Machine Vision Inspection of Web Textile Fabric

Dr. L. Norton-Wayne, M. Bradshaw and A.J. Jewell,
Department of Electronic and Electrical
Engineering and CIMTEX Centre,
Leicester Polytechnic,
Leicester, England.

Abstract

The paper describes instrumentation which uses machine vision to inspect rolls of web textile fabric in real time. This involves detection of "message" signals arising from defects buried in noise caused by fabric structure. Analogy with the detection of targets in radar and sonar is exploited to provide effective signal processing. The hardware implementation achieves efficiency with economy by using standard devices wherever possible - such as a CCD linescan camera for sensing and a 486 PC as host processor. A special interface card is provided which compensates for deterministic noise and eliminates more than 99% of the redundant data gathered by the camera.

1. Introduction

Textile fabric is often corrupted by defects introduced during manufacture or subsequent processing. It is customary therefore to inspect the fabric visually, as a moving web; this task is boring and hence inefficient and unreliable. A human inspector notices perhaps 60% of defects present, and copes with 2 metre wide fabric moving at about 30 cm/ second. The performance target for the work reported in this paper is to detect at least 95% of significant defects down to 2 square millimetres area, and to cover fabric 2 metres wide moving at 1 metre per second. It is hoped eventually to identify defects by type so that their causes may be ascertained and corrected. Initial identification work aims merely to specify defects as being from one of four groups based on superficial appearance:- along web, across web, no preferred elongation, slubs.

Though several fabric inspection machines are already being offered commercially, these are much too expensive for application to be widespread. The processing methods used remain undisclosed. Hence the present work.

This paper reports on a research programme aimed at producing an automatic web fabric inspection system whose target cost is perhaps an order of magnitude less than for present systems. Cost effectiveness is achieved by following two strategies:-

1) Using as far as possible hardware components (sensors, processor boards and computers) which are already available commercially and are hence inexpensive.

2) Configuring the processing as a sequence of consecutive stages, in which each stage passes only the small fraction of incoming data likely to include defect information and hence important enough to be delivered to the subsequent more

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expensive processing. Processing at each stage can become steadily more elaborate and hence more powerful.

Thus, although the camera must acquire 8 million eight bit pixels each second, only about 100 kilobytes of this (1.25 %) need reach the host computer even in the worst case. Inexpensive, PC-type computers can thus be used as hosts; there is no need for expensive parallel machines.

The research programme aims to produce a configuration (lighting, viewing etc), a processing scheme, and also software algorithms to implement the processing and report the results of the inspection.

2. Previous Work

There have been many attempts to apply machine vision to automate the inspection of moving webs, for a wide range of materials including tinplate [1], cold rolled steel strip [2], sand paper [3], etc in addition to textiles. Detection of defects is generally reasonably easy, provided the defects have sufficient contrast.

Identification of the defects is much more difficult; statistical pattern recognition has often been tried. Promising results have been reported for tinplate; [1] for example quotes 80% correct identification for ten classes using a linear classifier, but tinplate has a smooth and highly reflective surface. Moreover, the results are for simulation only, in which isolated samples of digitised data from real defects were processed off-line. Whether these results would be maintained in on-line operation is hard to judge. Chittineni [3] reports 82% correct identification of defects on sand paper with a linear classifier using only individual scans, which improves to 91% when tentative assignments from successive scans are combined. This is very impressive but the work considered only four classes of defect. Logan and MacLeod [8] reported 80% correct identification for steel strip using linear and quadratic feature space classifiers.

When Hill [3] attempted to apply a linear feature space classifier to identify defects in cold rolled steel strip he was able to achieve only 55% correct in his simulations despite using a least mean square linear classifier which was very carefully designed and thoroughly evaluated. His investigation however considered 37 classes of defect, which were of low contrast compared with the noise arising from surface roughness worsened by laser speckle. Hill claims reasonably that since random classification of defects from 37 equiprobable classes would yield only 2.7% correct, the 55% correctness he obtained is a significant success. However, the end user needed 85%. The inevitable conclusion is that feature space pattern recognition is inappropriate for classifying defects on a moving web unless the number of classes is small, of the order of five. Feature space pattern classifiers are, further, tedious and expensive to design; classification using decision trees seems more promising.

