully. The hardware and software setup that has been developed would significantly improve the weaving process by integrating the on-line inspection and feedback control into the process. It employs specialized scanning techniques, localized time frequency analysis and vision to detect and distinguish defects. With industry cooperation, the most frequent and costly defects have been identified. Integrating existing hardware with new technologies such as fractal scanning and fuzzy wavelet analysis so that the system can detect, identify and localize the origin of the fault, has also been achieved.

2. Project 0 bjectives

Development and testing of an on-line real-time monitoring system for defect detection and identification of textile fabrics

Goals Achieved:

- A new fabric defect categorization and prioritization method has been designed and implemented to meet the manufacturers' needs while accommodating the automated inspection and control goals.
- Based on an industry survey Fabric Defects were Categorized.
- Designed, installed and demonstrated the applicability and effectiveness of the hardware prototype.
- A powerful pre-processing tool (Fractal **Scanning)** for scanning the textile images has been developed.
- A methodology to extract defect features from various fabrics, using Multiresolution wavclet transform techniques have been developed.
- Fuzzy inferencing techniques have been implemented in conjunction with wavelet transforms to enhance the decision making capabilities of the algorithms.
- Off-Line and On-Line learning algorithms have been developed to generate the knowledge base for the expert system and to provide real time unsupervised adaptive capabilities to make the system more robust.
- A computer demonstration of a sequence of algorithms from the pre-processing steps through the final classification and control goals.
- A user friendly software has been developed for analyzing various kinds of fabrics
- A full laboratory prototype has been built for demonstration of the utility of the combined hardware/software capabilities as a proof-of-concept.

Goals Remaining:

- Further refinements of the detection and identification algorithms.
- A laboratory demonstration of the modified prototype installed on a loom at GT or NCSU and performing under "realistic" conditions.
- A series of reports, demonstrations and presentations to highlight the findings of the research effort.

3. Industry Research

In order to identify the most detrimental defects in testile fabrics, an industry survey was conducted to identify the most frequently occurring defects and the most costly defects as far as points were concerned. Data from five leading fabric manufacturers was collected for their typical defects and the number of points lost by each. A wide variety of fabrics were considered and were predominantly woven on projectile or air jet looms. The study included twills and plain weaves consisting of 100% cotton or of a cotton / polyester blend with a range of 36 to 60 picks per inch, and weights from 4.4 to 12.6 ounces per square yard. Polyester fabrics of 1.6 ounces per square yard and 14 picks per inch to 5.0 ounces per square yard and 32 picks per inch were also considered. Fabric widths were roughly 70 inches and yarns were produced with either ring or open-end spinning Survey results are displayed graphically in Figure 1, for the most frequent defects. Broken picks, harness drops, and start marks top the list of the most frequently occurring defects. Broken ends, broken picks, waste and coarse picks were the most costly defects, as they were assigned the largest number of points. Thus broken picks are both frequent and costly.

