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 March 1. 1994 to September 15, 1996 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-lint 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 testile 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. arc 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 are 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 .O to 1.5 cents/yard. The cost to inspect the annual production of a machine would be $12.50 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 Objectives

Development and testing of an on-line real-time monitoring system for defect detection and identification of tcstile 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 Catcgorizcd.
- 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 dcvclopcd.
- A methodology to extract defect features from various fabrics. using Multiresolution wavelet 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.
- An alpha test unit has been installed for experimentation and testing.
- A beta test prototype has been built and installed at Southern Phenis. Division of Johnston Industries. Phcnis City, Alabama.

Goals Remaining:

- Beta testing of multiple fabric styles.
- 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 4.1 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 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.

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 I.

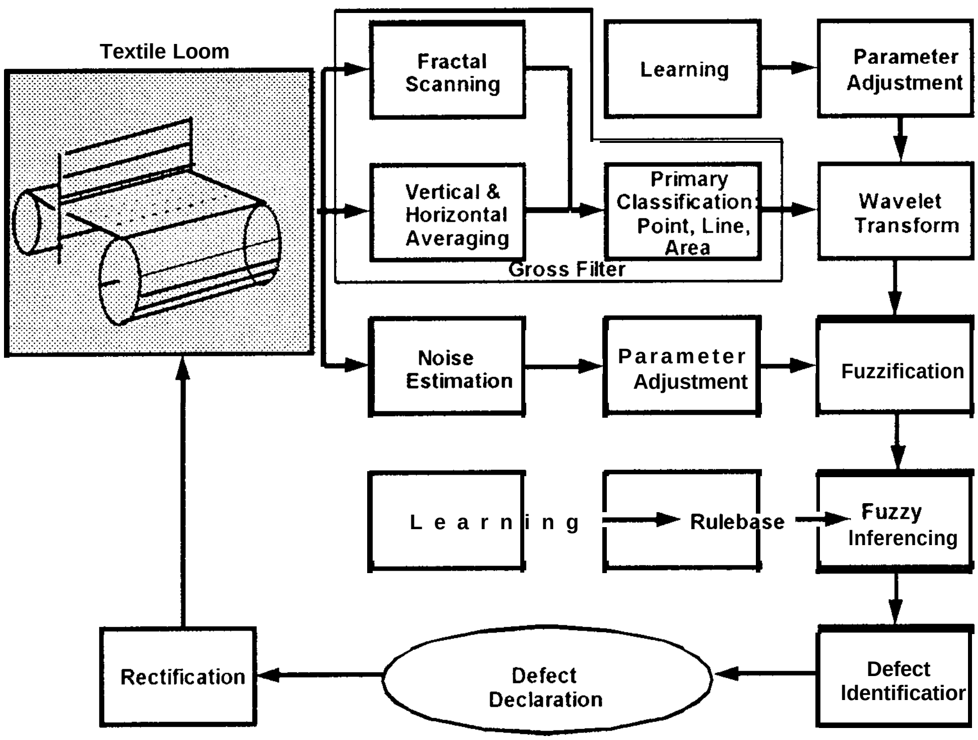

Figure I: General architecture of FWA.

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 onlyl -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 arc as shown in Figure 1.

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 I-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

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

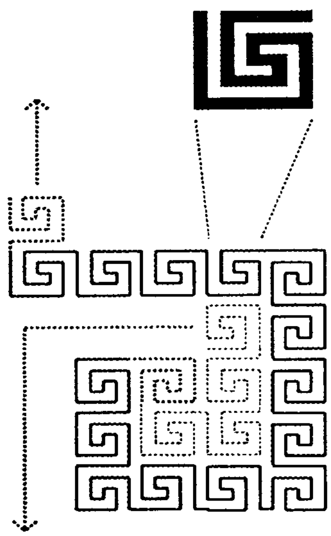

Figure 2 **: Typical fractal in nested arrangement.**

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.

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 wavelet transform has the property of giving both frequency and spatial information about an image. As detection of some faults, such as mispicks, requires information in both frequency and spatial domains, this property of wavelets is very important for the correct detection of such faults.

