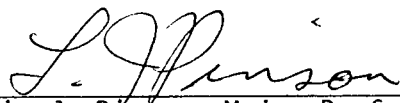
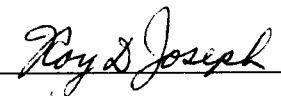


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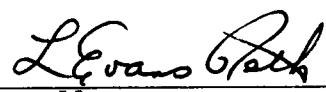
I am submitting herewith a thesis written by Jeffrey Paul Lankford entitled "Investigation of Image Enhancement Algorithms with Application to Target Acquisition." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Engineering Science.


Lewis J. Pinson, Major Professor

We have read this thesis
and recommend its acceptance:




Accepted for the Council:


Vice Chancellor
Graduate Studies and Research

INVESTIGATION OF IMAGE ENHANCEMENT ALGORITHMS
WITH APPLICATION TO TARGET ACQUISITION

A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Jeffrey Paul Lankford
March 1982

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ABSTRACT

Experimental investigation of selected image enhancement algorithms has been performed. Serial and parallel combinations of local area gain control, histogram modification, median filtering, adaptive low pass filtering, edge detection and convolutional windowing have been examined. Studies have been conducted on the candidate algorithms by digitally simulating proposed signal processors which would operate in a man-in-the-loop target acquisition environment.

Figures-of-merit were calculated for the signal-to-noise ratio, signal-to-clutter ratio, resolution and contrast. Evaluation of processor performance in terms of the probability of target detection has been executed using the above estimators of the system parameters.

Selected processors are recommended as operator controlled options for enhanced acquisition of small targets in a complex and cluttered background.

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NOMENCLATURE

a, c	Edge polynomial coefficient estimators
$B_{\alpha\beta}$	Local brightness bias term
C_a	Average contrast transfer
C_p	Peak contrast transfer
c_1, c_2	Global constants
$F(i, j)$	Discrete image of dimensions i by j
$F(\xi, \eta)$	Discrete Fourier transform of image F
$f(i, j)$	Intensity at pixel (i, j) of image F
$G^{-1}\{\cdot\}$	Inverse of point intensity transform operator
$G_{\alpha\beta}$	Local gain term
gr_a, gr_c	Gradient coefficient estimators
$h(i, j)$	Convolutional window intensity
j	Imaginary unit
M_a	Average modulation contrast
M_p	Peak modulation contrast
$P_{d,r}$	Probability of detection and recognition
P_F	Probability distribution function of F
P_h, P_v	Directional Prewitt masks
$p(F)$	Joint probability density of F
p_F	Probability density function of F
R_a	Resolution area
R_λ	Limiting resolution
SCR	Signal-to-clutter ratio
SNI	Signal-to-noise ratio improvement

SNR	Signal-to-noise ratio
S_h, S_v	Directional Sobel masks
$T\{\cdot\}$	Point intensity transform operator
T_h	Global threshold
$T_{\alpha\beta}$	Local threshold
V_f	Variance of function f
ε	Specified error parameter
θ	Direction orientation
$\nabla\cdot$	Gradient operator
$\partial/\partial x\cdot$	Partial derivative operator
$\ \cdot\ $	Determinant operator
$(\cdot)^T$	Transpose operator
μ_f	Mean of function f
σ_f	Standard deviation of function f

CHAPTER I

INTRODUCTION

Background

As real-time video image processing technology develops, the range of applications of image processing expands at a commensurate rate. From medical fluoroscopy to electron microscopy, from non-destructive testing to product inspection, from target identification to defense surveillance, the mechanics of image processing is becoming more reliant on developments in computer automation and electronics for real-time processing.

Optical and analog techniques for real-time applications may never be supplanted entirely by digital methods. However, the flexibility, portability, maintainability, and reliability of digital processing hardware makes it an attractive alternative in rugged and demanding environments.

Problems arising in connection with airborne reconnaissance/surveillance, target acquisition, and fire control offer an ideal opportunity for developing the conceptual techniques required for the successful application of digital image processing. The success of real-time reconnaissance systems incorporating a human subject in the control loop requires an understanding of the nature of direct man-machine interface, the nature of targets and the background environment, sensor design, the platform on which the sensor is mounted, and operational planning involving the use of the equipment. Integration of a digital processing component can improve the

overall system performance only after the above factors have been taken into consideration.

Image enhancement can be considered as a specialization of the techniques of digital signal processing applied to a select class of signals and their representation. If a digital image is viewed as a two-dimensional, discretized representation of a time-varying voltage, a firm theoretical foundation already exists for analysis.

Image improvement and information extraction are the primary goals of image enhancement techniques. The image features of primary interest are those which are mathematically descriptive measures of the imagery. Useful features are those which differ significantly for targets and backgrounds. The purpose of image enhancement techniques is to identify and enhance these differences so that potential target classes can be more readily detected and recognized. The mathematical formulation of characteristic feature descriptions are more readily amenable to quantitative evaluation of processor performance on a particular class of imagery than are subjective considerations.

Performance evaluation of the digital processing component provides an indication of the contribution to the overall signal transfer characteristics of the electro-optical system. Probability of detection and recognition have previously been related to qualitative definitions of feature enhancements through psychovisual experimentation. Performance of a human observer in acquiring a target has been formulated in terms of probabilities of specific

subjective decisions made by the observer. A useful electro-optical model of performance relates detection and recognition probabilities to quantifiable system performance measures of the image display system as,

$$P_{d,r} = P_1 \cdot P_2 \cdot P_3 \cdot P_4 , \quad (1-1)$$

where P_1 is a search term probability dependent on scene clutter, P_2 depends on contrast, P_3 depends on resolution, and P_4 depends on noise [1].¹

Investigation Constraints

Illustrated in Figure 1.1 is the information flow through a typical electro-optical system. This investigation focuses on the implementation of a digital processing component for image enhancement in the electronics element of the system.

This investigation is primarily oriented toward acquisition systems for airborne missile fire control. Major emphasis was placed on man-in-the-loop acquisition of low contrast targets. A demonstrable need exists for future generations of airborne missile fire control platforms to detect ground targets under realistic battle-field conditions. These helicopter-borne weapons systems would operate at nap of the earth altitudes at slant ranges where target detection capability is marginal.

¹Numbers in brackets refer to similarly numbered references in the Bibliography.

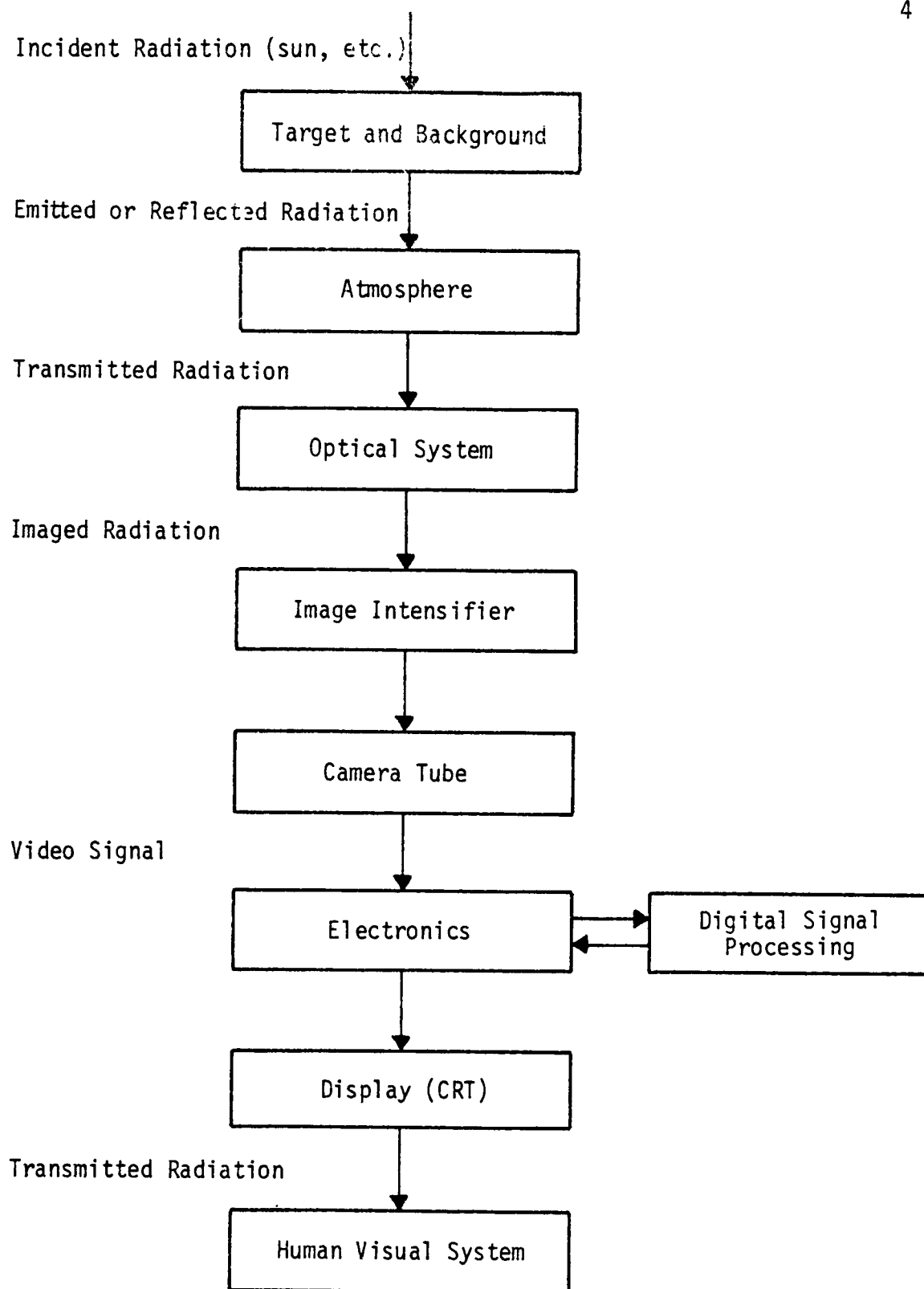


Figure 1.1. Information flow through an electro-optical system.

The primary object of interest is the single, high-threat target operating in a complex and cluttered scene. The target is detached from the main body of target vehicles and hence does not present many detection cues. A typical target in a complex background scene is diagrammed in Figure 1.2. The figure illustrates that various categories of background clutter compete for the observer's attention and that boundaries between clutter regions may be modeled as finite polynomials.

Target information is presented to the operator as live imagery at television rates from a complement of sensors spanning a region of the electro-magnetic spectrum from the visible to the far infrared. Infrared or video imaging systems are used as the primary seeker, perhaps supplemented by an active radar seeker. Silicon charge coupled large scale integration devices are currently being implemented as imaging mechanisms. Precise pointing and stabilization capability is a necessary condition to ensure that target detection and recognition requirements can be met. The implementation of stabilized mirror and stabilized platform demonstrates that this goal can be achieved [2, 3].

The video signal processor should operate in near real-time to minimize platform exposure time to a degree that provides adequate survivability. Additionally desirable are hardware implementations of the processor which allow modification to currently installed equipment. Due to the restricted nature of the carrier platform, minimization of such device characteristics as size, weight, complexity, cost and power consumption requires consideration.

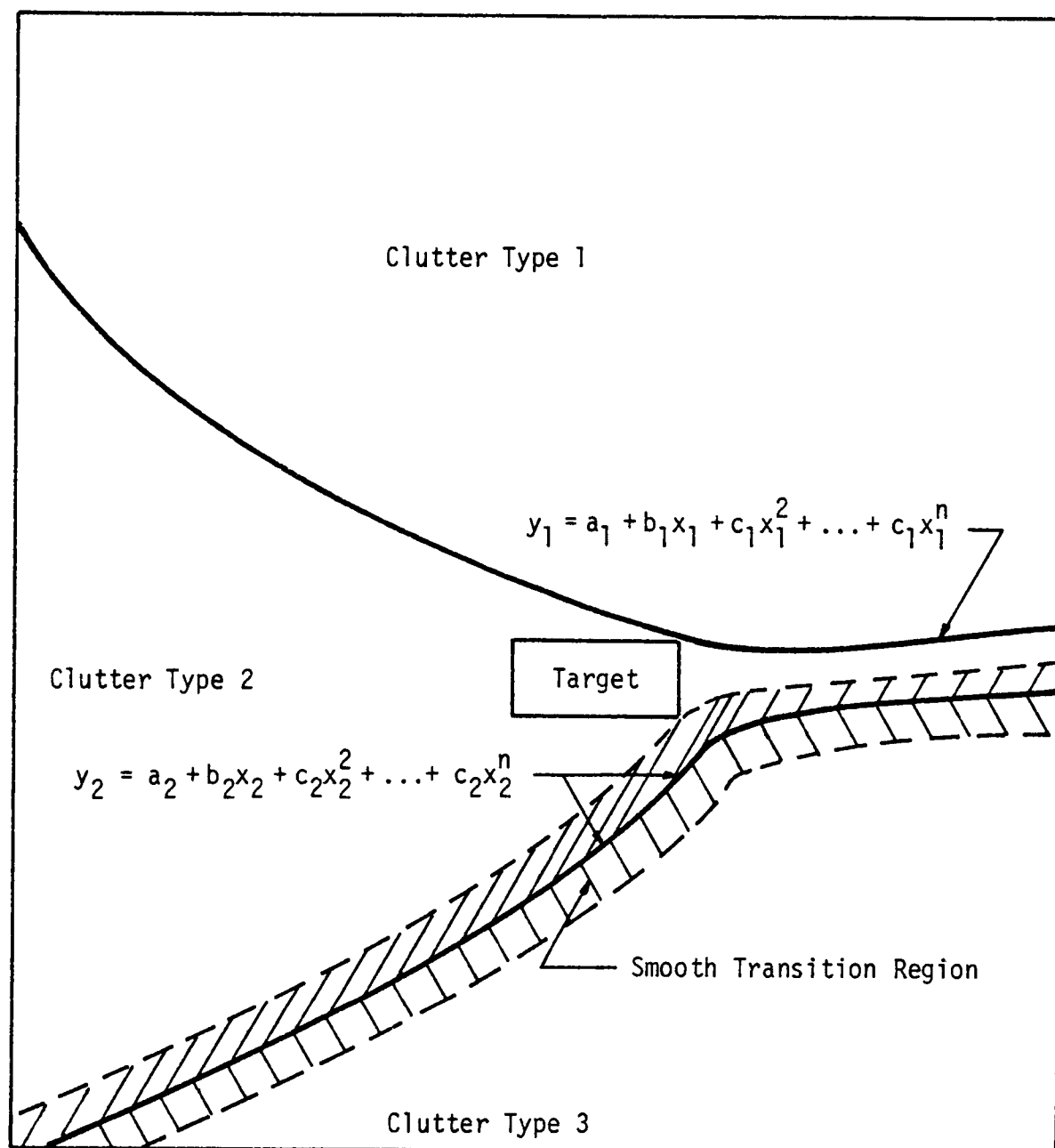


Figure 1.2. Typical target in complex background scene.