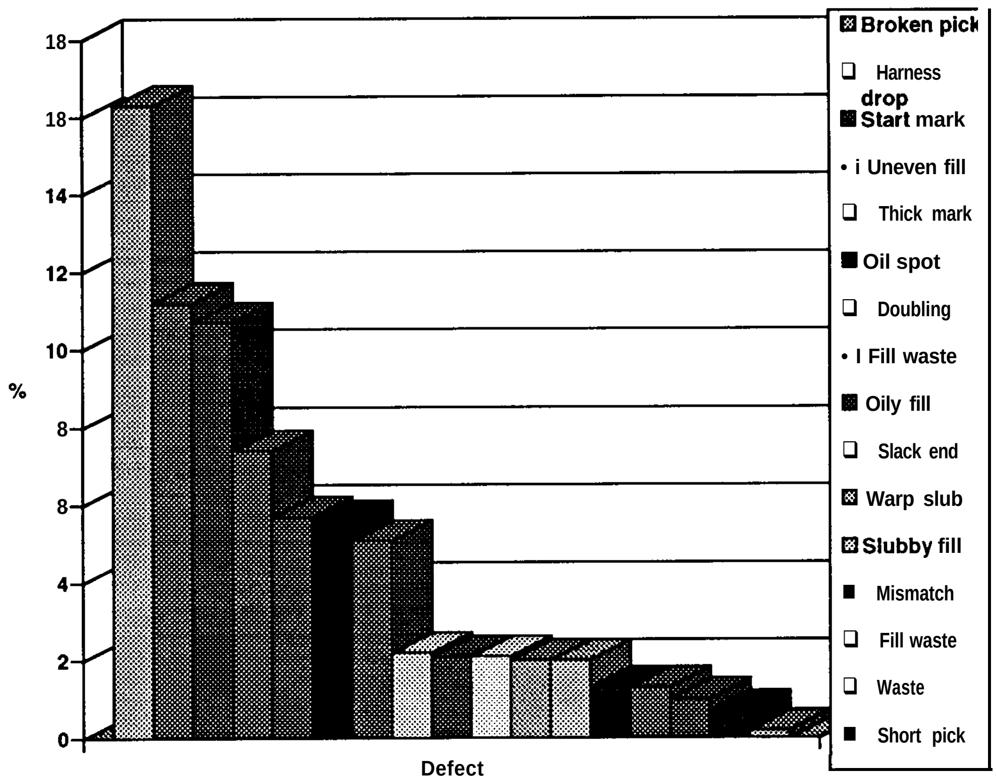

Figure 1: Most common defects.

A wide variety of defects are represented; many defects are a direct cause of machine malfunction while others are from faulty yarns. The most costly(most penalty points) defects for the air jet and projectile looms were also studied. For the air jet looms, the defects are predominantly broken picks and slubs. The projectile looms produce seconds via broken ends, start marks, lint balls. and coarse picks. Both types of looms suffer from machine faults as well as yarn faults that result in weaving defects.

4. Technical Methodology

The basic component of the approach is a combination of wavelet transform techniques and fuzzy inferencing methods. The resulting arrangement is called Fuzzy Wavelet Analysis (FWA) and entails attributes of a truly "intelligent" paradigm. The algorithms provide the ability to analyze image or target signatures in space/frequency localized manner while accommodating uncertainty. The FWA, as an intelligent paradigm, provides on-line adaptability and robust pattern classification through learning. The general architecture of the FWA scheme is shown in
Figure 2.

The data from the 2-D textile images is converted to 1-D data stream by using fractal scanning and a primary classification of point line or area is made at this stage. Fault features are extracted from this data using a wavelet transform. defect and its type is made. These features are then fuzzified using a fuzzification algorithm that incorporates dynamic noise rejection. The fault features are fed to a fuzzy inferencing mechanism which compares them with the templates stored in the rulebase. Based on this inferencing, a declaration about the defect is made. The procedure can be applied, in principle, to only 1-D data streams. However, it is just as applicable to 2-D images with a specialized scanning technique known as fractal scanning. This scanning tool converts the 2-D image into a 1-D stream, but unlike conventional scanning mechanisms, it retains the neighborhood relationship of the 2-D data. The main components of the fault detection and identification algorithms are as follows:

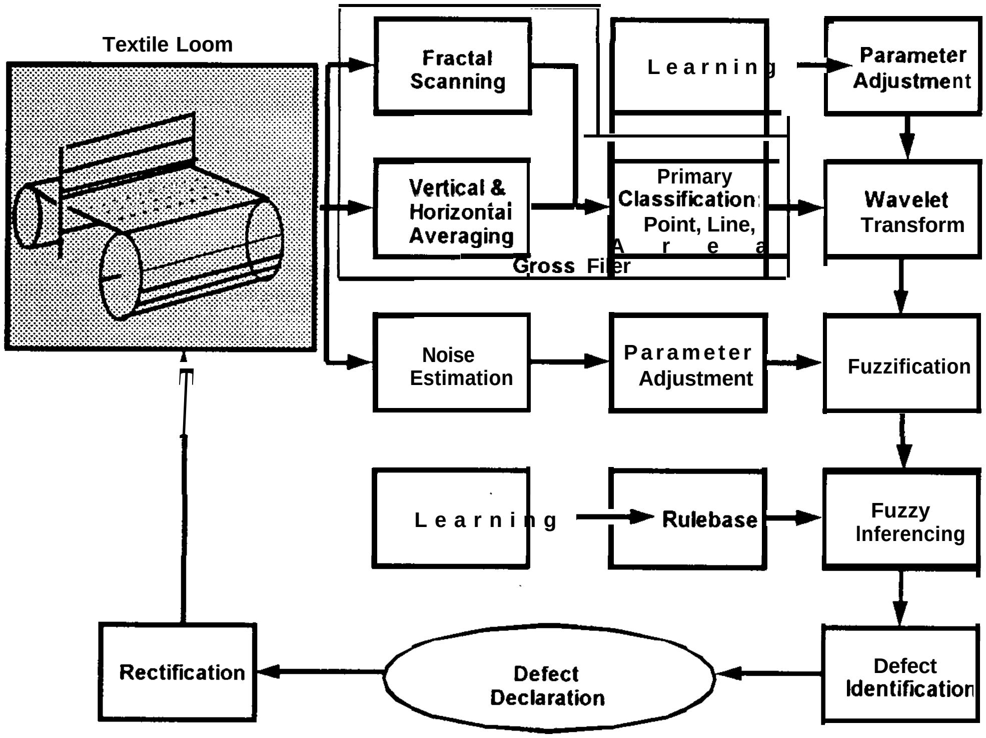

Figure 2: General architecture of FWA.

5. Pre-processing Tools

Pre-processing of raw images may entail filtering, normalization, averaging, etc. One particular pre-processing tool of interest in the analysis of fabric defects is transformation of 2-D image data into a 1-D data stream. Many conventional scanning routines, such as raster scanning, etc., do not preserve the neighborhood relationship of the 2-D data. To overcome this fundamental difficulty, a fractal scanning technique is employed because of the inherent scaling and nesting properties of fractals. Figure depicts a two-level fractal. The following attributes of the fractal scan render it ideal for the application at hand

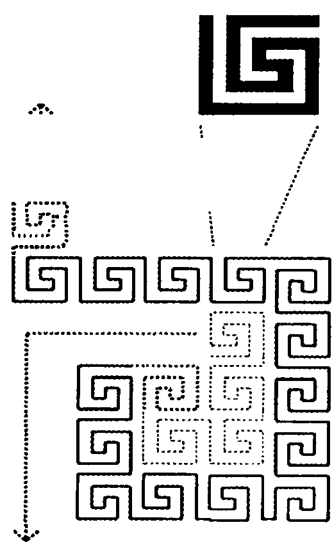

Figure 3 : Typical fractal in nested arrangement.

1. Nested recursively in a self similarity manner
2. Moves in all directions of interest within the lowest image dimension
3. Scaleable to the required resolution via the fractional dimension
4. Reduction in data
5. Considerable reduction in calculations
6. Availability of data in 1-D instead of 2-D format

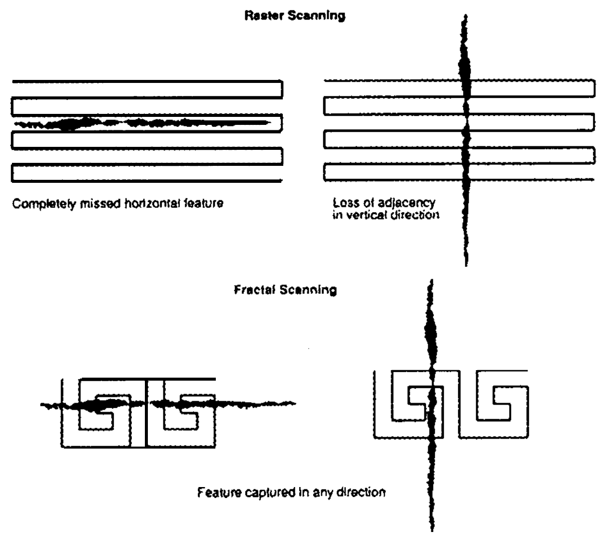

Figure 4 : Comparison of fractal scanning with raster scanning.

