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ABSTRACT

This paper discusses signal processing for the detection of defects in automated inspection using machine vision. A generalised methodology is presented applicable to a wide range of tasks. A method is presented for design of a system to achieve quantitative performance requirements in terms of probability of defect detection versus probability of false alarms. Some modifications which can improve performance of the basic scheme are described. Applications of the method are mentioned briefly.

1. INTRODUCTION

The purpose of this paper is to survey some ideas regarding automated detection of surface defects using machine vision. Machine vision involves computer image processing and machine pattern recognition. The use of machine vision to inspect materials produced in the form of a continuous web or strip is increasing rapidly. The range of applications is already very wide, and includes metal strip, wood, textile fabrics and photographic film.
Vision machines can see anything that the human eye can see; being faster than a human operative they are more cost effective. They are also more efficient since they are not subject to boredom and fatigue. Their spread to new installations and materials is determined very much by difficulty in keeping costs low enough to justify the savings produced. Many more lines could be covered if the cost of inspection systems could be reduced significantly.
Although the range of materials examined is very diverse, the signal processing required is in all cases very similar.The fundamental factor limiting performance is the requirement to sense defects against a background of random noise; if the detector is made sensitive enough to respond to defects of low contrast, "false alarm" indications are generated in which a defect is indicated when none is in fact present. The signal processing necessary to maintain adequate probability of defect detection with a low enough false alarm rate may be very complex and hence expensive.

We aim to present here a general methodology for defect detection, which is applicable to a very wide range of materials and thus obviates the need to devise, analyse and evaluate another processing scheme for each new task. This exploits an analogy between detecting defects on rough surfaces and detecting targets in radar and sonar systems. In both cases, the essential problem lies in recognising a message signal that conveys useful information and is wanted, in the presence of unavoidable random noise which tends to hide the message and is unwanted. However, considerable effort has been expended in studying target detection because of its obvious importance in defence and navigation (ref.1).
The methodology will be illustrated by detailed consideration of a specific problem: the inspection of knitted textile fabrics.

2. GENERAL APPROACH

2.1 Overall Concept

The surface is illuminated strongly (possibly from the rear as well as the front for translucent materials), and the intensity of light returned from each point is sensed using either an electronic camera (such as a CCD linescan device) or a laser scanner. The presence of a defect causes the light level to rise or fall locally, depending on the interaction between the light and the surface. If the change in light level exceeds a threshold a binary "trigger" signal is generated indicating the presence of a defect. Both positive and negative going thresholds are normally provided (fig.1). This decision process (block 2 in figure 2) is fundamental in automated defect detection.
If the detector is to sense low contrast defects, the thresholds need to be set close to the mean of the noise. This

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makes the probability of threshold crossing due to "noise only" very high, resulting in an excessive number of false alarms. A composite detection scheme is therefore needed, comprising a sequence of operations additional to the basic threshold detection.

This can be accomplished by adding the two extra stages indicated in fig.2:-

(a) Stage 1 operates on the analogue signal before it is thresholded, to maximise the contrast of the message signals relative to the noise. Filters matched to the expected shape of the message signal may be used, but the shapes of defect signals tend to be very variable and highly unpredictable.

(b) Stage 3 exploits the property that triggers due to noise (i.e. false alarms) are distributed uniformly and at random over the surface, whereas those arising from defects occur locally in clusters. That is, isolated triggers are probably false alarms due to random noise, whereas those forming compact clusters are assumed from a defect since the probability of their occuring naturally due to the noise can be shown to be vanishingly small. This trigger association is implemented using non-linear binary filters, which effectively measure the number of triggers in blocks of pixels, and reject all triggers within a block unless there are more than a certain minimum.

We now consider this processing in more detail.

2.2 Decision taking by thresholding - stage 2

This operation is indispensible, and constitutes the minimum signal processing necessary in a defect detection system.

To analyse this stage, we note that the noise in surface inspection problems may generally be regarded as being Gaussian and white. This is predicted by the central limit theorem and confirmed by experimental measurements. If a laser scanner is used (see ref.2) then speckle noise is often significant leading to a negative exponential pdf, but the combined effects of finite aperture size, surface movement and electronic filtering of the signal then turn this into a distribution which is effectively Gaussian.