The direct man-machine interface is the system component least amenable to quantitative analysis. The effectiveness of a time-limited observer searching for targets which compete for attention against a host of other similar artifacts was modeled above. Additional considerations are display size, the field of view, image blur and exposure time.

Investigation Procedure

The procedure for the investigation of processing methods is indicated in Figure 1.3. The figure shows that the previously specified constraints were used to restrict the number of candidate processors. Also, a feedback relationship exists between algorithm construction and algorithm evaluation. Algorithm development, simulation modeling, and performance evaluation were conducted for six image processing techniques: local area gain control (LAGC), histogram modification (HIST), median filtering (MEDN), adaptive low pass filtering (ALPF), convolutional windowing (WNDW), and edge detection (EDGE).

Image processing techniques which indicate improvement in contrast, resolution, signal-to-noise ratio (S/N), and signal-to-clutter ratio (S/C) were selected, on the basis of the performance model, as potential candidates for application to the target acquisition problem. The candidate processing methods generally offer the capability for improved performance through enhancement of target signature. Algorithms were developed for processors

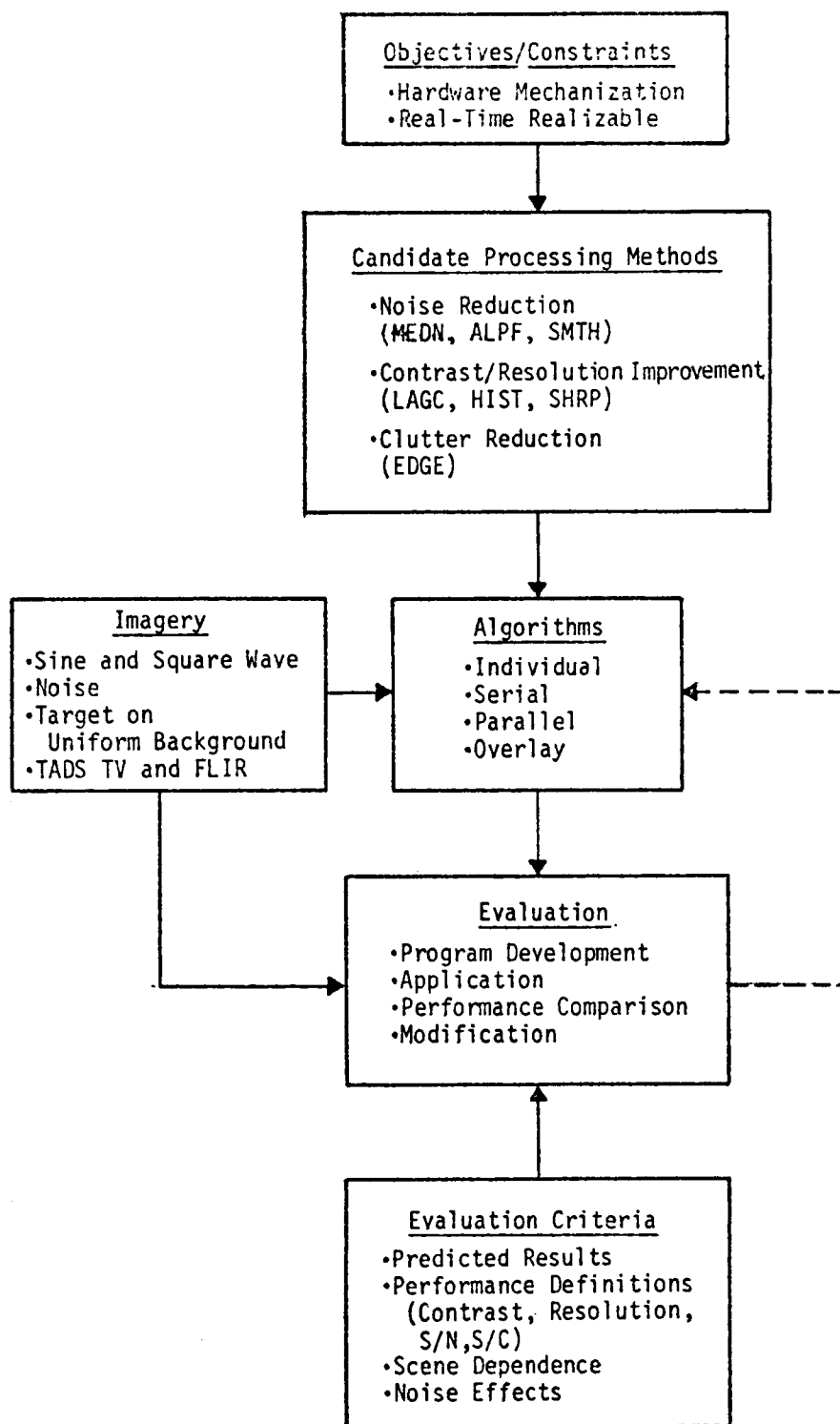


Figure 1.3. Procedure for processor selection.

operating individually. In addition, serial and parallel combinations of processor algorithms were implemented.

Simulation modeling experiments were conducted using the developed algorithms and varying parametric settings. The simulation modeling process involves implementing mathematical formulations of the candidate processors. Criteria were developed for the evaluation of algorithm performance. Subjective evaluation was accomplished by comparing known target objects before and after processing. Quantitative evaluation was conducted using mathematically formulated figures-of-merit for contrast, resolution, the signal-to-noise ratio, and the signal-to-clutter ratio and by comparing calculated measures for processed and unprocessed imagery.

Investigation Results

Results indicate that several image processing techniques have potential for improving system performance through operator acquisition of targets in less time and at greater standoff ranges or through automatic handoff of identified targets from a precision pointing and tracking system to the missile seeker. The following proposals, based on investigation results, have high potential for improving target signature for seeker lockon and tracking.

Noise reduction early in the processing chain was clearly advantageous. Median filtering has been recommended for implementation, as it entails the greatest amount of noise smoothing with the least amount of image blurring of the techniques investigated. Furthermore, it was recommended that additional cascade processing

be performed and combined in a parallel configuration with the output of the median filter.

The additional serial processing options would incorporate LAGC and gradient/edge processing for the enhancement of image contrast. It was determined that the gain term for the LAGC processing should be mean dependent since the mean independent gain introduced spatially modulated clutter. Locally adaptive edge thresholding was found to be useful in detecting low contrast objects with results dependent on the relationship between target object size and processor window size. The area over which local calculations are computed therefore should be operator selectable.

CHAPTER II

EVALUATION OF TARGET DETECTION PERFORMANCE

Image Characterization

The evaluation of the performance of electro-optical systems is a critical feedback element of the research process. Subjective evaluation of processor performance, both by trained and untrained observers, should be substantiated by quantitative measures of system performance. To this end, image characterizations were made to objectively measure image quality.

Most useful mathematical characterizations of discrete images are statistical descriptors based on probability density models for discrete images $F(n_1, n_2)$. The joint probability density,

$$p(F) = p\{f(1), f(2), \dots, f(N_1 \cdot N_2)\} , \quad (2-1)$$

completely statistically characterizes the image. When this information is presented in graphic format, the resultant tableau is the discrete histogram of the image.

From this information, it is then useful to extract the first several central moments which describe the geometric structure of the histogram: mean, standard deviation, skew, and kurtosis. If the discrete image probability density function is very nearly a normalized Gaussian distribution, then the joint probability density is approximated by,

$$p(F) = (2\pi)^{-\frac{N_1 \cdot N_2}{2}} \|V_f\|^{-1/2} \exp \frac{-(f - \mu_f)^T V_f^{-1} (f - \mu_f)}{2}, \quad (2-2)$$

and the third and fourth statistical moments are very nearly zero.

The discrete Fourier transform,

$$F(\eta, \xi) = \frac{1}{M \cdot N} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} F(m, n) \exp \frac{-2\pi j(\eta m + \xi n)}{M \cdot N}, \quad (2-3)$$

is also useful in characterizing the discrete image since it indicates the relative proportion of high and low spatial frequency components.

Objective Evaluation

Using the above image descriptors, it is possible to develop input/output transfer functions which evaluate the image processors. Figures-of-merit were defined for four quantitative measures of image quality: contrast, resolution, signal-to-noise ratio, and signal-to-clutter ratio. The quantitative evaluation measures based on the electro-optical performance model were developed so they bear a direct relationship to improved performance.

Contrast transfer is defined as the ratio of contrast in the processed (output) image to that in the unprocessed (input) image over the same area. Both peak and average values for modulation contrast over a specified composition of target/background area were computed.

The following definitions were employed for peak contrast transfer,

$$C_p = \frac{M_p(\text{output})}{M_p(\text{input})}, \quad (2-4)$$

average contrast transfer,

$$C_a = \frac{M_a(\text{output})}{M_a(\text{input})}, \quad (2-5)$$

peak modulation contrast,

$$M_p = \frac{|f_{\max} - f_{\min}|}{f_{\max} + f_{\min}}, \quad (2-6)$$

and average modulation contrast,

$$M_a = \frac{|f_1 - f_2|}{f_1 + f_2}. \quad (2-7)$$

For targets on a background, $f_{\max}$ is defined as the maximum value over the target, $f_{\min}$ as the minimum value over the background, f_1 as the average target value, and f_2 as the average background value.

Target values are calculated over a rectangular area bounding a specified target. Background value calculations are optionally selectable as shown in Figure 2.1. The side-by-side calculation derives background values from a zone of equal area adjacent to the target zone. The four-neighbor average background calculation derives background values from the aggregate of four zones adjacent and of equal size to the target zone. The surrounding background selection computes the background from a band of

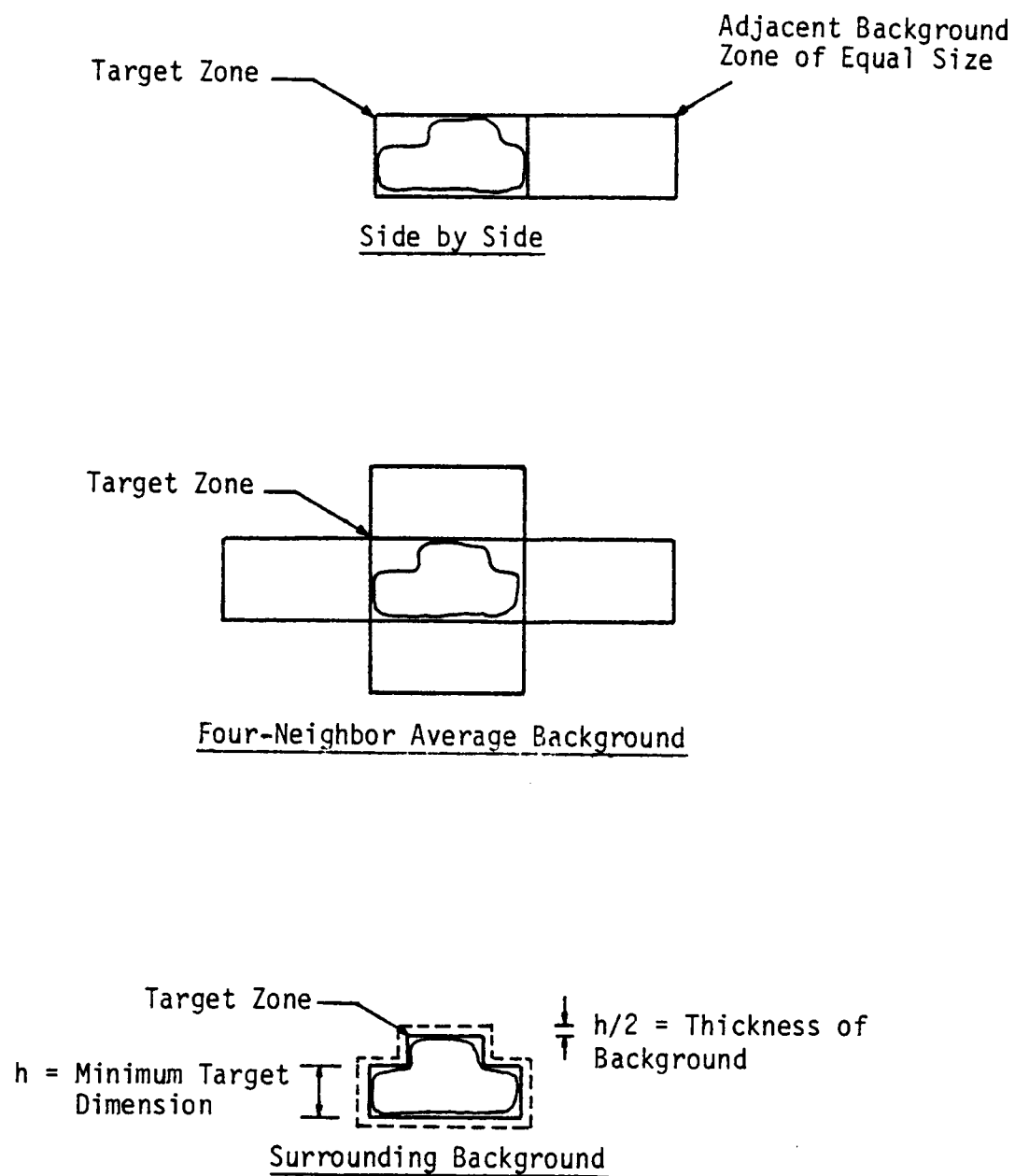


Figure 2.1. Background selection for contrast evaluation.

pixels whose thickness is adjustable as a function of target dimensions.

If the background can be modeled as a shift invariant random intensity, then the choice of background zone will not affect results obtained for contrast transfer. For scenes without identifiable targets (i.e., tree backgrounds or field backgrounds only), contrast transfer is undefined and hence is not calculated. For images containing definite targets, the target is located manually, the target dimensions are specified, a background option is selected, and the evaluation of Eqs. (2-4) through (2-7) is performed.

The detection of a potential target requires that the target exhibit some minimum contrast with its background. This threshold contrast is a function of target size and will decrease as target size increases, primarily because of the spatial integrating properties of the human eye. The definition of contrast transfer employed here reflects those properties.

Characterization of linear imaging systems resolution is most commonly presented in terms of the modulation transfer function which shows relative gain as a function of spatial frequency. However, for non-linear systems, the modulation transfer approach is confused by the generation of supplemental spatial harmonic frequencies as a result of processing.

For simplified resolution comparisons, single valued figure-of-merit descriptors have been defined based on the number of resolvable lines across the target's minimum dimension. The number of resolvable lines (N_R) is defined as the fundamental frequency of

a tri-bar pattern of a size such that the modulation on the output display exactly matches a relative gain of 2 percent as a limiting threshold of human resolution discrimination. Two useful resolution enhancement measures are defined as follows. Limiting resolution,

$$R_l = \frac{N_R(\text{output})}{N_R(\text{input})}, \quad (2-8)$$

is defined as the ratio of the number of resolvable lines of the output image to the number of resolvable lines of the input image. The resolution area,

$$R_a = \frac{\sum_0^{N_R(\text{output})} G(n)}{\sum_0^{N_R(\text{input})} F(n)}, \quad (2-9)$$

is then defined as the ratio of the sums of the transfer function from the origin to the number of resolvable lines of the respective images. Evaluation of the Fourier spectrum of the image before and after processing provides a more detailed appreciation of the effects of frequency content on a given processor.