7. Two Dimensional Adaptive Wavelets

Many textures, such as those of woven fabrics and composites, exhibit a regular repeat pattern. We have developed a new method to characterize such textures using optimal two-dimensional adaptive wavelet basis functions which are used to support multiresolution analysis. Fourier bases, comprised of sines and cosines. lack compact support and are, therefore, not the best choice to represent these textures. Wavelet functions, on the other hand, are finite duration signals and are capable of capturing the texture information from the repeat patterns of the fabrics/composites. By incorporating the texture information through texture constraints, the adaptive wavelet basis is also capable of locating defects within the fabrics and composites. These textures are highly structured and the defects tend to be hidden within the texture. However, the response of the adaptive wavelet basis is significantly different in the defect region enabling easy detection. We derive the wavelet basis directly from the texture data of the image. A two-dimensional, linear. spatially invariant filter is designed for a given texture such that the filter gives a zero response to that texture. On the other hand, disturbances in the texture due to noise and defects produce a non-zero Gltcr output.

Let c denote the coefficients of the linear filter which shall eshibit a zero-response in the presence of texture, and let P be the matrix of texture information. P is formed from a section of the texture and is assumed to represent the texture from a digitized image. P should not be too small in case some texture variations are lost. In general, it is better to choose a larger P since we want all long term effects of the texture to die down in the detail signal. In order to account for the testure, we propose to minimize a quadratic cost function, J, defined by:

$$\min_{c \in \Re^n} J = c^T P^T P c$$

subject to the orthogonality constraints

$$C_m(c) = \sum c_k c_{k-2m} - \delta_{0m} = 0$$

where C,,, is the mth element of the function vector C. Adjoining the constraint to the cost function yields:

$$J = c^T P^T P c + \lambda^T C(c).$$

A necessary condition to minimize the above Equation is that

$$\begin{bmatrix} \frac{\delta J}{\delta c} \\ \frac{\delta J}{\delta \lambda} \end{bmatrix} = 0$$

where λ is the Lagrange multiplier. J represents a quadratic cost function that can be minimized by numerical methods such as Newton-Raphson or Levenberg-Marquardt. Note that the row and column wavelets are separable, and as such we minimize J twice to separately determine the row and column filter coefficients. This procedure effectively yields a two-dimensional wavelet basis.

Woven fabric has two orthogonal yarn directions: a warp direction and a filling direction. Woven fabric has a very periodic structure. In order to construct the texture constraint equations, one must either know {\em a priori) the texture repeat pattern, or be able to estimate it. Currently, we have developed adaptive bases to characterize texture of woven fabric and to inspect the fabric for defects. The motivation for this approach is to develop an on-line loom based fabric inspection system. In most looms, the orientation of the fabric with respect to the loom is fixed. Also. once an optimal imaging distance (in terms of clarity and resolution) is determined, the cameras can also be fixed. In this rather constrained environment, the random events will be due to defects and changes in yarn properties.

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. Nest. these coeflicients 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 estent 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 severily 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 wavelet 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 wavelet coeflicients 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 wavelct 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 arc 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 coeflicients are calculated using the selected wavelct 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

After months of successful alpha testing of a defect detection system in the weaving laboratory at Georgia Tech, Beta testing was begun at a textile plant in Alabama. Lab testing cannot duplicate the environment of a full weave room and many questions lingered about electrical noise, lint and dust accumulation, vibrations, etc. The only way to answer those was to enlist an industry partner to allow us to do the testing. Southern Phenis Textiles in Phenis City, Alabama, Division of Johnston Industries, graciously accepted our proposal to participate.

The system was installed in July 1996 on a Sulzer projectile weaving machine with an Alesco off-loom takeup. The setup, as shown in Figure 3, allows for weaving of fabrics up to 240 cm in width. It is installed on a separate stand placed between the sky roll and the Alesco unit without relocating the existing equipment. The prototype unit is quite large and does somewhat restrict the roll diameter from the usual maximum. but it still allows about 1000 yard rolls with the style being woven. A smaller unit could minimize this interference. The specifications of the current style being tested are: 5.2 Oz/sq yd, 84 inches wide 56 epi. 18s Nec; 34 ppi, 9s Nec