Because the Gaussian function cannot be integrated definitely, no exact analytical relationship exists between the threshold setting expressed in standard deviations and the probability that a given pixel crosses the threshold and generates a "false alarm". However, an adequate approximation can be determined from the first term in the series expansion for the integral of the Gaussian function (ref.1):-

$$P = s.(pi)^{1/2}.v_t.\exp(-v_t^2/2s^2)$$

here:- s is the standard deviation of the noise
v_t is the threshold level

Some values computed using this relationship are shown graphically in fig. 3 (which also includes data for a negative exponential distribution) below; NB that v_t is expressed in standard deviations in figure 3.

2.3 Contrast improvement - block 1

The obvious approach here is to use a filter "matched" to the expected waveform for the defect signals. The matched filter maximises the contrast of the message (i.e., the defect) relative to accompanying white noise; it maximises the ratio:-

$$\frac{\text{peak message power}}{\text{mean noise power}}$$

The form of the filter matched to a particular waveform is identical to that waveform, and the output of the filter is the cross-correlation between signal and waveform.

Design of a matched filter requires explicit knowledge of the waveform of the defect; unlike the message signals used in radar and telecommunications, those arising from defects are designed by nature rather than by man, and will vary considerably even within a particular class of defect as well as between defect classes.
The response of a single matched filter to any waveform is easily determined computationally; table 1 below (taken from ref.2) shows the relative match between pairs of possible waveforms. If the various waveforms are equally likely, then it seems best to choose that having greatest average match.

TABLE 1

	Filter shape					Average match
Incoming signal	1	0.782	0.767	0.863	0	0.682
	0.782	1	0.600	0.950	0	0.664
	0.767	0.600	1	0.662	0.120	0.632
	0.863	0.950	0.662	1	0	0.695
	0	0	0.120	0	1	0.224

Surface defect detection schemes often use gradient enhancing filters which differentiate the signal, since line defects in web products are usually aligned either parallel or pendicular to the direction of web motion. This is risky, since the white noise field contains equal energy at all frequencies, and energy at the high frequencies is strongly enhanced on differentiation. It is best to low pass filter before the high pass filtering produced by differentiation, as in the example discussed in section 3.4.

2.4 False alarm rejection by trigger association - block 3.

This involves dividing the surface into regions (of arbitrary shape), and requiring that at least N triggers be generated in each region, or all triggers present in the region will be discarded. N must of course be much less than the total number M of pixels within the region.
The effectivenss of this scheme for selectively eliminating random noise triggers can be appreciated from the following analysis.
The probability P(N,M) that N or more triggers are generated in the region due to noise alone is given by the cumulative binomial distribution:-

$$P(N,M) = \sum_{L=N}^{L=M} M!/L!.(M - L)!.\ p^{L}.(1 - p)^{(M - L)}$$

For typical values, e.g. M=100, N=10, p=0.001, then P(10,100) turns out to be about 10^{-15}, which is vanishingly small. Thus, if fewer than 10 triggers occur within the ensemble of 100 pixels they are rejected, but ten or more are regarded as being due to a defect.
A large number of alternative schemes are possible using this general approach. These differ in ease of hardware implementation, sensitivity to elongation across preferred directions, etc. For comparison purposes, the performance of each scheme is specified by two parameters:-

U, the processing gain, defined as:-

$$U = \frac{\text{probability of a false alarm trigger after filtering}}{\text{probability of a false alarm trigger before filtering}}$$

and W, where:-

W is the number of triggers lost from a genuine defect cluster due to the filter.

The values of U and W for a number of alternative filters are shown below in table 2 (extracted from ref. 3, which describes the filters in detail):-

TABLE 2

Filter	Gain, - $\log_{10}U$	Distortion, W
simple association (N=100, M=10)	15.05	9
near median (N=20, M=10)	22.66	9
adjacency	23.5	9
'add, dump and threshold' (K = 10)	26.62	9 (in filt.dirn) inf. (perp.)

2.5 Design of a system

The statistical properties of the noise in a defect detection problem are generally well known in advance, whereas those of the message signals due to defects can often only be guessed. It is both possible and profitable nevertheless to select processing operations and adjust operating parameters to achieve explicit and quantitative specifications for performance.