The ability to recognize general target classes and to perform higher levels of discrimination is strongly dependent on the resolution with which an image is presented to the observer. This resolution is dependent on all the elements in the electro-optical system and is typically described in terms of the sine-wave spatial frequency response (i.e., the modulation transfer function for circularly symmetric systems). Resolution is related to observer

performance in terms of the number of resolvable lines in the display which appear across the minimum dimension of the target blob. The definition of resolution formulated above incorporates the threshold resolution required for observer decision making.

The procedure for evaluation of resolution is diagrammed in Figure 2.2. First, the Fourier transform of both the unprocessed and the processed images is computed. Then the number of resolvable lines is determined. The limiting resolution is then computed according to Eq. (2-8) and the resolution area is calculated according to Eq. (2-9).

For the evaluation of the signal-to-noise ratio figure-of-merit, the total signal model was extended to incorporate additive Gaussian noise with zero mean and a selectable standard deviation,

$$T(i,j) = F(i,j) + N(i,j) . \quad (2-10)$$

The noise is generated by the approximation to a random Gaussian distribution of zero mean and specified standard deviation. The combined image is formed by the addition, on a pixel-by-pixel basis, of the input image and the noise degraded image. By assuming statistical independence for the input image and the noise image, the variance of the combined image is then equal to the sum of their variances,

$$V_T = V_F + V_N . \quad (2-11)$$

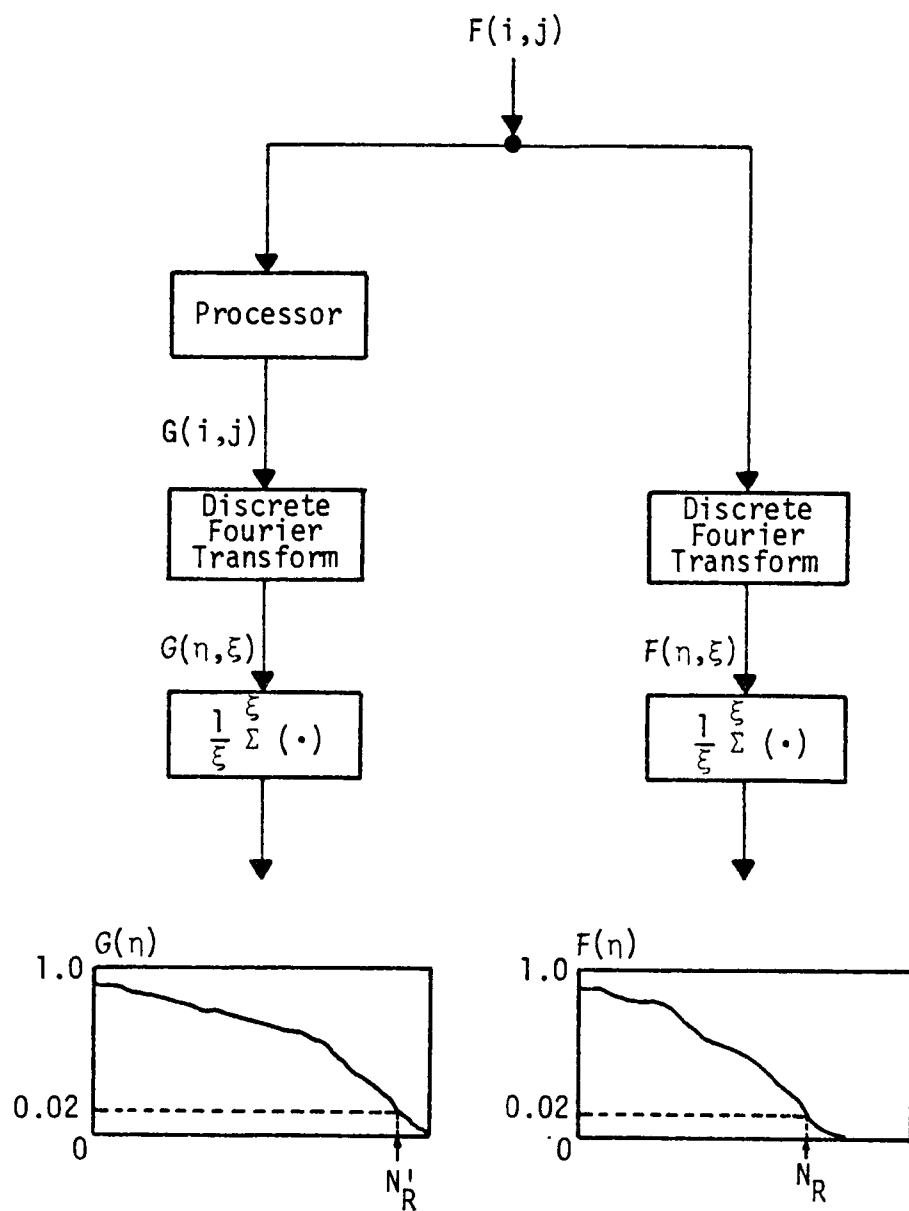


Figure 2.2. Evaluation of resolution.

The computational procedure for the signal-to-noise ratio evaluation appears in Figure 2.3. The signal-to-noise ratio improvement transfer function is defined by,

$$SNI = \frac{SNR(\text{output})}{SNR(\text{input})} , \quad (2-12)$$

the input signal-to-noise ratio by,

$$SNR(\text{input}) = \frac{\sigma_F}{\sigma_N} , \quad (2-13)$$

and the output signal-to-noise ratio by,

$$SNR(\text{output}) = \frac{(\sigma_H^2 - \sigma_{N'}^2)^{1/2}}{\sigma_{N'}} . \quad (2-14)$$

The performance of an observer viewing a displayed image is affected by the amount of noise in the image. Noise will originate from several sources and the effects can be described in terms of a suitably defined signal-to-noise ratio. The definition formulated above models the effect of the signal-to-noise ratio on observer performance.

One other factor which affects detection and recognition probabilities is the search process by which an observer scans the image presented. The search process is typically modeled probabilistically and depends on such parameters as display size, view time, background structure, observer pre-briefing and training, and search pattern.

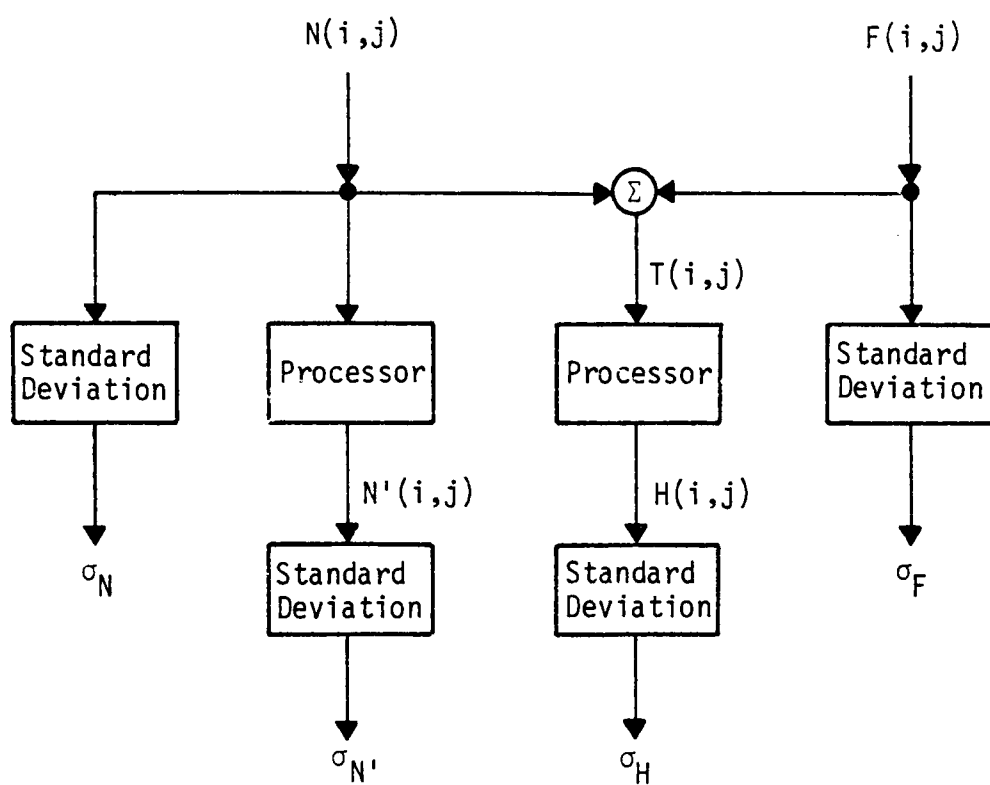


Figure 2.3. Signal-to-noise ratio improvement.

A simplified search term incorporates a figure-of-merit estimator for signal-to-clutter ratio,

$$SCR = \frac{|\mu_t - \mu_b|}{\sigma_s}, \quad (2-15)$$

where μ_t is the target object mean, μ_b is the local background mean, and σ_s is the standard deviation of target and background combined. Evaluation of more complex definitions is hampered by lack of adequate theoretical basis for defining and measuring clutter. A model including previously described parametric interactions is difficult to implement and validate. Although rudimentary, the above definition of the signal-to-clutter ratio does serve as an elementary model of the search process.

Subjective Evaluation

Subjective evaluation of imagery does provide a first-cut measure of processor performance. Subjective evaluation of processor performance is achieved by comparing the relative clarity of known target boards and/or vehicles contained in the live imagery to that contained in the processed imagery. Evaluations were conducted using the MICOM video image display system and photographs recorded from the video display.

CHAPTER III

IMAGE ENHANCEMENT ALGORITHM ANALYSIS

Algorithm Classification

Prerequisite to the digital simulation of the candidate image processors is an investigation of the general properties of each algorithm. This analysis incorporates the assessment of anticipated effects and prediction of expected modifications of image quality attributable to each algorithm. Variation of key parameters for each processor was conducted with the intention of maximizing performance under complex scene conditions. The effects of interaction among serial and parallel applications of multiple enhancement algorithms are considered. To simplify the analysis and interpretation of results, uni-dimensional system response characteristics were explored. Two classification schemes are adopted to assist in the conceptual organization of the processor characteristics.

Two concurrent classification schemes were developed for algorithm organization. The a priori scheme considers the methodology of the processor as the primary element of the categorization. The a posteriori scheme considers the results of processor application as the primary mode of classification.

The algorithms are classified by type and application as diagrammed in Figure 3.1. By type is meant the general characterization of the processor (e.g., linear or non-linear and global or

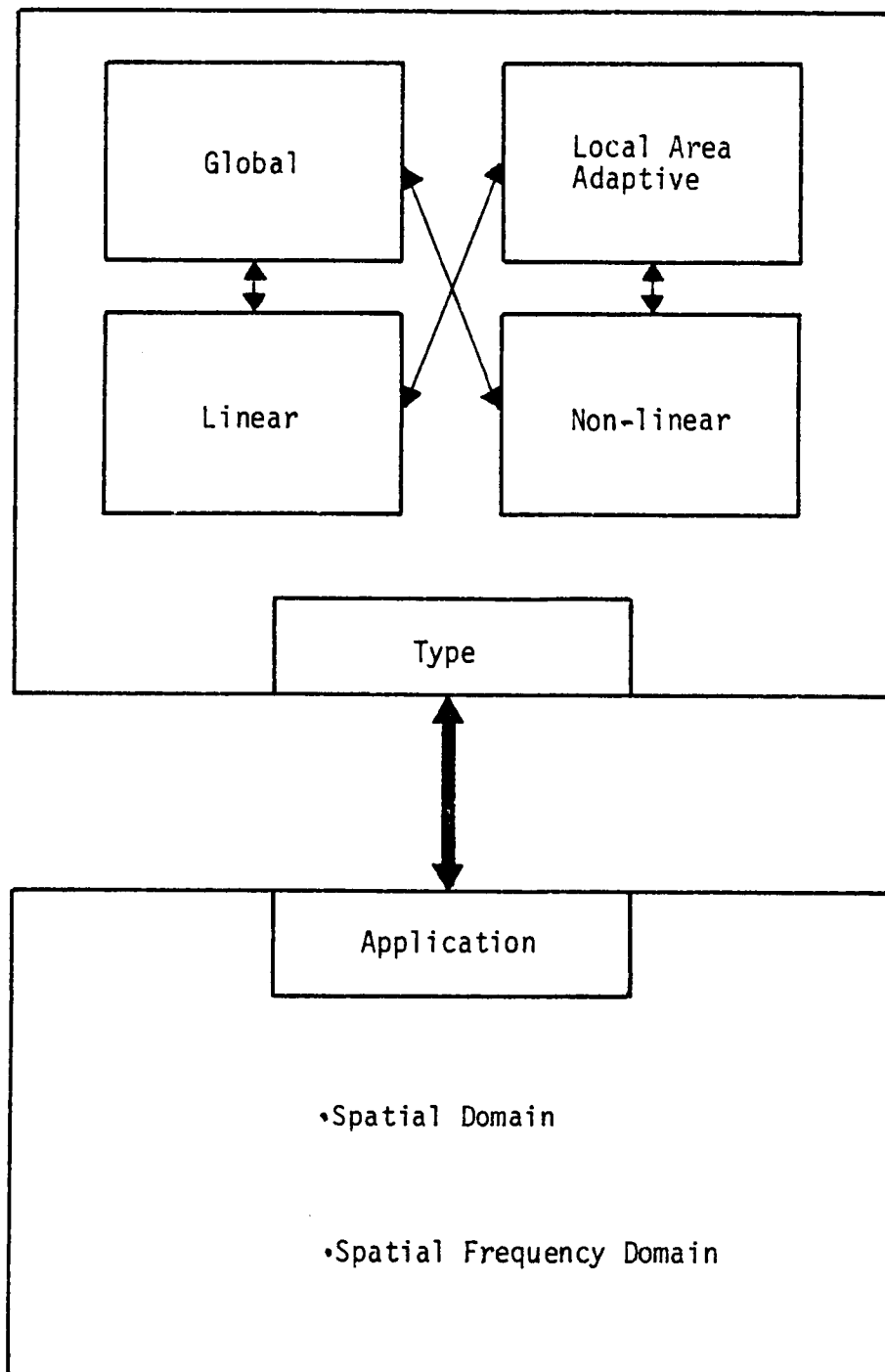


Figure 3.1. Procedural concepts for processing algorithms.

local area adaptive). By application is meant the particular domain in which the processor is applied, spatial or spatial frequency.

Performance classification distinguishes the algorithms on the basis of their effect on image quality measures (see Figure 3.2). For a specified set of image quality measures, the application of a given processor may have some resultant effect on image quality. The improvement or abridgment of the various evaluation criteria provides an effective mechanism for grouping algorithms, especially when considering multiple processors. By algorithms is meant the specific individual processor applied or any combinations thereof. By effect is meant all the positive or negative results on subjective or objective performance measures.