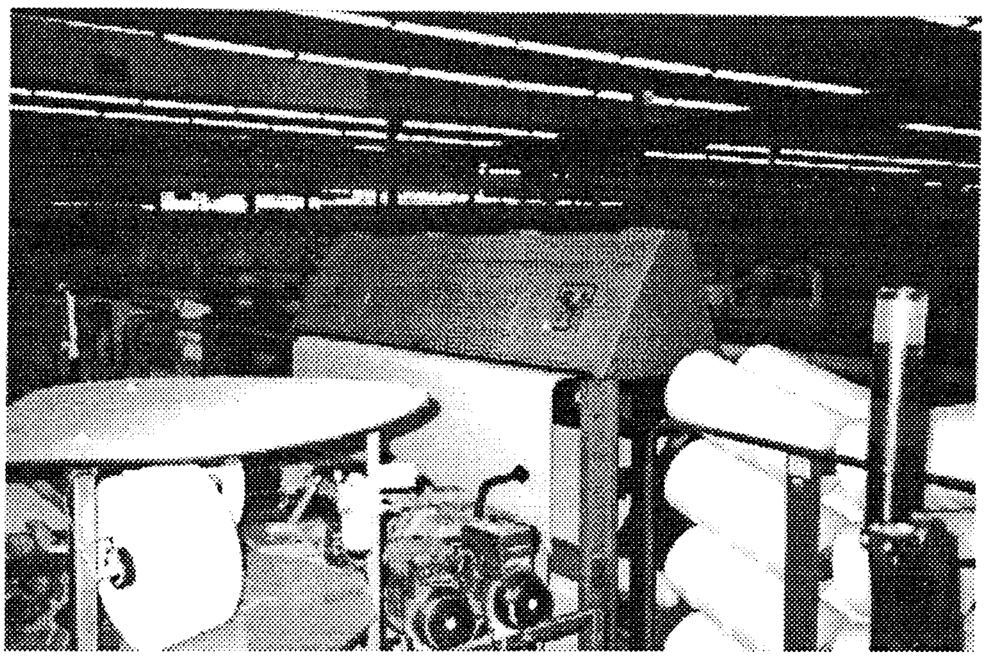

Figure 3 : Beta Testing setup at Southern Phenix.

The test system displays the last sis frames analyzed and indicates the type of defect detected or No defect for each frame. Figure 4 illustrates a typical screen view. In addition, the output at the end of the roll gives a defect mapping of detected defects. The detection and identification is done in real time, but a summary report filters that information to customize the grading to a particular operation and for fabric end-use. This filtering is done based on the severity of the fault and the frequency of small faults.

One of the most difficult tasks has been to take care of the subjectivity factor in grading. When trying to prove any new system, one must compare against the existing system. In this case the judgment is very subjective in borderline defects and an automatic system cannot agree with all graders. It is commonly known that many factors, including the urgency of need for the customer. affect quality decisions. When delivery schedules are tight, it is natural to be more lenient in decisions affecting delivery. In other words. a plant would usually rather deliver goods on time of a little lower quality than normal, than to cause the customer to curtail his production because of slow deliveries. This kind of variability is not easily programmed into an automatic system. The best way to handle that seems to be to objectively quantify the quality by the 4-point System of Grading and let the plant determine the point level for various quality levels.