The philosophy then adopted in setting the detection threshold depends on the application - is it essential to detect every single defect (in which case the number of false alarms may be excessively large), or will it suffice to miss a few low contrast defects to avoid the waste and inconvenience resulting from too many false alarm indications? Human operatives often see no more than 60% of defects on a surface in rapid motion.

The detection threshold is then selected to give a known probability of false alarm per pixel - denoted p - which is reduced to P = U.p by the trigger association filtering. P is determined by the fraction of good material which may be wasted by false alarms, and U depends on the filter chosen.

A more efficient design can be produced by incorporating properties of the defect signals if these are known. The latest work by the authors on web textile inspection aims to do this. One possible measure of the size of the defect signals relative to the accompanying noise is the defect contrast, C, defined as :-

C = peak message power/ mean noise power.

The mean value of the noise power is simply its variance. Contrast is normally quoted in db, where:-

$$C_{db} = 10 \log_{10} C$$

For cold rolled steel strip, for example (ref.4), the contrast of some important defects may be as low as 2 or 3 dB. Surprisingly, the contrast of defects on textile fabrics is normally significantly greater than this. Unfortunately defect signals vary very much in shape, and alternative measures are probably more useful, as follows. Fig 4 shows the Grey Scale Histogram (GSH) for a certain class of defect (neps) on knitted greige fabric, with the GSH for the accompanying noise plotted on the same axes. The GSH is of course an approximation to the probability density function (pdf) for the distribution. The degree of separation between the two distributions is quantified by various measures of statistical distance, D (ref 5), which take the general form:-

$$D = \frac{\text{separation of means}}{\text{function (variances of two distributions)}}$$

3. MODIFICATIONS AND IMPROVEMENTS

3.1 Two-threshold detector.

A simple but very useful improvement to the basic scheme is shown schematically in fig.5. This exploits the property that some high-contrast defects are so small that they appear only in a single isolated pixel. The solution here is to have two thresholds (fig. 6), i.e. effectively two processing channels working in parallel. Triggers generated when the signal excursion is large enough to exceed the outermost threshold are not subjected to the binary filtering, whereas those resulting from crossings of only the inner threshold are filtered. The outputs of the resulting two parallel channels are logically ORed together to provide the detector output.
A complete theoretical analysis can be undertaken only with explicit knowledge of the statistical properties of the defect signals in addition to that of the noise. It seems logical as a first step to set the operating parameters of both channels to give the same false alarm probability.

3.2 'Excess over thresholds' filter

This is another approach to getting rid of the excessive number of false alarms generated when a sensitive threshold is used to detect low-contrast defects.
As usual, pixels are examined in clusters and a threshold v_t is set for each individual pixel. All pixels below this threshold generate a zero output following thresholding. For pixels exceeding this threshold, however, the excess over the threshold is added to a sum for the cluster, denoted S. Only if this sum exceeds a second threshold, S_t, are the triggers retained; in this case, all triggers in the cluster are retained.
This scheme is found to work well in practice; it is the subject of continuing study and analysis.

3.3 Neural net approach

In this radically different solution appropriate to really difficult materials such as lace (ref.7), a neural net is used to take a final decision. The signal is first thresholded in the usual way. A block of pixels of size M by N (e.g. 5 x 5) is positioned over each trigger, and the UNTHRESHOLDED (i.e. analogue) amplitudes of the pixels are used as inputs to the net., in addition to the pattern of triggers. The net has been trained to distinguish the two classes 'defect present' and 'defect absent'. The ability of the net to extrapolate to cases not included in the sample data used for training is crucial here. Training may take a long time, but once it is complete decisions are taken quickly.
For lace, certain features such as steep gradients in pattern intensity seem to be particularly prone to generating false

alarm triggers. Including the unthresholded (grey scale) pattern of the lace in the neural net inputs as well as the pattern of triggers offers the possibility of improving performance significantly. We are still researching this approach energetically.