The ability of the fractal scan to capture image features of the smallest dimension of interest derives from the self-similarity nesting property of fractals. Each fractal is composed of self-similar fractals of smaller size, and so on. The recursion continues until the size of the fractal is comparable to the size of the smallest anticipated feature. The final fractal is one continuous line whose length depends upon the dimension of the fractal. As seen in Figure 4, when comparing with fractal scanning, the raster scanning suffers from loss of adjacency and possibility of missing a defect while the fractal scanning does not. In addition, the fractal scanning requires analysis of approximately 30% of the image to detect defects

6 The Wavelet Analysis

Texture Characterization and defect detection can be greatly improved by using multiresolution approaches. Multiresolution Analysis (MRA) decomposes the texture across several scales. By examining the texture at different resolutions, features which do not exist over several scales can be discarded as being insignificant. Features that are prominent over all/several scales can be used to obtain a description of the texture. Furthermore, since a defect edge is significantly different in strength and orientation from the surrounding testure edges a multiscale approach to locating the defect ridge leads to a better defect detection and low false alarm rates. Wavelet functions form an orthonormal basis that can be recursively used to generate a multiresolution analysis of a signal.

The wavelet transform is a fast tool to decompose a signal into lower resolutions, The lower resolution signals are accompanied by a detail signal that be used for reconstruction. The detail signal contains the high frequency information of the signal. The usefulness of transforms is that they project a function onto a new set of basis functions. The texture of a woven fabric can be described by periodic functions whereas a defect such as a missing yarn (a mispick) can be described by a high frequency event in one direction (across the weave direction) and a low frequency along the weave direction. The wavelct transform has the property of giving both frequency and spatial information about an image. As detection of sonic faults, such as mispicks, requires information in both frequency and spatial domains, this property of wavclets is very important for the correct detection of such faults.

7. Derivation of the Wavelet Transform

In this section we present the derivation of the Wavelet Transform using the Z-transform. This derivation is simpler and more compact than the conventional method using the Fourier Transform. We show the orthogonality of the detail and smoothing filters, and how the implementation of the wavelet transform is related to quadrature mirror filters. This derivation is then used for fabric defect detection.

Let Z denote the set of integers, and l_2 denote the vector space of measurable, square summable sequences f(n). For f(n) $\in l_2$, *we* denote the z-transform as

$$F(z) = \sum_{k=-\infty}^{\infty} f(k) z^{-k} \tag{1}$$

A useful fact is that the z-transform of the autocorrelation of two sequences $x(n)$ and $y(n)$

$$c(n) = \sum_{k=-\infty}^{\infty} x(k) y(n+k) \tag{2}$$

is given by

$$C(z) = \chi\left(\frac{1}{z}\right) Y(z) \tag{3}$$

where $C(z), \chi(z)$, and Y(z) are the z transforms of the sequences $c(n), x(n)$, and $y(n)$ respectively