Histogram Modification

The histogram modification process (HIST) is a monotonic increasing point intensity transformation,

$$g_k = T\{f_j\} , \quad (3-1)$$

where f_j is the intensity level over all pixels [4]. The input intensity random variable f_j , where $(f_0 \leq f_j \leq f_J)$ is mapped onto the output variable g_k , where $(g_0 \leq g_k \leq g_K)$. The output probability density function $p_G\{g_k = b_k\}$ traces the specified shape for a given input probability density function $p_F\{f_j = a_j\}$. Here, a_j and b_k are reconstruction values of the j^{th} and k^{th} intensity levels.

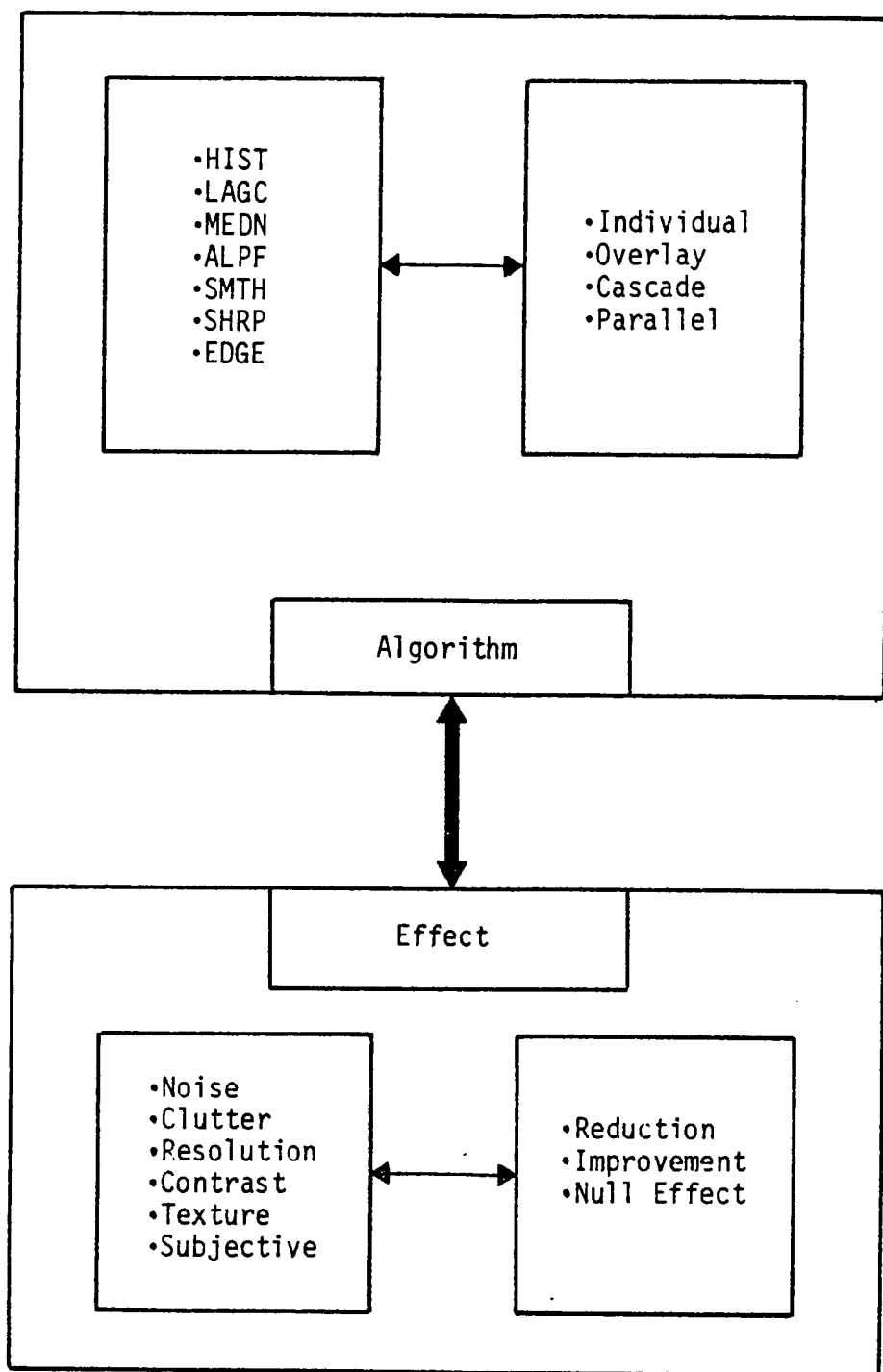


Figure 3.2. Performance concepts for processing algorithms.

The histogram modification process proceeds as shown in Figure 3.3. An image histogram is formed by tabulating the number of times that each intensity value occurs throughout the image. The intensities range over some specified number of quantization levels; $H_F(j)$ for $j = f_{\min} \dots f_{\max}$ represents the number of pixels in the input image whose intensity is quantized to j brightness levels. Histogram modification will produce an image field $G(n_1, n_2)$ by point rescaling such that the normalized gray scale histogram $H_G(k)$ for $k = g_{\min} \dots g_{\max}$ equals, or is nearly equivalent to, the specified probability density function $p_G(g)$.

Probability axioms require that the probability density functions sum to unity, so that,

$$\sum_{j=0}^J p_F\{f_j = a_j\} = 1 = \sum_{k=0}^K p_G\{g_k = b_k\} . \quad (3-2)$$

Furthermore, the monotonic transformation requires that for $b_k = T\{a_j\}$, the probability of pixels in the input with intensity less than or equal to a_j must equal the probability that pixels in the output image have intensity less than or equal to b_k . Then,

$$\sum_{n=0}^k p_G\{g_n = b_n\} = \sum_{m=0}^j p_F\{f_m = a_m\} . \quad (3-3)$$

For a given image, the probability function on the right is replaced by the histogram function of the input, so that,

$$\sum_{n=g_{\min}}^g P_G(g_n) = \sum_{m=0}^j H_F(m) = P_F(f) . \quad (3-4)$$

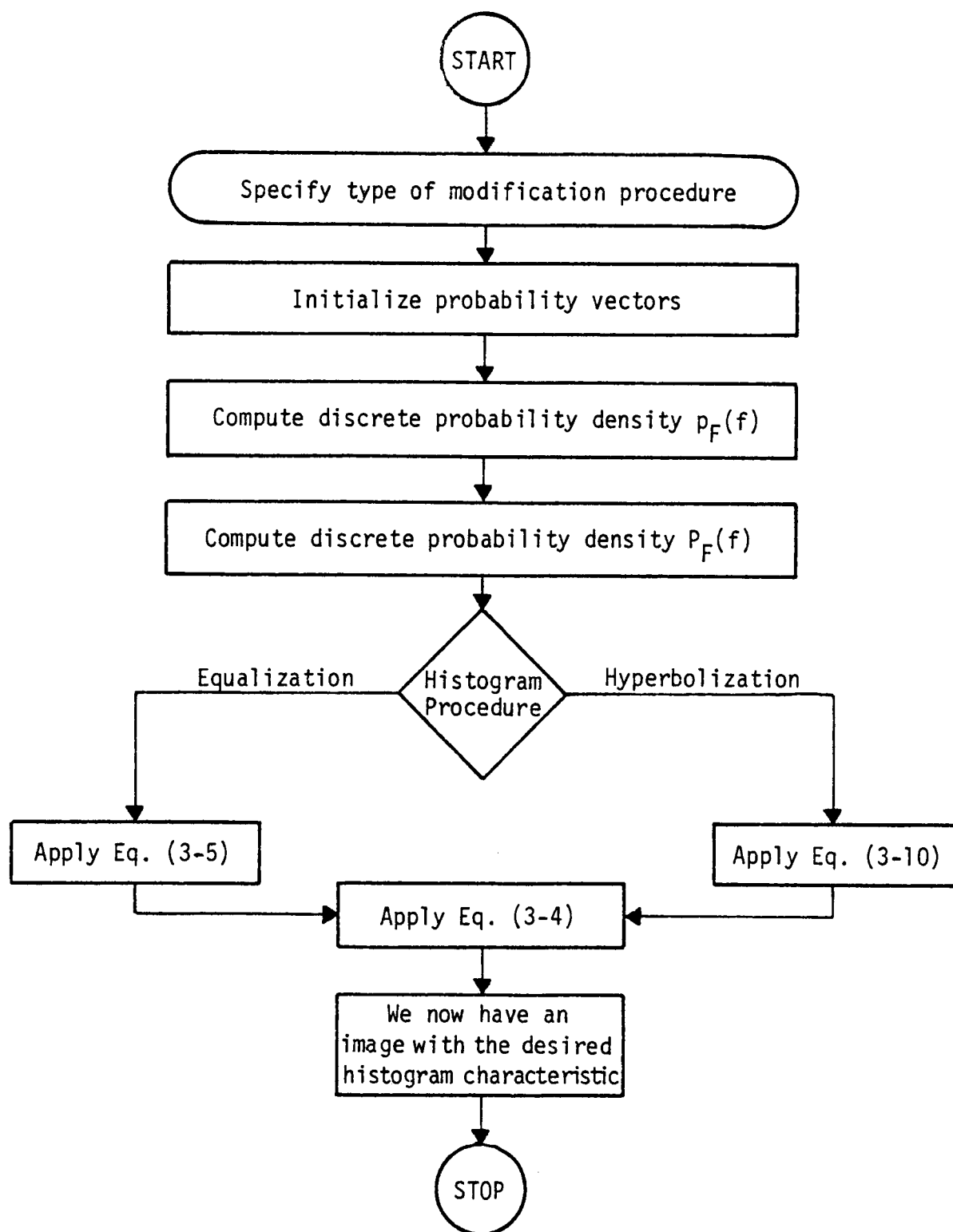


Figure 3.3. Logic flow diagram for HIST.

Equation (3-4) is inverted to yield a solution for g_k in terms of f_j . Typically, this is performed by numerically obtaining a tabular solution which yields the output level for each input level.

For the case of uniform output density, the output probability density is,

$$p_G(g) = \frac{1}{g_{\max} - g_{\min}} , \quad (3-5)$$

with $g_{\min} \leq g \leq g_{\max}$. Inserting this density into Eq. (3-4) yields,

$$\left[\frac{1}{g_{\max} - g_{\min}} \right] (g - g_{\min}) = P_F(f) , \quad (3-6)$$

or,

$$g = (g_{\max} - g_{\min}) P_F(f) + g_{\min} . \quad (3-7)$$

Since $g_{\min} = 0$ and $g_{\max} = 255$ for the display limits, then,

$$g = \frac{255}{K \cdot L} P_F(f) , \quad (3-8)$$

where $K \cdot L$ equals the total number of pixels in the image and is a bias normalizing factor.

For the case of hyperbolic output density, the output probability density, following Frei's [5] use of the logarithmic Weber-Fecher law of human vision, is,

$$p_G(g) = \frac{1}{(g + c) \ln \left| 1 + \frac{g_{\max}}{c} \right|} . \quad (3-9)$$

so the histogram transfer function becomes,

$$g = c \left\{ \exp \left[\ln \left| 1 + \frac{255}{c} \left| \frac{1}{K \cdot L} P_F(f) \right| \right] - 1 \right\} , \quad (3-10)$$

using Eq. (3-4).

The histogram modification technique is characterized as a point intensity gray scale transformation. For a given discretized image $F(n_1, n_2)$, the discrete probability density function $p_F(f)$ can be readily calculated as a function of the image point intensity $f(i, j)$, which is assumed to be a random variable. Similarly, the discrete cumulative probability distribution function $P_F(f)$ can easily be computed as the sum of all input image probability density values,

$$P_F(f) = \sum_{m=f_{\min}}^f p_F(m) . \quad (3-11)$$

Likewise, for an unknown output image $G(n_1, n_2)$, the discrete probability density function $p_G(g)$ can be specified as a function of the image point intensity $g(i, j)$, which is also assumed to be a random variable. Again, the discrete cumulative probability density function $P_G(g)$ can be easily computed as,

$$P_G(g) = \sum_{n=g_{\min}}^g p_G(n) . \quad (3-12)$$

Using this information, a transformation is derived in terms of the desired output probability function and the input image histogram.

Histogram rescaling proceeds as follows. The histograms $H_F(j)$ and $H_G(k)$ are both equalized such that,

$$S = T(j) = \sum_{w=f_{\min}}^f p_F(w) \quad (3-13)$$

and,

$$V = R(k) = \sum_{u=g_{\min}}^g p_G(u) . \quad (3-14)$$

Hence, $p_S(s)$ and $p_V(v)$ are uniform and both results are identical (e.g., $V = S$). To get k in terms of j , the transformation,

$$k = G^{-1}\{s\} = G^{-1}\{T\{j\}\} , \quad (3-15)$$

is used. The image with k levels is the desired result.

To obtain the equalized histogram, the average value of the histogram is computed. Then, starting from the lowest gray level of each histogram, the pixels in the quantization bands are combined until the sum is closest to the average. All of these pixels are then scaled to the first reconstruction level at the midpoint of the first quantization band of the equalized histogram. The process is repeated for higher value gray levels until all pixels have been placed in the equalized histogram. For the special case of histogram equalization, the histogram output image need not undergo the equalization process since it was specified previously to be a uniform density histogram.

The histogram modification process described is a full frame non-linear pixel intensity transformation derived from global statistical properties of the image. It tends to enhance scene

contrast by redistributing the information content carried by the gray level distribution.

For the case of histogram equalization, the amount of information related to the level of occurrence of each gray scale is distributed such that each intensity level in the displayed image carries the same amount of information. According to Shannon's [6] theory of communication, this is the distribution that maximizes the transmission of information by minimizing the entropy of the signal,

$$H = - \sum_{g=g_{\min}}^{g_{\max}} p_G(g) \ln |p_G(g)| . \quad (3-16)$$

For the case of histogram hyperbolization, the amount of information is distributed such that the logarithmic response of the rod and cone photoreceptors in the retina of the human eye will result in histogram equalization after biological processing is performed by the human eye.

One difficulty with the histogram modification technique is that brightness levels which show a low level of occurrence in the histogram are compressed and hence, contrast in these regions is not enhanced as a result of processing. Typically, however, it is precisely these areas that contain the object information whose contrast enhancement is desired. Local area histogram modification has been proposed as an alternative [7], although the difficulty of determining the window size so as to obtain statistically significant estimators is formidable.

Real-time hardware mechanization for local area histogram modification has been realized. Full-frame histogram modification also lends itself to hardware implementation since it operates directly in the spatial pixel domain. However, due to the need to calculate statistical properties of the entire image, a minimum lag of one time frame is required for processing.