3.4 'Focus of attention' detectors

It is often claimed that efficient machine detection of defects is impossible without emulating the actions of the human eye-brain system. In ref.6 D'Haeyer describes another novel approach to automated defect detection which incorporates consideration of the way the human eye-brain system probably accomplishes this task.
The processing is aimed at detecting defects on cold rolled steel strip, and once again uses filters appropriate for (matched to?) the expected shape of the defect. To detect defects appearing as thin horizontal lines, the image is differentiated in the vertical direction with a first order finite difference filter. Since this operation enhances noise due to surface texture, the surface is first low pass filtered to reduce the noise. Adaptive thresholds based on the GSH and cumulative GSH are then used for taking the decision; it seems that thresholds are used which are exceeded by a specified small fraction (typically 0.01%) of pixels. The results shown in the paper quoted are impressive, but the fundamental question of achieving adequate probability of detection at an acceptable false alarm rate for a range of defects which are different physically is not addressed.

4. EXPERIMENTAL COMPLICATION

Practical systems drift; for example, the light output from the fluorescent tubes usually used for illumination may vary by 2 percent for each degree centigrade change in envelope temperature away from the intended optimal value of 40 deg.C. The measured drift for a typical system with fluorescent illumination and CCD linescan viewing is shown in fig.7.
Reference to fig.3 shows that the false alarm probability per pixel varies rapidly with change in light intensity. One solution here is to provide feedback correction via an independent sensor which responds directly to the instantaneous illumination. Our preferred alternative is to allow the system to re-calibrate itself periodically, but sufficiently often to follow any drifts. Whilst the web is being scanned for recalibration it cannot of course be inspected, so any defects on a small fraction of surface will not be noticed. However, the loss in inspection efficiency this causes is acceptably small since most of the surface is defect-free anyway (or the process would be out of control). Further, both the illumination and the sensitivity of the scanning device generally vary significantly across the width of the scan. The 'periodic recalibration' approach enables this spatial variation to be corrected even if it varies also with time.
This correction is implemented by having specific thresholds for each pixel. Early experiments computed a mean value for each pixel, determined the variance over the whole width, and set the thresholds for each pixel at a specified distance (e.g., 3.5 standard deviations) from the mean for that pixel. However, in our equipment the variance of the noise is found experimentally to decrease steadily as one moves away from the axis of the viewing system (see fig.8), and it seems more appropriate to acknowledge this variation of the noise when setting the thresholds.

5. PRACTICAL APPLICATIONS

The approach described in this paper was originated for inspecting cold rolled steel strip (ref.4) which is hard since the contrast between defect signals and background noise is poor. The steel surface is purposely made rough so it will take paint and flow in a press; to work at the rolling linespeed of 25 metres/second it is necessary to use laser scanners which double the noise component through speckle noise arising from laser coherence.
More recently, the investigation has concentrated on the inspection of textile fabrics: from greige knitted material ref.8) which is relatively easy, through to lace (ref.9) which has a complex and intricate pattern and is exceedingly difficult. For knitted textiles, the noise component of the signals arises from the structure of the fabric - if a high resolution (5 pixels/millimetre) is used, then energy at a frequency inversely related to the thread spacing is seen to dominate in the Fourier spectrum of the signal. Practically, a lower resolution of about 2 pixels/millimetre is found to give better performance, and then the stitch component is no longer prominent. The noise is white and Gaussian.

Inspection of a strip 1 metre wide at a resolution of 0.5 mm. at 1 metre/second presents no difficulty with hardware costing only a few thousand pounds; web speed is limited chiefly by lack of light.

6. CONCLUDING COMMENTS

This paper has presented a general and universal scheme for detecting surface defects in the presence of noise, based on published methodology. The scheme can be implemented in available hardware to run on-line and in real time, at modest cost. The methodology enables systems to be designed to have specified performance characteristics provided information is available on the properties of the defect signals and the accompanying noise. The more the information available, the better the design can be.

Getting the methodology to work in practice requires solution of many problems, including the elimination of drifts and spatial variation in the properties of the background noise.

The methodology is based on many years' analysis and study of publications. It is likely unfortunately that much good work on this topic remains unpublished for reasons of commercial confidentiality. It is clearly both beneficial and necessary to extend and hence improve the approach to cope with more challenging materials, and we have indicated the directions our current investigations are taking.