Next Consider a digital smoothing filter h(n), with a z transform $H(z)$ such that

$$H(z) H\left(\frac{1}{z}\right) = 1 \tag{4}$$

Using this filter, we can generate an orthonormal basis Φ as follows

$$\Phi(z) = \prod H\left(z^{\frac{1}{2^i}}\right) \tag{5}$$

From the above equation, the following recurrence relationship can be deduced

$$\Phi(z^2) = H(z)@(z) \tag{6}$$

Also using H(z), let us define a new filter G(z)

$$G(z) = \frac{1}{z} H\left(\frac{-1}{z}\right) \tag{7}$$

In signal processing terminology, G(z) and H(z) are known as *quadrature mirror filters.* Let $\Psi(z)$ be the z transform of a sequence defined by

$$\Psi(z^2) = G(z)\Phi(z) \tag{8}$$

We will now show that $\Phi(n)$ and $\Psi(n)$ are orthonormal, and span the space of l_2. By direct substitution, it can be that Equation (7) satisfies the equation

$$H(z) G(1/z) + H(-z) G(-1/z) = 0 \tag{9}$$

Since $\Phi(z)$ satisfies the orthogonality condition, and using Equations (6) and (8), we get

$$H(z) G(1/z) \Phi(z) \Phi(1/z) + H(-z) G(-1/z) \Phi(-z) \Phi(-1/z) = 0 \tag{10}$$

$$2\Phi(z^2)\Psi(1/z^2) = 0 \tag{11}$$

$$\sum_{k=-\infty}^{\infty} \Phi(k/2) \Psi\left(\frac{k+n}{2}\right) = 0 \tag{12}$$

Therefore, the space spanned by $\Phi(k)$ is orthogonal to the vector space spanned by $\Psi(k)$, and the sum of the two subspaces span l_2. Thus, any vector in l_2 can be projected onto an orthonormal basis in term of Φ and Ψ. The inverse transform of Equation (7) gives

$$g(n) = (-1)^{1-n} h(1-n) \tag{13}$$

where h(n) is the smoothing filter.

8. The Fuzzy Wavelet Analysis

The fuzzy wavelet analysis procedure employs Wavelet Transforms (WT) of different wavelet functions to process the output data streams from the scanning operation. The wavelet transforms generate the appropriate coefficients that are nonlinearly combined by a fuzzy inferencing mechanism. Since most features of interest produce signatures in a wide range of frequencies, a number of wavelet coefficients are buffered and subjected to a transformation, such as envelope extraction, in order to obtain the trend of the signature. Next, these coefficients are stacked in a matrix arrangement, referred to as the Information Matrix, whose elements row-wise provide the frequency response of the input signal at a particular instant, while column-wise elements portray the relative frequency over a period of time, or space. A knowledge base is constructed off-line by exploiting any heuristic or experimental evidence available about the morphological and other distribution characteristics of fabric defects. The elements of the knowledge base are fuzzy sets whose membership function is viewed as a similarity measure. These membership functions may be interpreted as severity indices, duration and magnitude, of each image feature. A defect is classified into one of several categories in terms of a production rule base. The latter is cast as a fuzzy expert system.

9. Detectability and Identifiability

Detectability and Identifiability metrics are defined to assess the robustness of the analysis scheme. Detectability measures the extent to which the defect recognition algorithm can detect the presence of a defect. It relates to the smallest defect signature detectable. Identification goes one step further in distinguishing between various defects and assessing their severity once their presence has been established. Identifiability targets questions like the location, type, extent and consequence of the defect. In an intelligent scheme, detectability depends upon a number of system-specific factors.

10. Intelligent Attributes

Intelligent attributes of the proposed imaging analysis architecture are enhanced via off-line and on-line learning methods. Off-line learning is used to tune the wavelct scales through a process of optimization whose objective is to maximize the detectability and identifiability indices. On-line learning is aimed at minimizing the sensitivity of the recognition algorithms to high frequency, random. low frequency, DC bias, and noise effects.

11. Automatic Rulebase Generation

As seen before, the wavclet coefficients act as frequency discriminators on a localized time basis. Different fault features respond differently to various frequencies. Hence, it is important to choose a set of wavelet functions that covers the frequency range of all the anticipated defects. It would also be helpful if the wavelets in this set are tuned to different fault features. This implies that the wavelet coefficients generated by one defect would be quite distinct from coefficients of other defects. thus increasing the identifiability of the system.