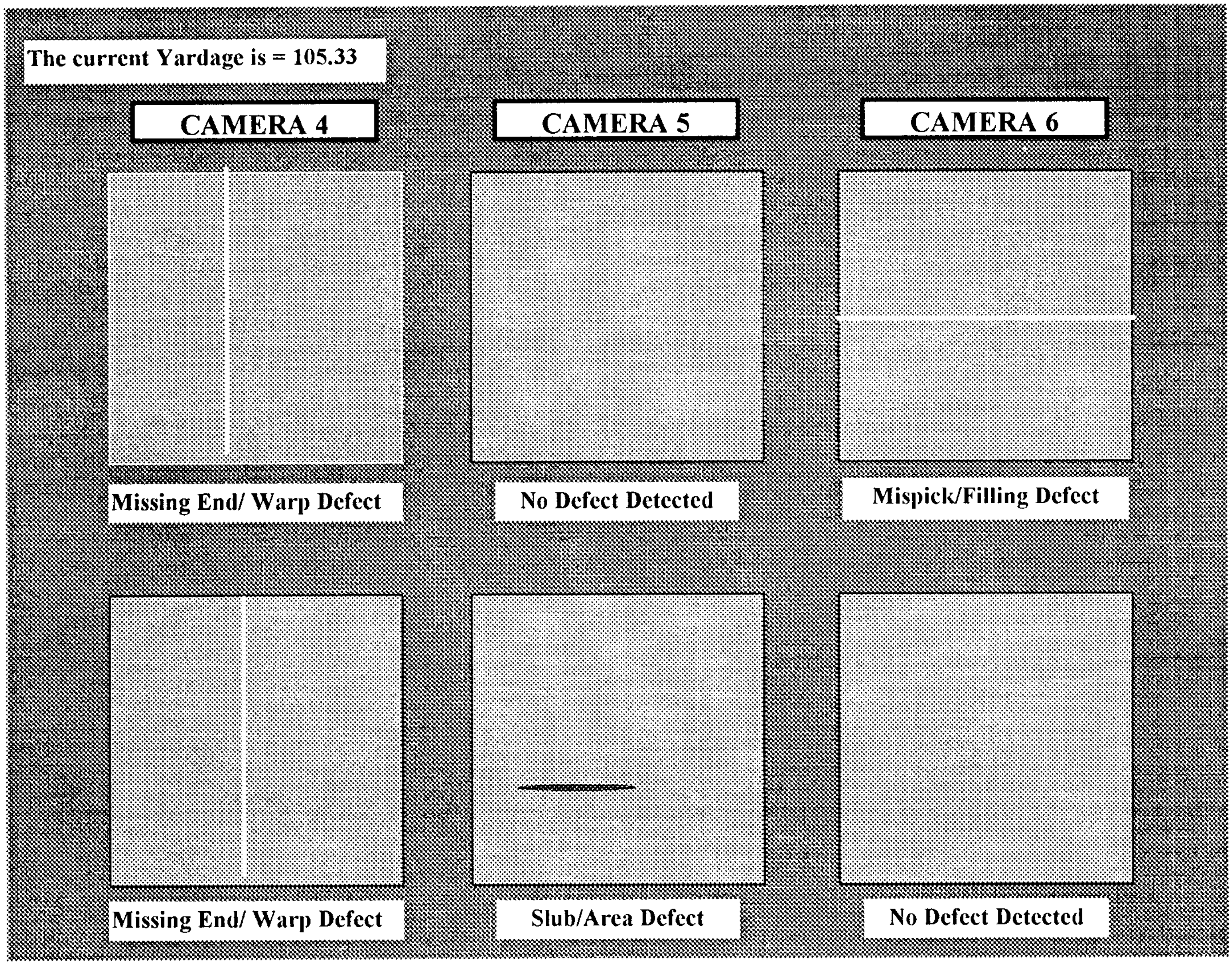

Figure 4 : Typical Beta Test System Display Screen

The system has been operating successfully around the clock for about three months with only a computer monitor failure shortly after installation. Numerous adjustments to the software have been made to make the system more accurate and repeatable.

We were also pleased that during the last quarter, Appalachian Electronic Instruments, Inc. of West Virginia agreed with Georgia Tech to license this technology. Their plans are to develop and market systems to the textile industry. A patent has been applied for.

For texture characterization data image shown below was captured from a Pulnix camera by an Imaging Technology frame grabber in a VxWorks environment. The camera resolution is 750x480. Fast implementations of the wavelet transform are possible when the image size is a power of two. Therefore, samples of size 256x256 are presented here.

Denim fabric was used in these experiments. Typically, the repeat pattern in denim fabric is five yarns. Some samples of the fabrics had defects. Defects in fabrics are mostly caused by missing or broken yarns, tension changes when the loom starts/stops, or misfeeds/misalignments. Typical weaving parameters are: 60 filling yarns/inch, 72" wide looms, and 18" per minute weaving speed. These parameters are well within the range of current imaging hardware, thus making it possible to install inspection systems directly on the loom.