The processing concepts described here could of course be used to design efficient processing for automated inspection using other kinds of sensing than vision - acoustic, x-ray, infra-red and ultra violet, microwave, etc.

7. ACKNOWLEDGEMENTS

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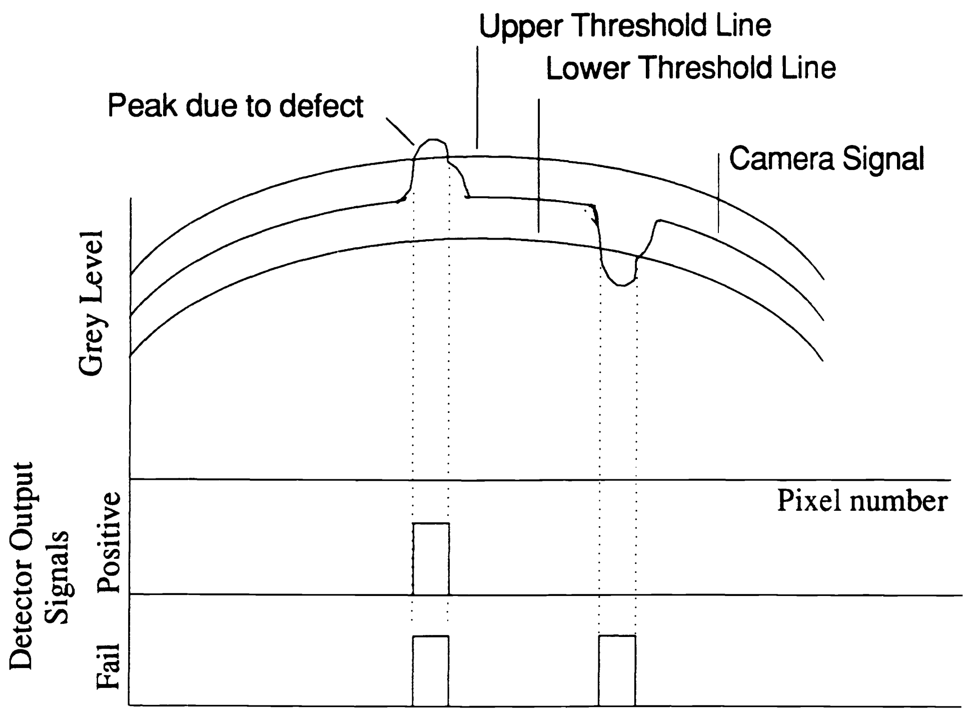