Local Area Gain Control

The formal mathematical definition of the local area gain control [8] processor (LAGC) proceeds as follows. The transformed intensity is,

$$g(i,j) = G_{\alpha\beta} [f(i,j) - \mu_{\alpha\beta}] + B_{\alpha\beta} , \quad (3-17)$$

with the local gain term being defined as,

$$G_{\alpha\beta} = c_1 \frac{1}{\sigma_{\alpha\beta}} , \quad (3-18)$$

or,

$$G_{\alpha\beta} = c_1 \frac{\mu_{\alpha\beta}}{\sigma_{\alpha\beta}} , \quad (3-19)$$

and the local brightness bias term being defined as,

$$B_{\alpha\beta} = c_2 \mu_{\alpha\beta} , \quad (3-20)$$

where the output pixel brightness $g(i,j)$ is specified as a function of a gain term based on local neighbor statistics. The gain term can be alternately selected to incorporate the local mean if desired. A functional flow description of the local area gain control algorithm appears in Figure 3.4.

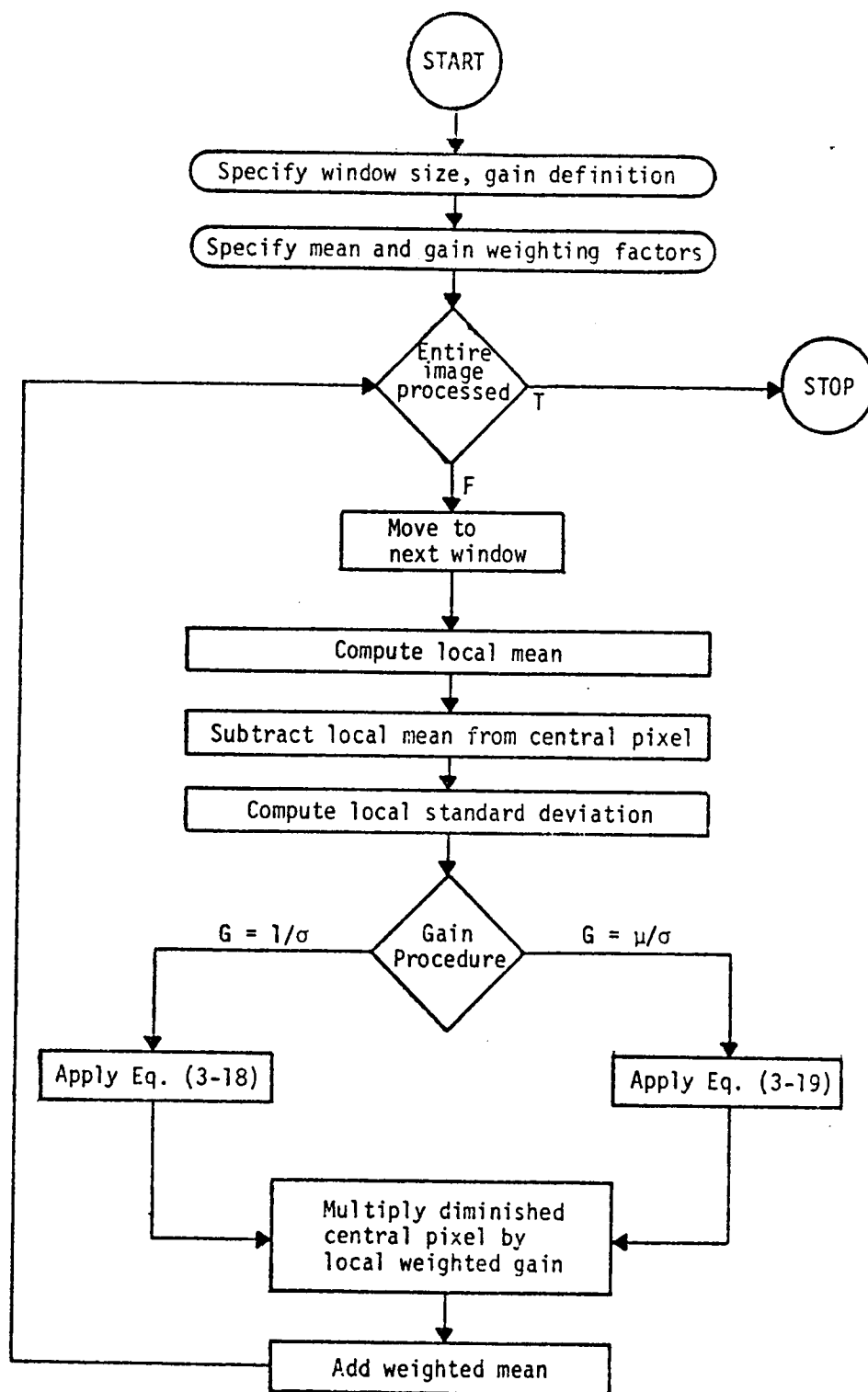


Figure 3.4. Logic flow diagram for LAGC.

The LAGC processor is typical of other locally adaptive processors in that it is applied within a window sliding across the image. A small fixed-size rectangular field sweeps the full-frame image, limiting the current processing area. Within this region, the local area statistics are calculated and the local mean is subtracted from the central pixel. A variable gain is applied to this difference to amplify the local variation. A portion of the local mean is then added back to restore the desired brightness to the image.

The properties of the LAGC process are a result of the visual psychophysical considerations that derive from the Weber [9] law governing the contrast sensitivity of the human eye. This law holds that contrast sensitivity (C_s) is a constant proportional to the ratio of the contrast sensitivity threshold (ΔI) and the average local intensity (I).

The LAGC formulation operates to vary the local brightness (bias) so that the overall dynamic range of the scene is compressed and to enhance local variations above the contrast sensitivity threshold of the human eye. The brightness and gain variables are specified as functions of locally computed statistics and hence, effectively increase the contrast of the local area without causing saturation of the display in other locations.

The brightness bias term is proportional to the local mean. The gain term is inversely proportional to the local standard deviation so that an area with small local variance receives a larger

gain and can be set proportional to the local mean to satisfy subjective psychovisual considerations.

Several parameters are operator adjustable. The window size typically will be selected to match the estimated target size in pixels. The gain magnitude multiplying factor can be given a value from zero to unity, inclusive. Likewise, the brightness bias multiplying factor can be assigned a value from zero to unity, inclusive. Normally, these two parameters will be set equal to unity.

Several hardware mechanizations of the LAGC processor have been realized. These implementations work directly in the spatial domain and hence are readily implemented by mechanizations which operate at video rates. The two-dimensional recursive filter approach presented above would require only a simple configuration of delay lines and summers (adders) to accomplish the LAGC function in hardware. Additionally, the effective size of the local area window can be altered by simply varying the summer weights. The selective local area video contrast stretching scheme can also be realized by employing a non-recursive computation of the local statistics on a sliding window. However, to alter the local area of the non-recursive sliding window, the filter size must be changed. The non-recursive implementation would therefore be difficult to realize at real-time video rates.

Median Filtering

Median filtering (MEDN) is a non-linear processing technique designed for smoothing and noise reduction/suppression. The median

filtering process is defined as follows. For a given input image $F(n_1, n_2)$, a window of dimension $m \times n$ pixels (m, n are odd integers) scans the entire image matrix on a pixel-by-pixel basis. The central pixel lying within the window limits is replaced by the median value of all pixels within the window borders. The median will be that element whose value is larger than or equal to $\frac{(N \cdot M - 1)}{2}$ elements of the window and smaller than or equal to $\frac{(N \cdot M - 1)}{2}$ elements of the window. The resultant intensity $g(i, j)$ is equal to the median of the intensity levels of the pixels lying in the window centered at pixel (i, j) of the input image.

In the median algorithm of Figure 3.5, the running median is computed using a histogram binning method. For the computation of the next output pixel, the median window slides only one column over the input image. To get numbers in the next window from those in the previous window, the points from the new column are added and the points from the old column are deleted. The remaining pixel values are unchanged. A fast median algorithm was implemented to take advantage of this property by storing the intensity level histogram of the window elements and updating the histogram bin as the window slides across the input image. For $n \times n$ window sizes, $2n$ pixels must be resorted at each window relocation. Additional comparisons are required to identify the median of the sorted pixels.

Although the median filter is an effective mechanism for noise suppression, cases of signal suppression may also occur. The median filter will not affect step or ramp functions, but pulse functions whose period is less than one-half the window width will

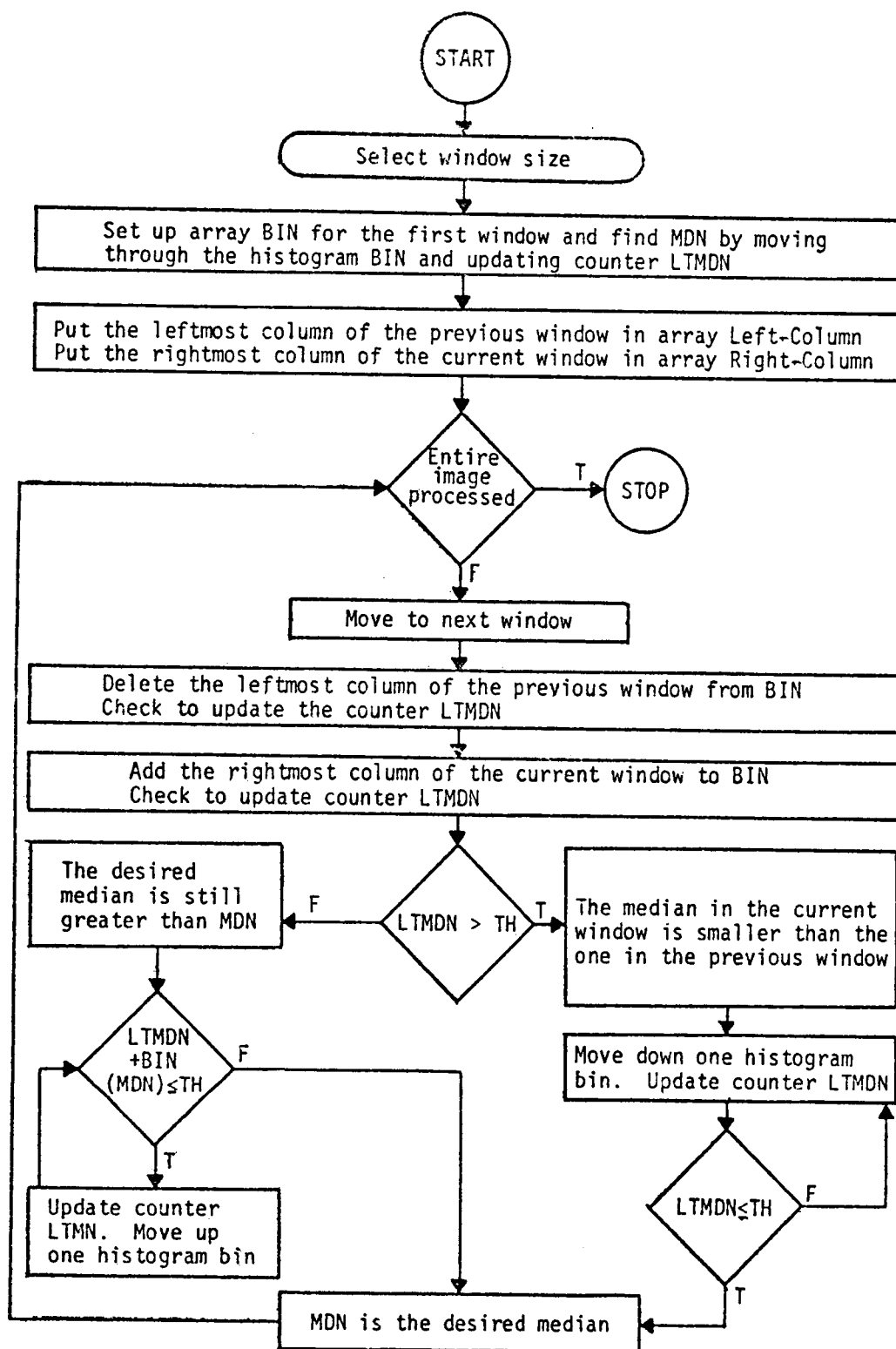


Figure 3.5. Logic flow diagram for MEDN.

be suppressed. Edge degradation is significantly less than that associated with low pass filters and related smoothing windows. The median filter is far more effective in reducing the effect of discrete impulse noise than smoothly generated noise, such as additive Gaussian noise. The tendency toward signal suppression can be somewhat mitigated by the sequential horizontal and vertical processing with a uni-dimensional median filter, but at the cost of some loss in noise suppression capability [10].

Several alternative real-time algorithms exist for computing the running median: selection network, radix, and histogram binning [11]. All methods can be used as exact or approximate estimators of the median, although the radix technique of determining the k^{th} bit of the median by inspecting the k most significant bits of the sample yields the closest approximation. The complexity of the hardware is dependent on the word size in all cases. Speed of selection network, a specialized application of the quicksort algorithm, is dependent on the window size. Speed for the radix is directly proportional to word size, while the histogram technique is exponentially proportional to word size. Hardware implementation as parallel, uni-dimensional filters allows single frame processing for real-time realization at video rates with only slightly degraded performance.

Adaptive Low Pass Filtering

Adaptive low pass filtering (ALPF) is basically a cosmetic process which tends to reduce the spurious effects of noise at the

expense of some image sharpness. Edges and other sharp transitions in the gray levels of an image, such as noise spikes, contribute greatly to the high frequency content of the Fourier spectrum. Image smoothing can thus be achieved in the frequency domain by attenuating a specified range of high frequency components in the transform of the image. The difficulty with smoothing using a non-adaptive linear low pass filter is, although the overall signal-to-noise ratio will typically improve by a factor directly proportional to the equivalent rectangular averaging window, the target edges will be blurred. In order to circumvent this undesirable side effect, adaptive variable width filters that are guided by the local curvature of the image object are used to detect target and other significant edges and to direct the degree of smoothing in each local area [12].