The on-line defect detection algorithm has the capability to generate a rulebase for the anticipated defects by a self monitored optimization process. The performance indices. like detectability and identifiability, form the objective function of the optimization routine. The problem is stated as follows:

$$J=\max\{\min(D(k)+\sum I(k)\} \text{ s.t. } D(k)>T_1 \quad \text{and } I(k)>T_2$$

where D(k) and I(k) are the detectability and identifiability for the defect. T_1 and T_2 are the minimum acceptable levels of detectability and identifiability, respectively.

The optimization process is detailed below.

- **Experimental Analysis of Known Faults:** Signal data from the system under observation are collected and stored.
- **Initial Guess of Wavelet Functions:** A finite number n of wavelet functions is initially chosen with arbitrary wavelet scales. The choice of *n* is initially based on heuristics, but if the FWA system fails to perform adequately after optimization, its value can be increased.
- **Formation of the Information Matrix:** The wavelet coefficients are calculated using the selected wavelet function and are stored in the information matrix.
- **Optimizing the Wavelet Scales:** The components of the information matrix are optimized by changing the wavelet scales to maximize the detectability and identifiability.
- **Formation of the Rule-Base:** The results of optimization, obtained from the above mentioned process, constitute the knowledge-base

12. Experimental Results

A laboratory prototype monitoring apparatus, as depicted in Figure 8, has been developed to simulate actual loom conditions. The apparatus can accommodate up to 36 inch wide fabrics and moves fabric 0.1 to 1.5 meters/minute. A CCD camera travels the width of the fabric extracting images to be analyzed at predetermined intervals. The fabric is backlit with fluorescent lighting for diffuse transmitted light. The camera height and the lens focal length can be changed depending on the fabric to be analyzed. In addition, the lighting may be altered from transmitted to reflected or any combination to better illuminate the defects. Utilizing the above to test the validity of the FWA, defects such as mispicks, misreeds, slubs and oil spots are being detected and analyzed. Figure 5 displays these common defects of point, line or area classification. The features from these images are obtained by taking wavelet transforms. The wavelet coefficients show the analysis in three frequencies, high, medium and low. Mispicks and misreeds are typical line defects and are distinct in the high frequency, while slubs, point defects, and oil spots, are area defects, and are more prevalent in the middle and lower frequencies, respectively. These wavelet coefficients, shown in Figure 7, demonstrate the higher frequency characteristics of the misreed defect. For this research, ten of the most common and costly faults were selected as a representative sample of the fabric defects. The ten common

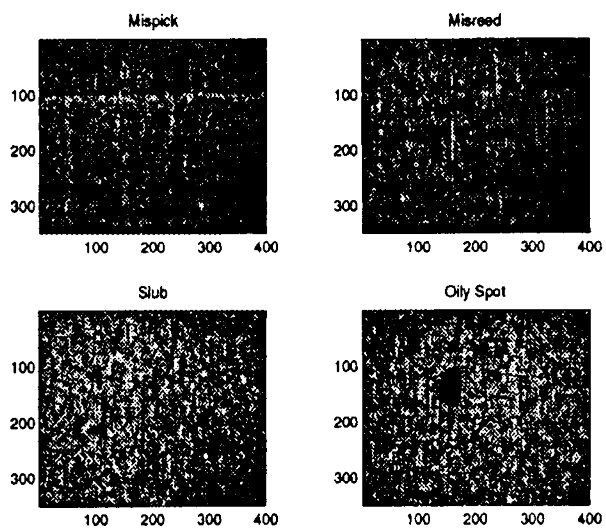

Figure 5: Four major textile defects.

and costly defects are [1] Broken Pick, [2] Coarse End, [3] Knots, [4] Oil, [5] Woven in Waste, [6] Harness Drop. [7] Start Mark, [8] End Out, [9] Slub, and [10] Double Pick. Three distinct weights of fabric light, 1.6 oz/sq. yd., medium 6.6 oz/sq yd., and heavier 12.6 oz/sq. yd. , were used to study the ten defects in each. The light weight fabric consisted of a polyester gauze type of fabric as well as a plain weave polyester fabric. Medium weight fabrics were cotton plain weave, while the heavier weight fabrics were cotton or cotton/polyester blend twill weave.