Several publications [9, 10] have appeared which describe signal processing methodologies applicable to fabric inspection, but none provides a comprehensive and detailed technical description of an actual system.

Some [11, 12] have used standard area cameras with associated hardware, but they require many cameras due to their inherent low resolution, making the systems excessively expensive and complicated. They also require either an extremely controlled lighting environment, or a normalisation pre-processing stage to accommodate lighting variations and unevenness.

3. Principle of Operation

The general arrangement is indicated in figure 1. Light returned from the web is sensed using a CCD-linescan electronic camera. The presence of a defect causes the received signal to rise or fall momentarily, and the resultant peaks or troughs are detected by thresholding.

The complete inspection process can be regarded as the sequence of processes shown below:

A) The initial detection stage establishes that a defect of some kind is present.

B) The delineation stage determines the region covered by a defect; it specifies the information which must be used to identify the defect. Delineation also supplies the extent (length, width) and area of a defect.

C) The final stage is identification. This process is the most expensive computationally.

We shall consider detection first. The ideal case is illustrated in figure 2; however, the signals received in practice look like figure 3. Here, two kinds of noise are present which tend to mask the defect indications: low frequency modulations caused mainly by non-uniform illumination, and high frequency modulations. These latter arise partially from variations in responsivity between the photosites in the photodetector array, and partially from the stitch structure of the fabric. Both the illumination variations and the photosite non-uniformity may be compensated following calibration, but the stitch structure noise is effectively a random signal which cannot easily be removed. It is this stitch structure which restricts a pure thresholding operation to detect only defects whose high contrast exceeds the signal excursions due to stitch noise.

To permit low contrast defects to be detected, an analogy is used with the detection of target signals in radar and sonar. Here the problem is to detect a message (of known form) in the presence of noise introduced by clutter, reverberations, and thermal motions. The detection process may be split into three consecutive stages [4], as shown in figure 4. Stage 2, the fundamental decision process implicit in message detection, comprises the thresholding illustrated in figure 5. The incoming signal is analogue but the output is binary; a considerable quantity of data is discarded at this point. Its success can be improved by enhancing the contrast of defects with respect to noise prior to thresholding (stage 1). Stage 1 is most commonly implemented with a matched filter [4], but there are many other possibilities such as the textural filters described in [8]. The form of the message signals generated by defects is very variable, and two dimensional filters may be needed. In certain circumstances, the signal is a vector, and linear transformations may be used to enhance contrast [4].

Stage 3 exploits the property that the false alarm triggers generated by random noise are spaced uniformly and at random over the surface being examined, whereas those due to defects form compact clusters. The map of triggers resulting from stage 2 is therefore scanned and isolated triggers are removed. The trigger clusters which remain are almost invariably due to defects. Many alternative schemes are available for eliminating noise triggers; they differ in efficiency, convenience and in the corruption they cause to genuine defects. Some of these are compared using mathematical analysis in [7], which demonstrates how effective they are quantitatively.

4. Static Experiments

These used a purpose built system, capturing 512*319*8bit images and storing them to disc for subsequent processing. Back lighting was initially used, but due to the open structure of the fabric, an excessive number of noise triggers is generated by the detector. Front lighting was then tried, and although the defect signal amplitude was reduced, its contrast relative to the fabric structure noise was very much improved.

An adaptive threshold (figure 5) is used which compensates for uneven illumination on a pixel by pixel basis, with positive and negative thresholds to detect light and dark defects respectively. Selection of the threshold parameters is automatic, partly due to the wide variations in thresholding requirements of even very similar fabrics, and partly to avoid error prone operator intervention. It involves quantifying the spread of noise in the image, which is Gaussian (Figures 6a and 6b), and calculating the threshold parameters from the equations:-

$$T_{upper} = \mu + k\sigma \qquad \text{and} \qquad T_{lower} = \mu - k\sigma,$$

where k is a constant between 2 and 5. Altering k alters the sensitivity of the detector, as shown in Table 1.