Figure 1. Adaptive Thresholding For Defect Detection

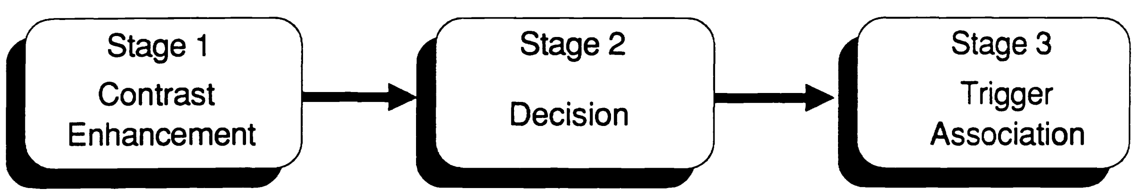

Figure 2. Decision Process

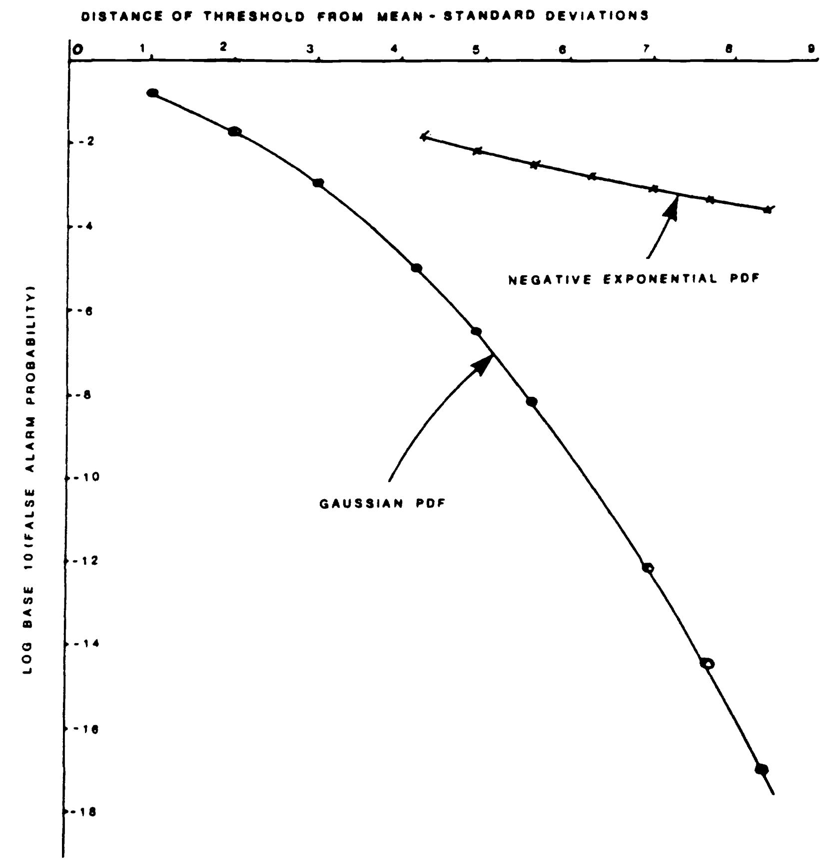

Figure 3. Probability of False Alarm vs. Threshold Level