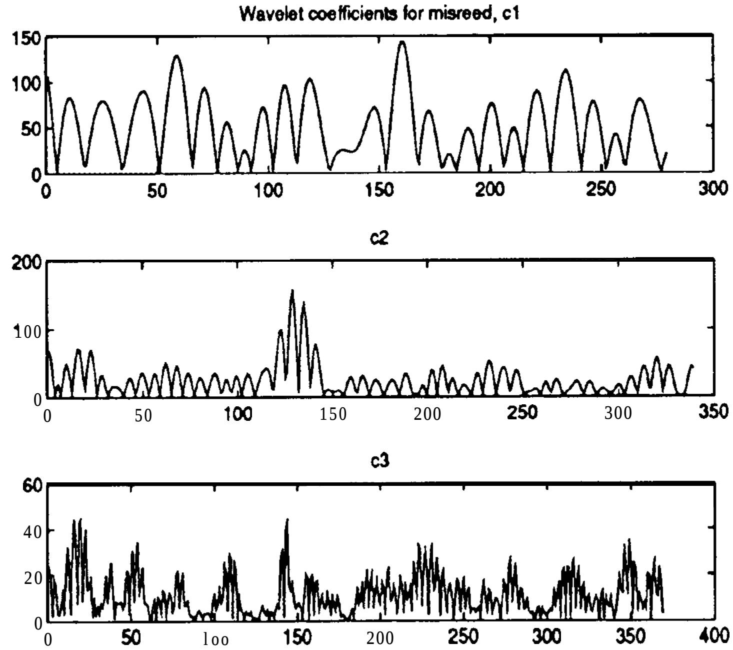

Figure 6 : Wavelet coefficients for misreed

Each weight and type of fabric presented unique challenges. The gauze was a fairly open weave, while the twill had the diagonal line with which to contend. Cotton fabrics also have inherent shade variations. Thus, each weight and type of fabric required a unique set of wavelet scales. These were determined by optimization routines

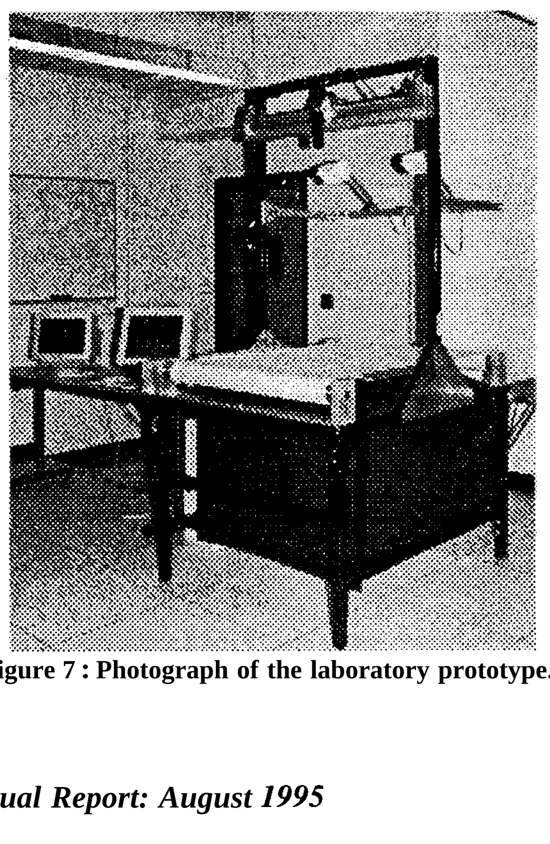

Figure 7 : Photograph of the laboratory prototype.