The local curvature directed adaptive low pass filter appears in Figure 3.6 and is mathematically formulated as follows. First, the simplifying assumption is made that when the digitized image is examined over some suitably small area, any edge can be described by the intensity,

$$f(i,j) = a + bx + cx^2 + dx^3, \quad (3-21)$$

where x is coterminous with the i -coordinate and is in the direction of the gradient. The smoothed intensity for an ideal rectangular filter is then defined as,

$$g(i,j) = \frac{1}{L^2} \sum_{m=-L/2}^{+L/2} \sum_{n=-L/2}^{+L/2} f(i+m,j+n), \quad (3-22)$$

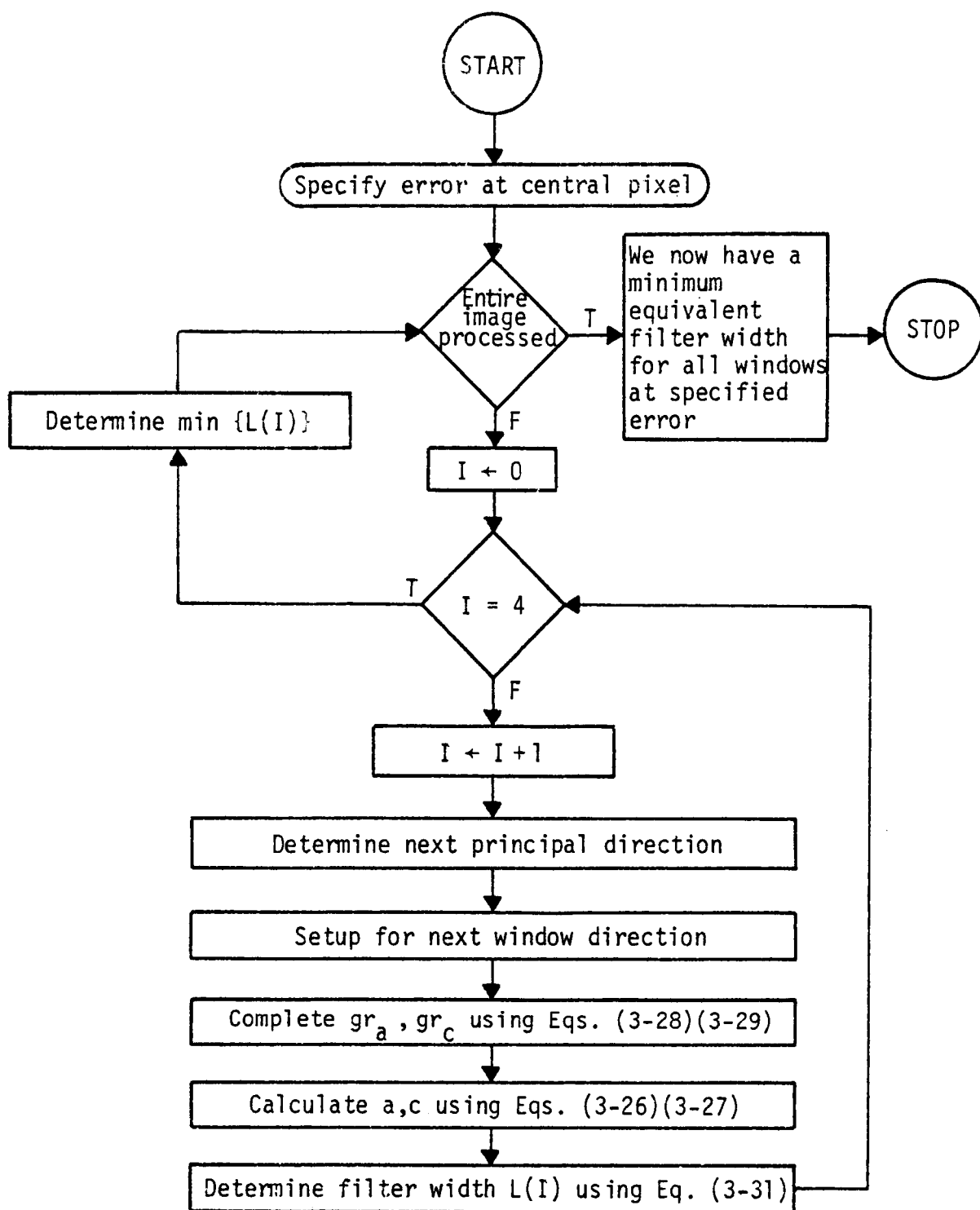


Figure 3.6. Logic flow diagram for ALPF.

or in terms of the gradient expansion,

$$g(i,j) = \left(a + c \frac{L^2}{12}\right) + \left(b + d \frac{L^2}{4}\right)x + cx^2 + dx^3. \quad (3-23)$$

If the restriction is made that,

$$\frac{L^2}{12} \left| \frac{c}{a} \right| \leq \epsilon, \quad (3-24)$$

then for a specified error of the smooth value at the central pixel of the window one obtains,

$$\frac{|g(i,j) - f(i,j)|}{|f(i,j)|} \leq \epsilon. \quad (3-25)$$

Hence, one observes that the smoothing error is not dependent upon the local gradient b , but rather on the local curvature c . Moreover, a criterion for selecting the smoothing window size to achieve a specific error has been established.

The equivalent rectangular filter width estimation proceeds as follows. Under the assumption that x is in one of the four principal directions (e.g., 0° , $\pm 45^\circ$, or 90°), least square error estimates of the coefficients a and c are computed at each pixel of the image. With a seven-pixel, uni-dimensional window one obtains,

$$a = \frac{(7gr_a - gr_c)}{21}, \quad (3-26)$$

and,

$$c = \frac{(gr_c - 4gr_a)}{84}. \quad (3-27)$$

The following definitions are employed for the determination of the above coefficients,

$$gr_a = \sum_{i=-3}^3 fr_i , \quad (3-28)$$

with,

$$gr_c = \sum_{i=1}^3 i^2 (fr_i + fr_{-i}) , \quad (3-29)$$

and finally,

$$fr_i = f(i + x\Delta i, j) . \quad (3-30)$$

Employment of the seven-pixel window offers the additional benefit of some noise smoothing in the filter width selection criterion.

Using the above information, the minimum equivalent filter width is determined as follows. The maximum filter width L for which,

$$L^2 \leq 12\epsilon \left| \frac{a}{c} \right| \quad (3-31)$$

is satisfied is found for each of the four principal directions for which a and c have been computed. The minimum of these four maximum filter values is then selected as the adaptive filter width at that particular pixel location.

The ALPF process is a linear smoothing filter adaptive to the curvature within a fixed window. It is designed to remove noise with less edge blurring than standard low pass filters. Parameter selection for the adaptive low pass filter involves the determination of the optimum value selected for the permissible error

parameter ϵ . Typically, it is adjusted so that maximal overall noise smoothing is achieved while the target edges are maintained. The resultant smoothing error is chosen empirically to reduce the S/N of the output image. Generally, a wide filter size is selected for a background scene and a narrow filter size is selected for a scene containing a target.

There are several approaches that may be pursued for the hardware implementation of adaptive smoothing filters and the determination of filter shape. Non-recursive filter structures can be constructed using a Gaussian filter approach. However, such filters are time consuming in simulation and expensive in hardware, requiring up to 10×10 pixel window convolution, although they do preserve the linear phase of the total transfer function. Second-order Butterworth recursive filters closely approximate the Gaussian filter response with a more compact hardware mechanization at real-time video rates [13].

Convolutional Windowing

Convolutional windowing (WNDW) involves the application of a related family of techniques to input imagery for the purpose of extracting frequency content information based on a luminance edge model. A two-dimensional luminance edge is characterized by its height, the slope angle and the orientation with respect to coordinate axes. The image may also be considered a linear combination of low and high frequency component signals. This distinction and separation of such component waveforms is a useful preliminary to

further edge or noise processing. Using digital filtering of high and low frequency components from the input image it is possible to pursue different quality goals utilizing related processing methodologies. Sliding window convolution is a flexible processing tool for noise cleaning or edge improvement. Smoothing or gradient detection operations are specified by selecting the appropriate convolutional window coefficient magnitudes and signs. In the spatial domain, convolution is given by,

$$g(i,j) = \sum_{k=-m}^m \sum_{\ell=-n}^n f(i+k,j+\ell) h(i,j) , \quad (3-32)$$

where $h(i,j)$ is the convolutional window matrix which slides across image $F(i,j)$. In the frequency domain, the convolution corresponds to,

$$G(\eta,\xi) = F(\eta,\xi)H(\eta,\xi) , \quad (3-33)$$

where $H(\eta,\xi)$ is the transfer function. Contained in Figure 3.7 is the logic flow diagram for the convolutional windowing algorithm.

The smoothing (SMTH) of the input image for the purpose of noise removal makes use of the convolutional window method in several manners. The neighborhood averaging method is adapted from convolutional windowing as follows,

$$g(i,j) = \frac{1}{M \cdot N} \sum_{k=-m}^m \sum_{\ell=-n}^n f(i,j) , \quad (3-34)$$

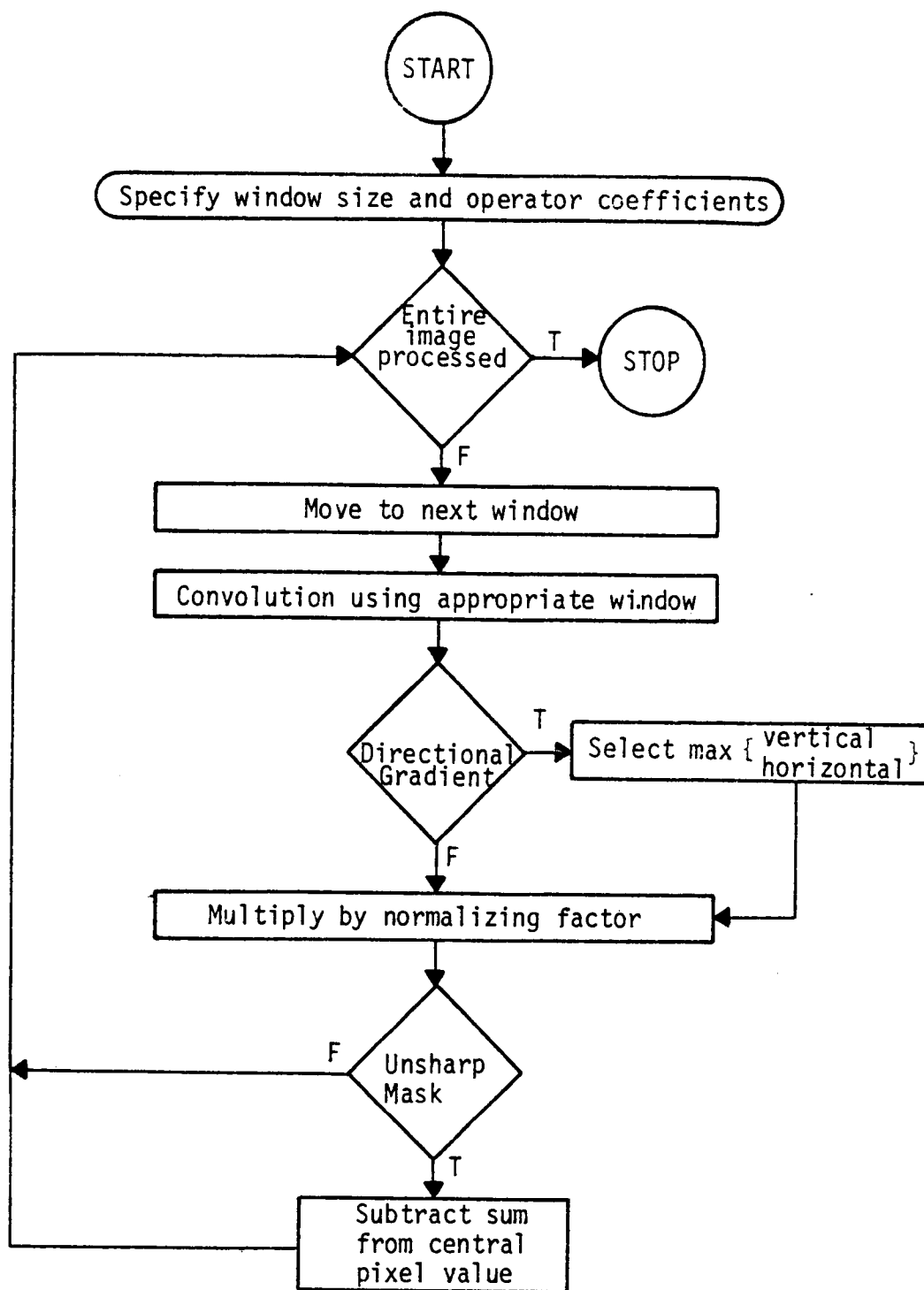


Figure 3.7. Logic flow diagram for WNDW.

with,

$$h(m,n) = \frac{1}{M \cdot N} \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}, \quad (3-35)$$

and typically, $M = N = 2m + 1 = 2n + 1$, where usually $m = n = 1$ or 2 . Note that for all following examples of $h(m,n)$, $m = n = 1$ has been set. Low pass filter transfer functions with zero-phase shift characteristics are used extensively to smooth images. Butterworth, exponential, trapezoidal, and ideal circular shaped low pass filters are extended into the spatial domain through the use of low pass convolutional arrays. One non-linear approach to edge variation smoothing is the replacement of the central pixel by the local mean within the convolutional window if the absolute difference between the mean and the central pixel value exceeds a specified threshold error.

The differential approximation of the input image for the purpose of edge sharpening (SHRP) also makes use of the convolutional windowing technique. The digital gradient approximation to the directional derivative estimates values for the magnitude and the directional orientation of the edge. Additionally, high pass frequency resolution emphasis filters also serve as effective mechanisms for the location of edge boundaries.

The technique of unsharp masking is simply the replacement of the central pixel value by the difference between the central pixel value of the window and the local mean within the window. With this technique the phenomenon of filter ringing is occasionally

observed, whereby edges are marked by alternating dark and light bands. If the masking is mathematically formulated in terms of convolution, one obtains,

$$g(i,j) = \sum_{m=-1}^1 \sum_{n=-1}^1 f(i+m, j+n) h(m,n) , \quad (3-36)$$

where,

$$h(m,n) = \begin{pmatrix} -\frac{1}{8} & -\frac{1}{8} & -\frac{1}{8} \\ -\frac{1}{8} & +\frac{7}{8} & -\frac{1}{8} \\ -\frac{1}{8} & -\frac{1}{8} & -\frac{1}{8} \end{pmatrix} . \quad (3-37)$$

The difference approximation of the gradient for edge crispening is the approximation of,

$$\nabla f(i,j) = i \frac{\partial}{\partial x} f + j \frac{\partial}{\partial y} f , \quad (3-38)$$

where the magnitude is approximated by,

$$|\nabla f(i,j)| = [(\frac{\partial}{\partial x} f)^2 + (\frac{\partial}{\partial y} f)^2]^{1/2} , \quad (3-39)$$

and the directional orientation is indicated by,

$$\theta = \tan^{-1} \left[\frac{\frac{\partial}{\partial x} f}{\frac{\partial}{\partial y} f} \right] . \quad (3-40)$$

Isotropically, or rotationally invariant, operators are the ideal gradient processors. Laplacian or symmetric convolutional windows are defined as,

$$h(m,n) = \begin{pmatrix} c & b & c \\ b & a & b \\ c & b & c \end{pmatrix}, \quad (3-41)$$

where typically the coefficients are set as $a + 4b = -4c$.

Directionally oriented windows include compass masking, statistical differencing, and Gaussian weighting. Sobel [14] and Prewitt [15] directional masks are defined as,

$$P_h(m,n) = \begin{pmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{pmatrix}, \quad (3-42)$$

with,

$$P_v(m,n) = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{pmatrix}, \quad (3-43)$$

and,

$$S_h(m,n) = \begin{pmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{pmatrix}, \quad (3-44)$$

with,

$$S_v(m,n) = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}. \quad (3-45)$$

Directionally oriented windowing involves multiple convolutions which detect gradients along the principle directions and then select the largest gradient value from all directions. For the bi-directional (horizontal and vertical) Prewitt and Sobel windows, the larger of the horizontal and vertical gradient convolution

values was selected for the output image value. Such high frequency band pass filters as the Butterworth, exponential, trapezoidal, and the circular ideal shaped filters are constructed in terms of equivalent spatial convolutional windowing.