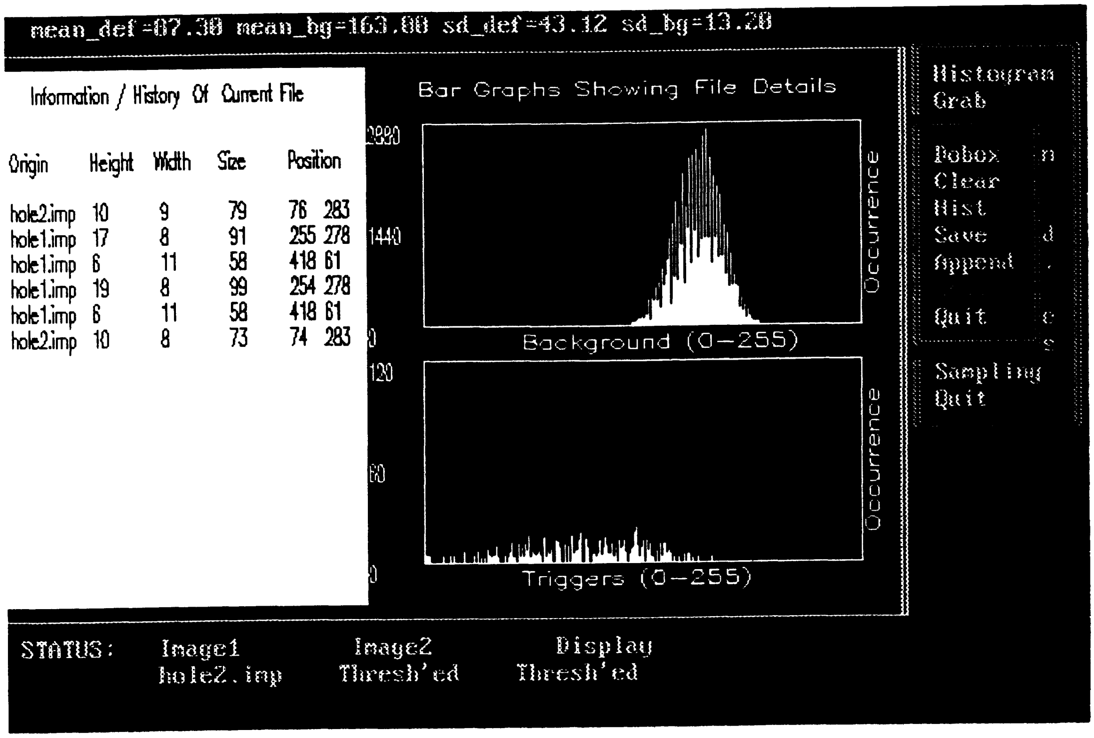

Figure 4. Grey Scale Histogram of Noise and Defect Signals

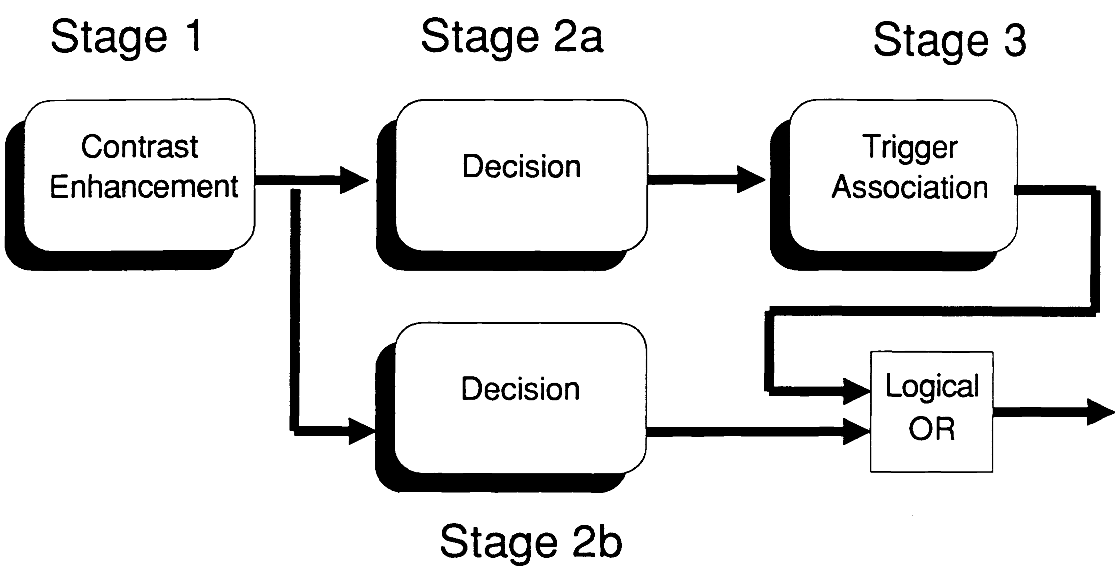

Figure 5. Decision Process

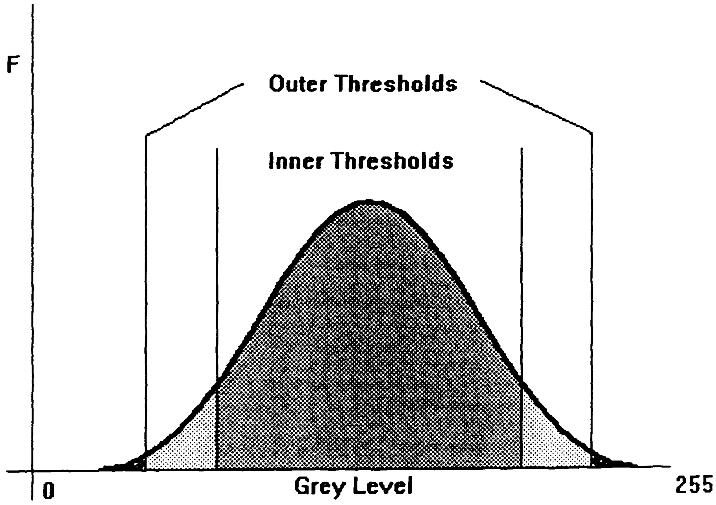