Table 1. Triggers Generated With Varying Detector Sensitivity

k	P(k)	Quantity of triggers predicted	Quantity of triggers counted
5	0.0000006	0.1	0-10
4	0.000064	10	30-50
3	0.0027	441	500-1000
2	0.0454	7415	5000-12000

Selection of the optimum value for the threshold in terms of the noise variance (specified by k) is vital to ensure that subsequent stages of noise trigger elimination and defect delineation are effective. It was found that setting the thresholds 4 standard deviations from the mean produced optimal results.

Figure 6a shows the PDF for a region of fabric which is defect free, figure 6b shows the PDF for a region containing a defect. The defect is manifest to the left of the main distribution. This high contrast is typical of fabric defects.

The delineation process then aims to associate triggers arising from the same defect using tests of local adjacency. Initial results using static boundary spatial distance measures are good, correctly clustering all the triggers arising due to a defect with the local triggers arising from fabric structure distortions around the defect. Triggers due to noise are clustered individually in small, localised groups. Needle lines and horizontal defects, which tend to be broken into many smaller clusters by the detector, have their component parts clustered together correctly (Figure 6c). It is envisaged that better results will be obtained by dynamically modifying the adjacency model according to a predetermined plan, biasing it either horizontally or vertically. Research into the use of an optimal estimation filter to implement this is underway.

As the delineation stage works on edge (transition) information only, it is very fast and highly memory efficient, processing many thousands of clusters per second and using around 40 bytes of memory per active cluster.

Placing a size threshold and trigger density threshold on each cluster provides a test for distinguishing a cluster arising from a defect or from noise. The clusters identified as defects are then subjected to a 2 dimensional linear feature space classification system that assigns a cluster to a group based on information obtained from the delineation stage. The catchment rectangle shape factor and cluster size are used to classify a cluster into one of the following classes:-

Horizontal, Vertical, Local, Slubs. (Slubs are essentially horizontal, but have peculiarities that enable a separate classification to horizontal defects.)

A number of images containing various defects from a range of greige fabrics have been subjected to the processing strategy outlined above. In each case all the defects present were correctly detected, delineated and classified, with no false alarm signals being generated. It was found that fabrics with wider stitch spacing resulted in more triggers arising due to noise being present in the signal, but these were very satisfactorily dealt with by the delineation scheme.

5. Experimental Online System

The system used for initial experiments on a moving web (rather than on isolated samples) is based on a commercially available manual tubular fabric inspection machine. The front side only of the web is viewed by a 2048 element linescan camera with the array axis across the fabric perpendicular to the direction of movement. This gives a resolution of 0.5mm across the 1m web. Lighting (figure 1) is provided by a fluorescent tube operating at 35kHz to avoid flicker. The tube is about 25mm away from the fabric; a simple mask with a slit for the camera field of view shields the lens from direct light. Because only the centre portion of the fabric is illuminated only the centre 0.5m width is inspected although the whole width is scanned. The camera is focussed below the tube and perpendicular to the surface; a dark strip is placed under the fabric to maximise the contrast of hole-like defects (since the greige fabric being inspected is light coloured).

The initial system comprised a Fairchild CAM1500R linescan camera, Sentel CCU-M frame store and linescan interface board installed in a 33Mhz 386 AT compatible computer, and a standard Sheltons Tubular Inspection Machine (TIM). A relay driver was incorporated to stop the machine when a defect was found, for evaluation purposes. The set-up was good enough to perform useful inspection, albeit at a slow speed of 5cm/second. The interface board performed no processing, passing the digitised grey scale data to the host computer.

The final system uses a board designed in-house that performs not only the thresholding operation, but binary filtering and data compression as well. The binary filtering examines two adjacent trigger pixels, and outputs a signal based on the rules shown in Table 2.

Table 2. Binary Filter Operating Rules

Input	Output
00	0
01 or 10	No change
11	1

Because of the good noise reduction properties of this filter, the thresholds can be set closer to the signal mean, 3 standard deviations away as opposed to 4 without the filter, thus detecting lower contrast defects. An advantage of using lower thresholds is that more defect information is produced (Table 3). Also, the filter is not destructive to clusters that arise due to a genuine defect (as these are compact), but only to noise triggers which are spread randomly throughout the image. Figure 7a shows the result of using 3 standard deviations for thresholding an image, and figure 7b shows the result of filtering with the binary filter.