The WNDW process is a linear local area system which produces image smoothing or image sharpening depending on the selection of window coefficient magnitude and signs. The resultant images have either low frequency (SMTH) or high frequency (SHRP) emphasis. Typically, smoothing results in increased S/N, while sharpening promotes improved contrast. Hardware implementation can be either digital or analog. Both implementations would be inexpensive add-ons to existing systems. Real-time operation is realizable with a digital implementation, and analog implementation involves only simple delay lines and amplifiers.

Edge Thresholding

Edge selection (EDGE) typically follows gradient emphasis. This allows more accurate edge identification than with simple high frequency emphasis. The EDGE processor is illustrated in Figure 3.8. Given an input image $F(n_1, n_2)$, each pixel intensity level $f(i, j)$ is compared to a specified threshold Th , and $g(i, j)$ is set to zero if $f(i, j)$ is less than Th , or $g(i, j)$ is set to the maximum intensity level if $f(i, j)$ is greater than or equal to Th . The threshold value may be specified based on global image statistics or local area statistics. Likewise, threshold selection may be based on percentile or modal distribution considerations. The threshold is formulated as,

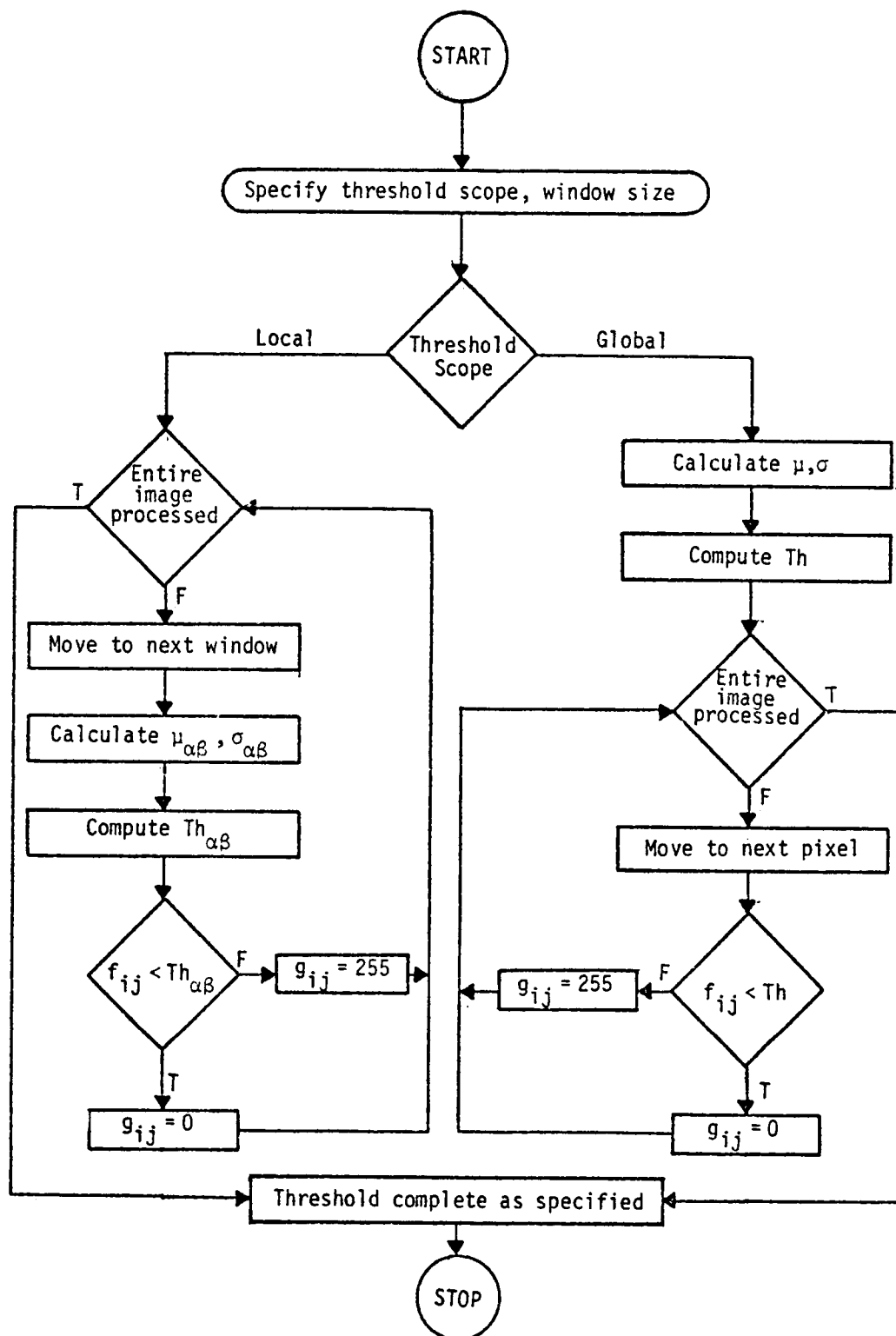


Figure 3.8. Logic flow diagram for EDGE.

$$Th = \mu + k\sigma , \quad (3-46)$$

where k is a parameter which controls the effect of the standard deviation on the threshold. The setting for k is usually in the range $-3.0 < k < +3.0$ assuming a roughly Gaussian distribution model of input image intensity level.

The EDGE processor is a non-linear system intended as a follow-up step to gradient image detection and produces a binary edge map. The selection of the threshold is made using either global image or local window statistics. Thresholding may considerably reduce scene information content. Varying threshold settings may produce strikingly different results; a target may be masked out entirely or certain backgrounds may produce worse scene clutter. Typically, however, scene clutter is reduced and S/N is improved. Generally, global thresholding will pass only the strong gradients, suppressing the weak gradients that adaptive threshold selection would pass. Edge detection thresholding is readily implemented in hardware. It is a simple add-on/follow-up step to gradient processing. Both digital and analog realizations would be inexpensive add-ons.

Processor Combinations

Multiple processor combinations were developed under the following guidelines. It is desirable to attempt to incorporate as many positive performance characteristics as possible while minimizing the number of image degrading processor characteristics. Combining

processors which have similar performance results would be redundant and should not be implemented. Likewise, combining processors with contradictory effects would be counterproductive and should not be implemented.

Overlay combinations involve the merging of the input image and the gradient or edge processed image. It is desired that an output image which utilizes the full dynamic range of the display device intensity levels be produced. One procedure simply adds the two images and rescales the sum as shown in Figure 3.9. The difficulty here is that the rescaling is biased by large gradient values. Therefore, the result is a dark original with bright edges. Alternatively, the two images may be compared and only the larger value for each pixel passed. This effectively maintains the intensity level of pixels in the original image but replaces pixels where strong gradients occur, as shown in Figure 3.10.

Simulation modeling of serially combined processors was implemented as shown in Figure 3.11. Typically, only two or three processors were run in cascade. The output image was rescaled to correspond to the original image dynamic range after each process.

Simulation modeling of parallel combination processors was implemented as shown in Figure 3.12. Typically, only two or three processors were run in parallel. The output images were rescaled to the dynamic range of the original prior to combination. The weighting factors used in the three-processor case were $(a + b + c = 1)$ and in the two-processor case were $(a + b = 1, c = 0)$.

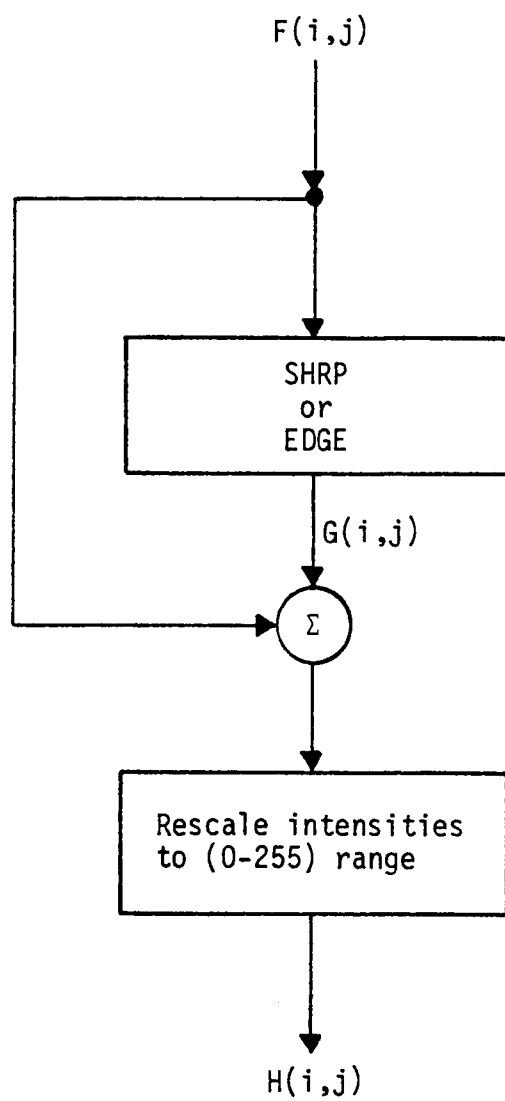


Figure 3.9. Rescale sum overlay.

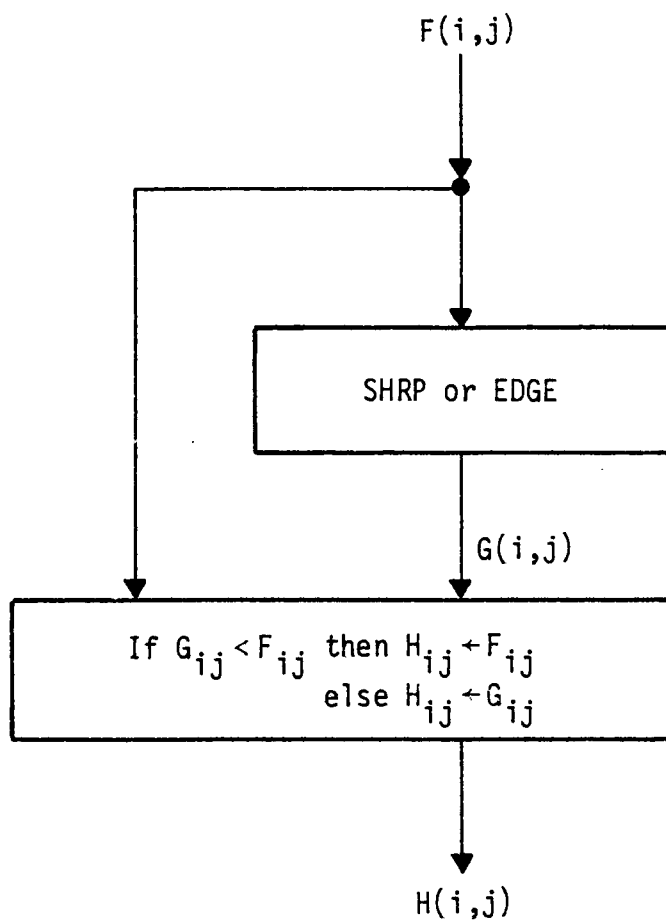


Figure 3.10. Edge replacement overlay.

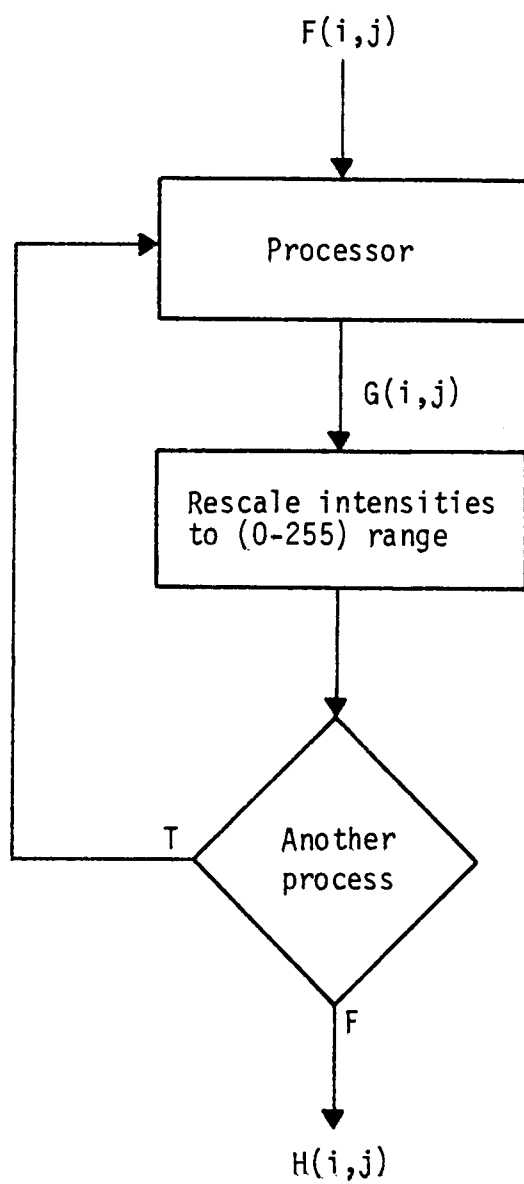


Figure 3.11. Serial combination.