Figure 6. Double Threshold Selection

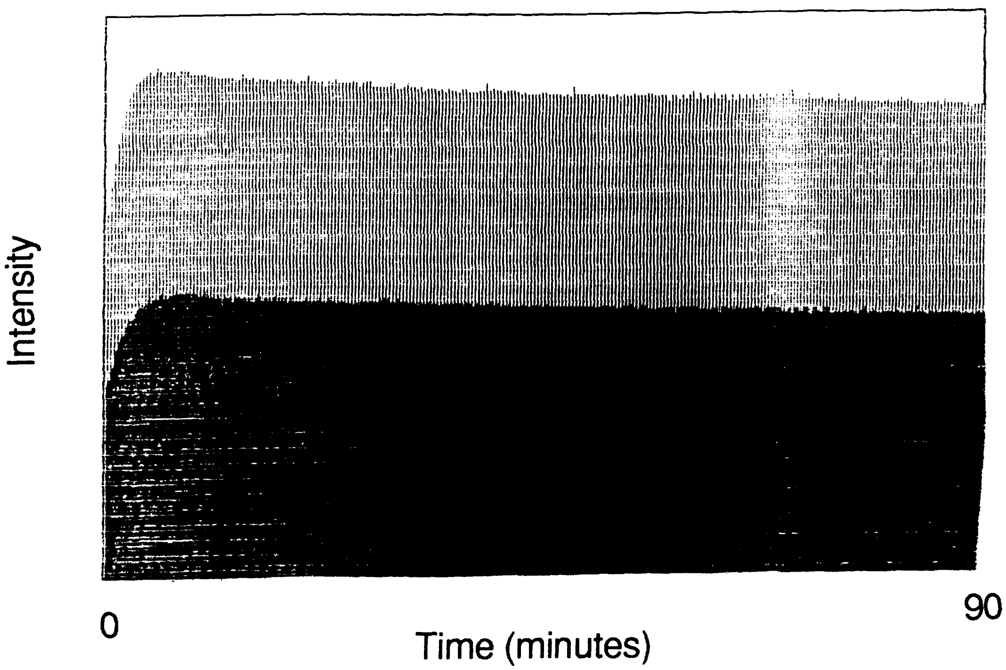

Figure 7. Light Intensity vs. Time

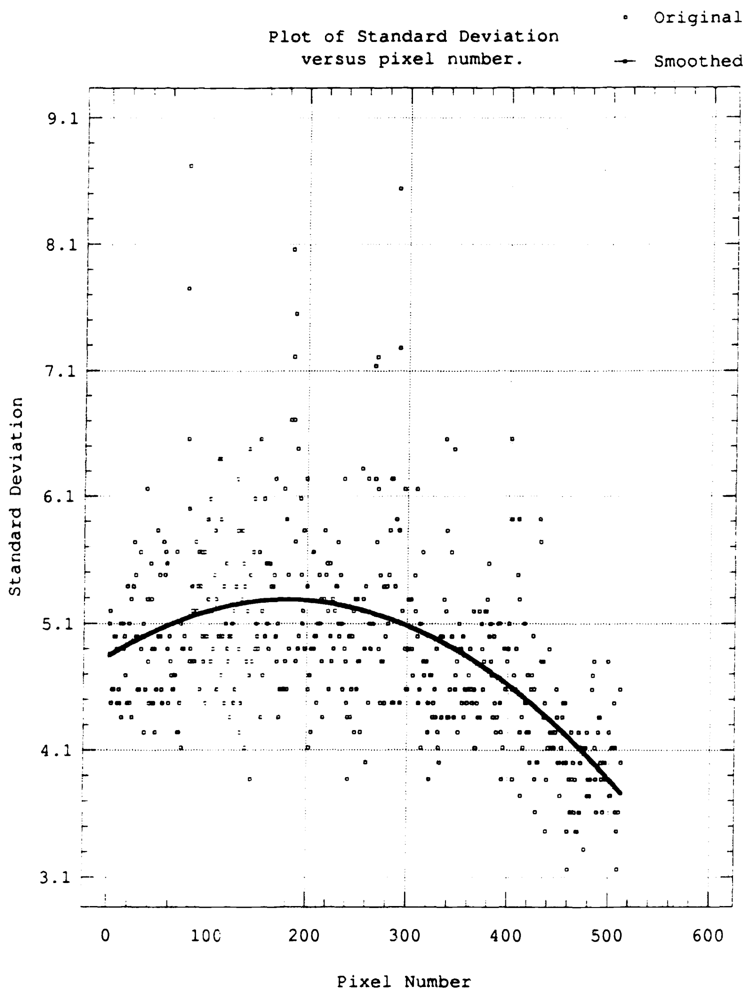

Figure 8. Variance vs. Distance