Table 3. Comparison of Results With and Without Binary Filter

Binary filtered?	Threshold	Triggers	Individual clusters	Associated clusters
✗	3 SD	633	143	6
✓	3 SD	394	16	1
✗	4 SD	272	16	1
✓	4 SD	NA	Not applicable	Not applicable

Table 3 shows that the defect is correctly delineated using 4 SD's with no binary filtering, and also when using 3 SD's with binary filtering (figure 7c). However, the latter approach retains 45% more information, 394 pixels as opposed to 272, giving a more accurate delineation and classification.

The signal processing methodology described above was successfully implemented into the online system using the following sequence of operations:

```
do
    grab line of data
    threshold data
    perform binary filtering
    delineate any clusters present
    if cluster complete
        if cluster is due to defect
                classify defect
                output results, or stop machine
while not end of roll
```

As in the static trials, all defects present were detected. A few false alarm clusters were however generated.

6. Hardware

To achieve the objective of low cost, a commercially available line scan processor board was used originally that was specifically designed for high speed adaptive thresholding. This board could not realise our full operational requirement of 2000 lines/second for a number of reasons, and to achieve the target operating speed a special interface card has been constructed. Its functions are as follows:-

[a] To allow the system to accept and synchronise with exposure and readout pulses generated by the camera, and to receive and condition the video pulses received from the camera.

[b] To correct for deterministic noise corruptions in real time. Individual correction must be provided for each pixel.

[c] To perform the thresholding operation fundamental to defect detection.

[d] To examine the triggers generated by operation [c] and reject as many as possible which have arisen from random noise.

[f] To transition encode the trigger signals selected as being most likely to indicate

defects with their locations over to the PC host, along with certain other information, such as end and edge of web.

Operation [a] is made difficult because there is no standard interface for linescan sensors as there is for two dimensional cameras, and so the interface used in the prototype stage is specific to the IPL linescan camera. Each pixel in the camera signal is digitised to 8 bits and then compared with stored upper and lower threshold values specific to that pixel. This combines thresholding and correction for deterministic noise in one operation. Only those pixels whose values lie outside the thresholding band are retained as potential defects. Some of these are noise pixels arising from the fabric structure, but because they are isolated most can be removed by the simple non-linear binary filter explained previously. It is necessary to choose a form for this filter which is both effective and easy to implement in hardware.

The defect data and end-of-line markers transferred to the computer are further reduced by transition encoding; the four possibilities, transition to light defect, transition to dark defect, end of defect and end of camera scan line are distinguished by two data type bits. These bits together with the pixel address of the transition are passed to the FIFO's for writing by DMA transfer to a circular buffer in the computer.

The development system uses an IPL 5000 series 2048 element line scan camera driven by the camera internal clock; the master clock, exposure strobe and combined video signals are passed to the interface. The exposure pulse is extended to cover the dark reference camera pixels and is used to clamp the video signal and to control the timing. In normal operation the camera scans continuously passing only the essential data to the computer buffer via the FIFO's. The data is processed asynchronously but must be removed from the 64kbyte buffer fast enough to avoid buffer overflow; the processing time increases with the number of the defects present at any given time.

At the start of a fabric roll a number of lines of camera data are read and averaged to provide a relatively noise-free reference line of data. Thresholds for each individual pixel are then computed and written to the threshold RAM's to initiate defect detection. The threshold values reflect changes of pixel sensitivity, uneven light transfer through the lens and non-uniformity in the lighting so that the effects of these anomalies are effectively eliminated. During the inspection process new pixel data is periodically read from the camera and used to update the reference line and the thresholds so that slow changes in lighting and temperature drifts are countered.