to produce the best detectability and identifiability. For the light weight fabrics the wavelet scales were 1.5, 0.75, 0.25, for medium weight fabrics 1, 0.75, 0.125, and for the higher weight fabrics 1, 0.5, 0.0325. Different scales produce different levels of detectability and identifiability different defects for a particular fabric

Wavelet Analysis was also carried out on denim fabrics. An image of a denim fabric with a mispick defect was used to validate the theoretical concepts. The response of the wavelet basis to the texture is analyzed. The wavelet basis has a smooth response in the detail signal. The defect edge peaks give a much higher response when a wavelet basis is used. In fact, a simple thresholding of the edge peaks produces a ridge corresponding to the defect in the case of the wavelet basis (Figure 9a). Thus, wavelet basis are useful for texture characterization as well as defect detection. Another defect, "thin-place", caused by a lower density of filling yarns in that region, The response of the wavelet basis to the texture is shown in Figure 9b. The response of this basis to the defect edge is shown in Figure 9c.

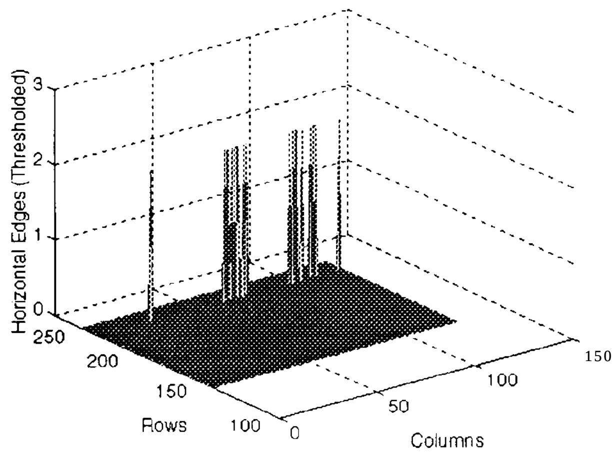

Figure 9a: Denim image with mispick defect

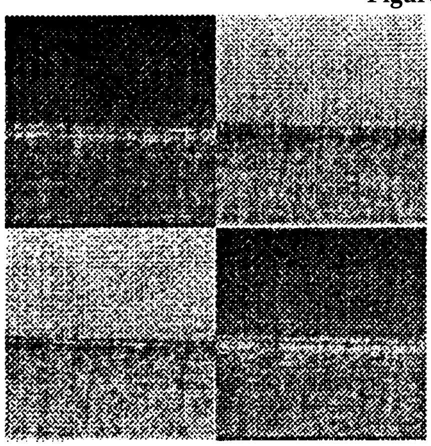

Figure 9b: Wavclet Transform of twil1 image

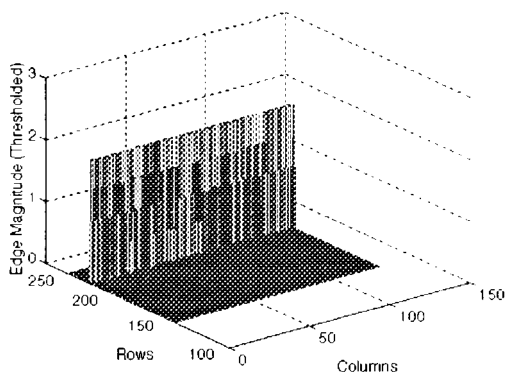

Figure 9c: Twill image with thinplace defect

13. Conclusions

Due to the inherent pcriodicity and variability of textile fabrics, as well as noise, traditional frequency techniques fail to perform adequate analysis. This is overcome by applying localized frequency analysis, or wavelct transforms. Further improvement is also made by neighborhood dcpcndcnt scanning techniques like fraclal scanning. This is a viable and robust algorithm to detect and identify fabric defects. It was demonstrated that on-line fabric detection is the next logical step for fabric inspection, With the above mentioned technology, this also becomes an economically sound option as well, Various types of defects, representing common and costly ones according to industry research, have been detected and analyzed by this new technology.