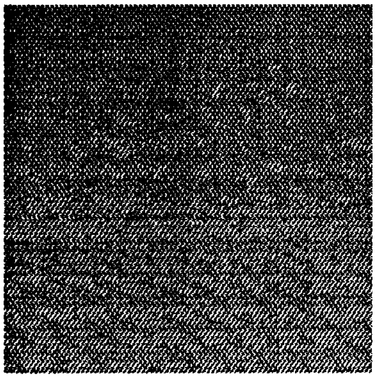

Figure 5: Twill Image with thinplace defect

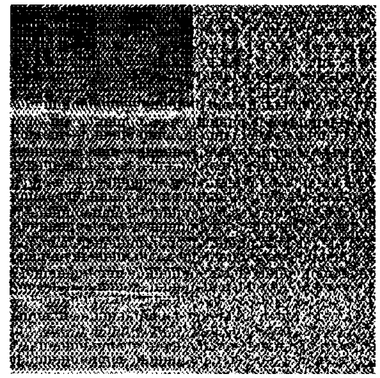

Figure 6: Adaptive wavelet basis response to twill texture

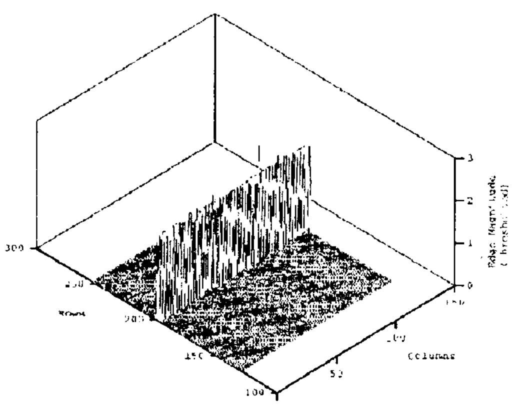

Figure 7: Thinplace defect edge response to adaptive wavelets

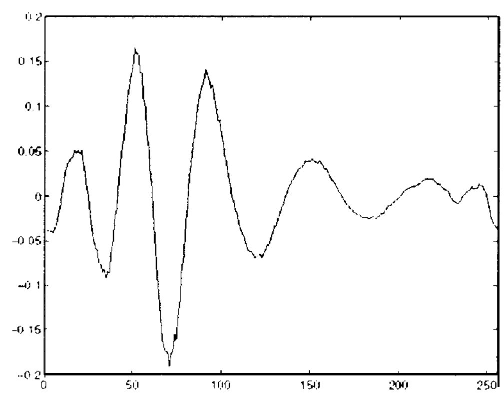

Figure 8: Adaptive wavelet basis e_{10}

Figure 5 shows an example of fabric texture with a defect. In this case, the defect is a "thin-place." caused by a lower density of filling yarns in that region. Figure 6 shows the response of the adaptive wavelet basis to this texture. As before, this basis was generated from this texture. The thresholded response of the defect edge to this basis is shown in Figure 7. Figure 8 shows an example of a wavelet basis generated from real data. For the given images. there are 256 different wavelet bases (which corresponds to the size of the image) for the rows and 256 wavelet bases for the columns. All the wavelet bases look like Figure 8 csccpt that they are dilated and shifted. The roughness of the basis is partly due to noise in the data used to determine the wavelet filter.

Our experiments demonstrate that adaptive wavelet bases are very useful in characterizing texture. They are also useful in locating defects within testure. In sonic cases, the defect edge is overwhelmed by the surrounding texture edges. Standard edge detectors do not perform well under these conditions. The experimental results shown here indicate that adaptive wavelet bases are capable of locating these defects. We are currently developing methods to characterize textures in which there are no obvious repeat patterns. This will enable us to generalize. this method and lead to greater applicability of this analysis technique.

13. Conclusions

Due to the inherent periodicily and variability of testile fabrics, as well as noise, traditional frequency techniques fail to perform adequate analysis. This is overcome by applying localized frequency analysis, or wavelet transforms. Further improvement is also made by neighborhood dependent scanning techniques like fractal scanning. This is a viable and robust algorithm to detect and identify fabric defects. It was demonstrated that on-line fabric detection is the nest 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. A beta lest prototype has been installed at Southern Phenix, in collaboration with Appalachian Electronics.

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