All data transfers are 8-bit in the prototype interface which appears as four 8-bit I/O ports and an 8-bit DMA channel to the computer; the 16-bit DMA data needs two 8-bit transfers accessing the FIFO's alternately. A hardware line counter, read as two bytes from separate ports, is provided but its main use has been checking that the number of line markers counted is correct. The prototype is of wirewrapped construction and is based on a standard prototyping card on which buffering and initial decoding are already provided; programmable logic is used for many of the decoding, status and control functions. A 16-bit version is now being developed to improve the data transfer rates. This version will use a pcb and will make extensive use of programmable logic both to reduce the chip count and to simplify modification for different camera parameters.

7. Concluding Remarks

The system has recently been shown in the laboratory to detect all significant defects on greige fabric 1 metre wide moving at 1 metre/second. Doubling of the resolution to enable full width (2 metre) fabric to be inspected to the same specification awaits completion of the updated interface card. Further work is however required, to extend system capability to identify defects by type, to cover patterned and multicoloured material, and to examine "difficult" fabrics such as denim which is dense, dark and has unusual defect types such as loose threads.

Stage (1) of the defect signal enhancement sequence has not as yet been utilised. The analogue processing required is more difficult to implement than the purely digital processing which seems to have been adequate so far. Analogue contrast enhancement may well have to be incorporated to cope with more difficult fabrics.

8. Acknowledgements

This work forms part of the CIMTEX project ongoing at Leicester Polytechnic, whose objective is to apply state-of-the-art technology to apparel manufacture. The consent of the directors of CIMTEX to publication of this paper is gratefully acknowledged, as is the co-operation of Alan Shelton Ltd who are aiming to exploit the results of the work.

9. References

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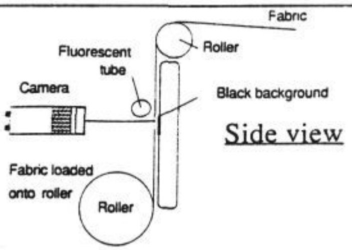

Figure 1. Layout of the Inspection System

Figure 2. Ideal Signal

Figure 3. Actual Signal

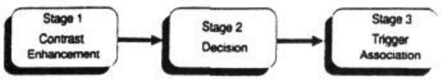

Figure 4. Decision Process

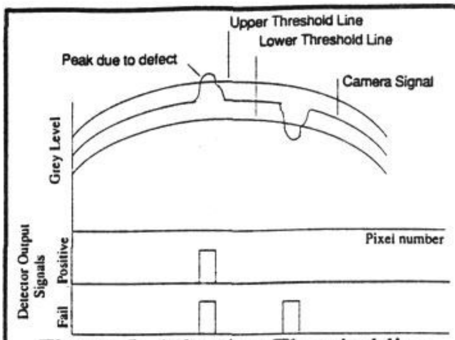

Figure 5. Adaptive Thresholding For Defect Detection

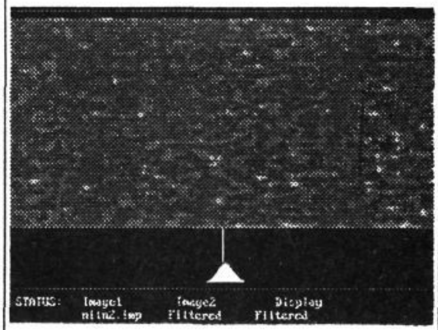

Figure 6a. PDF of whole image.

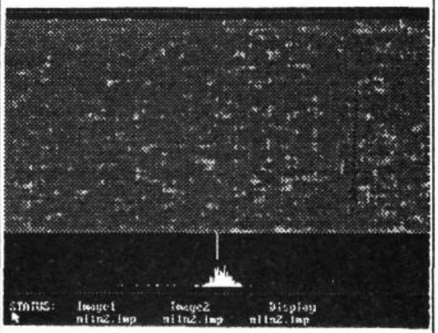

Figure 6b. PDF at the location of a defect.

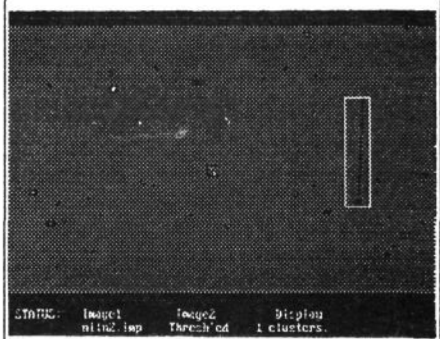

Figure 6c. Noisy binary image successfully delineated.

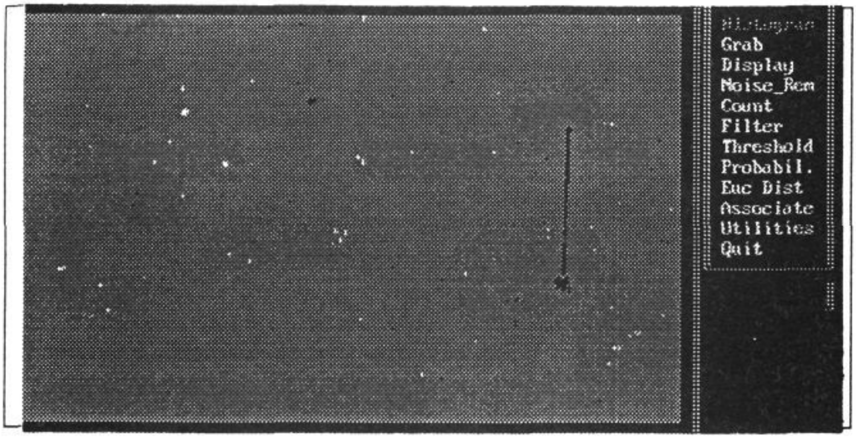

Figure 7(a). Region thresholded at 3SD.

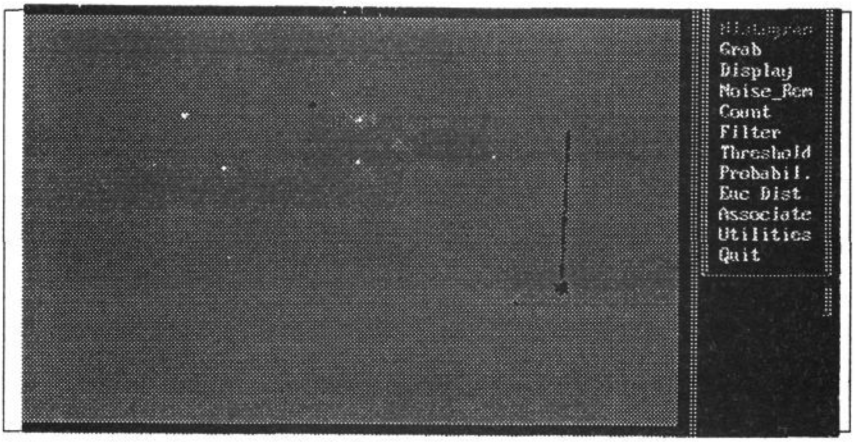

Figure 7(b). 7(a) after binary filtering.

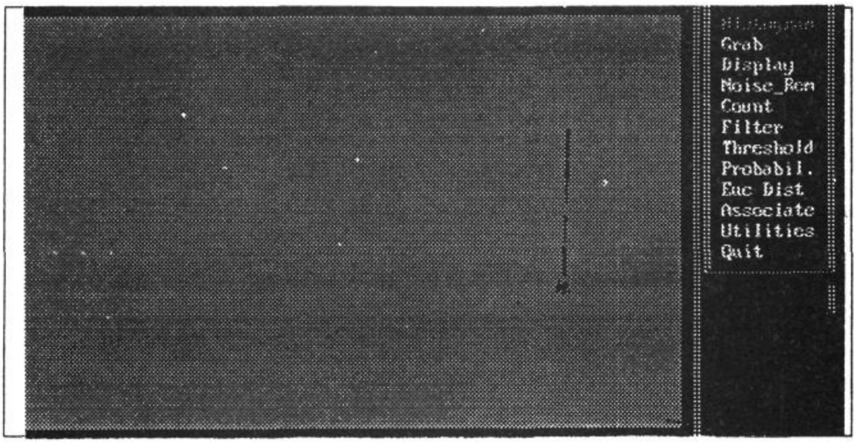

Figure 7(c). Same region thresholded at 4 SD.