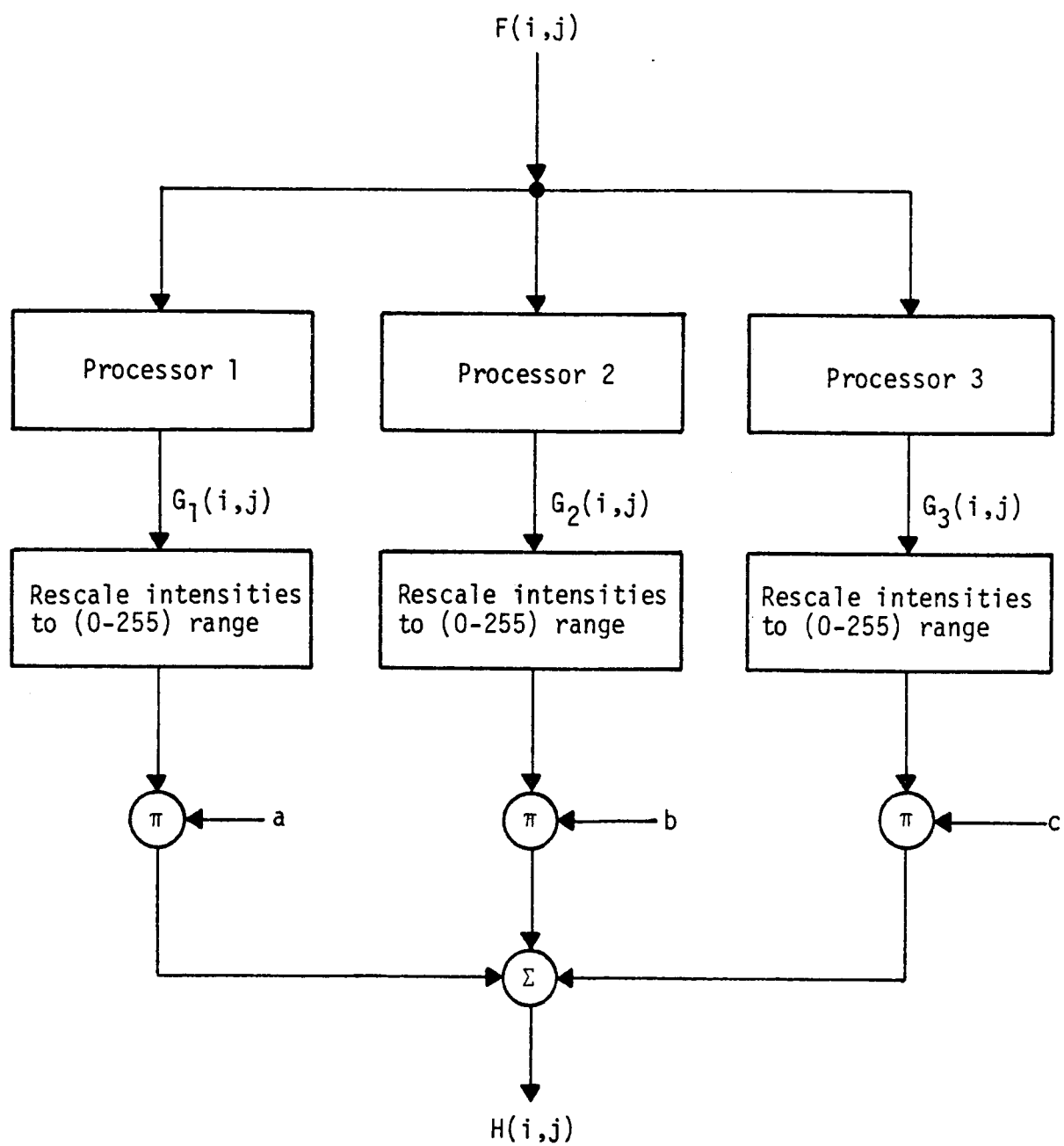


Figure 3.12. Parallel combination.

CHAPTER IV

RESULTS OF DIGITAL SIMULATION

Simulation Survey

A representative range of individual, serial, parallel, and overlay processing techniques was mathematically simulated and applied to typical electro-optical imagery. Simulation modeling of candidate processors proceeded in three stages. These three phases encompassed the initial analysis of algorithms, the preliminary small-scale simulation of candidate processors, and the final full-scale production simulation of processors. The simulation procedure steps from input of real-time imagery to display of simulation imagery are given in Figure 4.1.

The real-time imagery was decoded from magnetic tape and stored on-line on hard disk packs. Selected sub-image scenes were extracted from the full-frame images. Both the images and sub-images were characterized statistically, their quality recorded in terms of the quantitative evaluation measures described previously, and print plotted along with their corresponding Fourier transforms. After being subjected to processing, the images were again characterized and then compared both subjectively and quantitatively with the unprocessed images. Processed sub-images were reinserted into the full-frame images to provide ready comparison between the original and the processed results. The resultant imagery was recorded on magnetic tape in a format compatible with the MICOM video format display system.

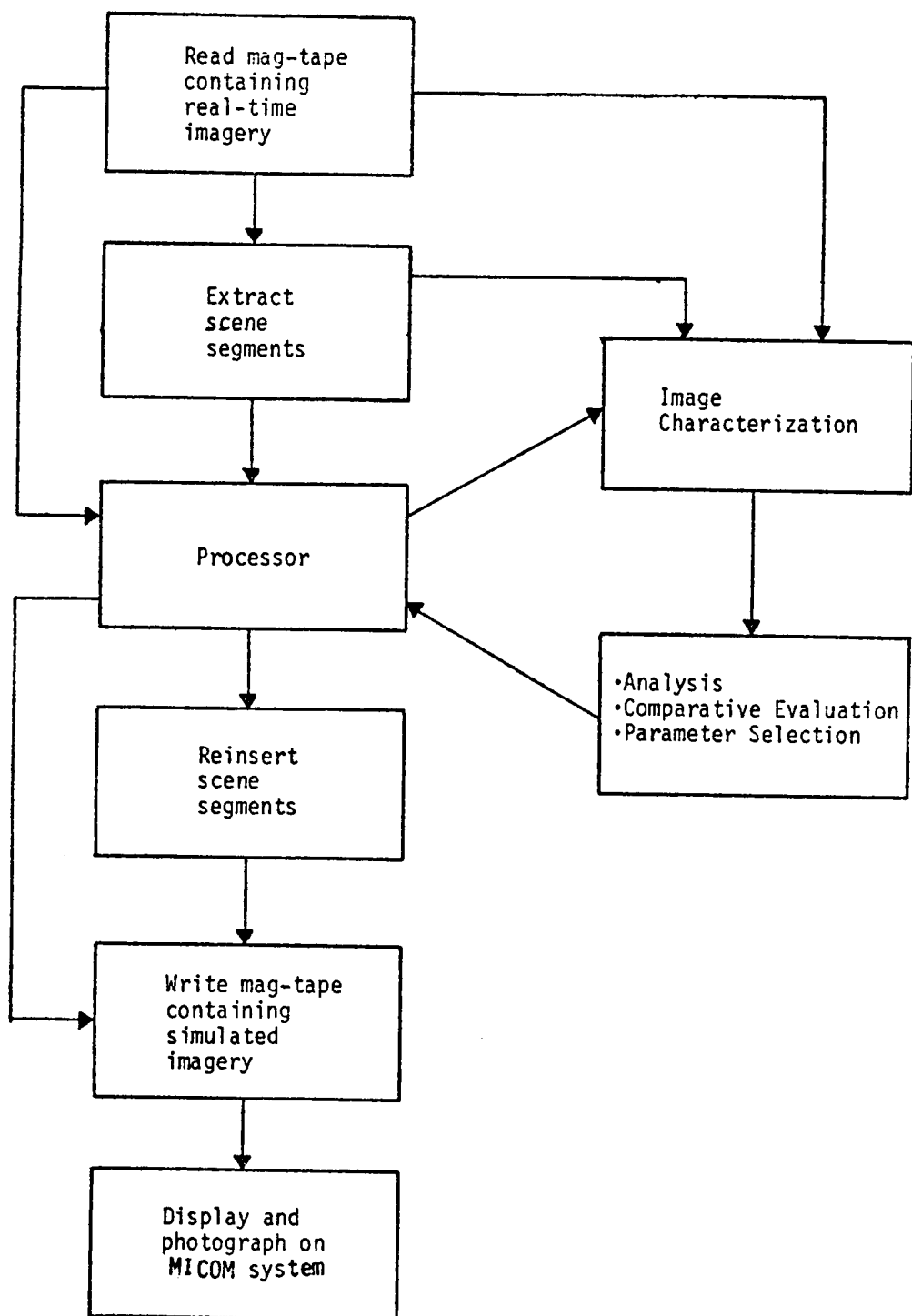


Figure 4.1. Simulation procedure.

Initially, concurrent with the analytic evaluation of the candidate algorithms, three primary processor categories were established and candidate processors were grouped as follows: noise reduction (MEDN, ALPF, SMTH), contrast improvement (LAGC, HIST, SHRP), clutter reduction (EDGE). The reduction of clutter as a result of EDGE processing entails reduced information content available from the processed image to that of the unprocessed image. The second phase consisted of preliminary simulation of processors conducted on smaller scene segments which were extracted from the real-time imagery. Complete characterizations were recorded with minimal processing costs and the more promising candidates were identified for further processing. The final phase consisted of full-scale production tests conducted on the total imagery utilizing the most promising candidates. Complete characterization was recorded of the imagery and tuning of parametric settings for optimal results was performed.

Candidate processors were modified and parametric settings adjusted to reflect the results of simulation testing. A number of preliminary iterations for the processors were designed to evaluate the effect of parameters and combinations of processors. A grand total of more than two hundred processing method steps were simulated and the results were encoded on digital magnetic tape. The following is a list of real-time simulation input imagery:

1. POS B TADS TV WFOV TGT2

(407 x 392 pixels video image).

2. POS B TADS FLIR WFOV TGT2
(407 x 392 pixels FLIR image, white hot).
3. POS D TADS TV WFOV TGT2
(407 x 392 pixels video image).
4. POS D TADS FLIR NFOV TGT2
(407 x 392 pixels FLIR image, white hot).
5. Sub-scene segments from Image 1
(64 x 64 pixels video segments).
 - a. Tree background.
 - b. Field background.
 - c. Target in tree background.
 - d. Target in field background.
 - e. Target in tree/field background.
 - f. Targetboard in tree/field background.

Initial processing was performed on 64 x 64 pixel sub-images extracted from silicon vidicon imagery. Six segments were selected as representative of various scene content with anticipated target/background conditions. Processing was later applied to entire full-frame images from video and FLIR sensors.

Representative simulation results are included to illustrate intra-processor parametric effects and to provide inter-processor comparisons. Tabulations of statistical characterization and quantitative evaluation measures for representative simulation results are reproduced in Appendix A. The first four central moments and the four quantitative figures of merit (e.g., contrast, resolution, signal-to-noise ratio, and signal-to-clutter ratio) are included.

Simulation results are reproduced in pictorial form in Appendix B. The photographs of simulation results were taken of images displayed on the MICOM system. To ensure equal gain and contrast settings of the display system, all photographs were taken during a single session with few exceptions. Although some image quality is lost in the photographic process, relative comparisons can still be performed. Figure B.1 (Appendix B)¹ contains the full-frame unprocessed images and sub-images listed on pages 59 and 60.

Individual Processors

Noise reduction algorithms examined included median filtering, adaptive low pass filtering, and smoothing window averaging. Figure B.2 illustrates the comparative results of median filtering and sliding window averaging techniques applied to sub-image segments from Figure B.1 (a). In Figure B.2, (a) and (b) are median filtered, while (c) and (d) are smoothed. Furthermore, (a) and (c) use a 3 x 3 pixel window, whereas (b) and (d) use a 5 x 5 pixel window. As anticipated from preliminary analysis, blurring is more prominent with the smoothing window technique. This effect is demonstrated more completely in Figure B.3 wherein 5 x 5 pixel window median methods (a) and (b) and smoothing methods (c) and (d) were applied to full-frame images (a) and (b) from Figure B.1. Figure B.3 (e) and (f) illustrate the 5 x 5 pixel median processor applied to full-frame images (c) and (d) from Figure B.1.

¹All figures with numbers preceded by the letter "B" are presented in Appendix B.

Significant blurring was observed with both 3×3 and 5×5 pixel window sizes for the smoothing window averaging technique. Since the smallest practical window size is 3×3 pixels, it was anticipated that the adaptive window would not give substantially different results, because the processor would attempt to minimize blurring by always selecting the smallest window size. The maximum values for the adaptive equivalent rectangular filter width were computed for selected allowable errors of 0.01, 0.05, and 0.1 percent. The values for the filter width were often equal to one and always less than three, apart from a few isolated pixels. This indicates that the ALPF would generally elect as the equivalent rectangular filter size the minimum practical smoothing window size of 3×3 pixels. Hence, any averaging window applied to the imagery would degrade image quality and therefore, the median filtering window was used for subsequent noise reduction processing.

Contrast improvement techniques explored included histogram equalization, histogram hyperbolization, and local area gain control. Histogram equalization and histogram modification are illustrated in Figure B.4 (a) and (b). These sub-image results indicate that globally applied histogram modification does not produce clearly desirable results. Further simulations confirmed this subjective evaluation based on the relative ease of identifying known target objects in the scene. Figure B.4 (c) is a 3×3 pixel window LAGC filter applied to sub-image segments and (d) is a 5×5 pixel window LAGC filter applied to the same sub-scene segments. Figure B.4 (e), is a 5×5 pixel window LAGC filter applied to image (b) from

Figure B.1. Figure B.4 (f) is a 5 x 5 pixel window LAGC filter applied to image (b) from Figure B.1. The gain factor for the LAGC for these simulations was selected as $G_{\alpha\beta} = 1/\sigma_{\alpha\beta}$, which does enhance image detail. However, high frequency noise is also generated which gives the image a grainy texture. This effect is further demonstrated in Figure B.5 (a) and (b) with 3 x 3 pixel window filtering of images (a) and (b) from Figure B.1. Figure B.5 (c) and (d) demonstrate that increasing the sliding window size to 15 x 15 produced the expected result of greatest contrast improvement for object sizes most nearly equal to the window size. The resulting images still exhibit the disturbing textural graininess.

An alternative gain factor of $G_{\alpha\beta} = \mu_{\alpha\beta}/\sigma_{\alpha\beta}$ was selected for LAGC filtering. Results are illustrated in Figure B.6 using a 5 x 5 pixel window for (a) and (b) and a 15 x 15 pixel window for (c) and (d) applied to images (c) and (d) from Figure B.1. The smaller sliding window provides some measure of contrast improvement without the confusing textural graininess observed with the alternative gain term definition. However, this gain term definition is much more sensitive to sliding window dimension, as revealed by the excessive blurring for the larger window size.

The various gradient processors examined included the Prewitt, Sobel, and unsharp mask operators. The results of gradient processors applied to sub-image segments are illustrated in Figure B.7, where (a) is a 3 x 3 Prewitt window, (b) is a 3 x 3 Sobel window, (c) is a 3 x 3 unsharp mask window, and (d) is a 5 x 5 unsharp mask window. Steep gradients are equally well detected by

all methods. Further results are provided for 3×3 Prewitt and unsharp mask applied to images (a) and (b) from Figure B.1 in Figure B.8, and to images (c) and (d) from Figure B.1 in Figure B.9, respectively. These gradient images are useful in identifying and locating objects or for image registration. However, without further processing they are not effective in identifying obscured, low-contrast target objects.

One approach to emphasizing edges is to apply a selected threshold to the gradient image and represent all edges above the threshold by a single brightness level. The threshold is typically selected based on image statistics and chosen in terms of either edge point percentiles or the mean and standard deviation. Results of edge detection with a global mean threshold are provided in Figure B.10 with a 3×3 pixel window where (a) is a Prewitt operator and (b) is a Sobel operator. As with their corresponding gradients, sharp edges are detected easily but weaker edges are missed.

An alternative approach for detecting low-contrast edges is to choose a threshold which is locally adaptive and based on statistics within some specified window about each pixel. Results from this local edge detection using the local mean value from a 3×3 pixel window as a threshold is given in Figure B.10, where (c) is a Prewitt operator and (d) is a Sobel operator. This technique produced a number of edge points equal to nearly 50 percent of the total number of pixels, as would be expected from selecting the local mean of a 3×3 sliding window as a threshold. Low-contrast

edges were identified, although they were obscured by noisy edge points.

Simulations were performed with varying thresholds and window dimensions for threshold statistics to investigate the local edge detection approach further. Figure B.11 illustrates the result of varying the threshold in a 3 x 3 pixel window for Figure B.1 (c) and (d). Thresholds were selected as $T_{\alpha\beta} = \mu_{\alpha\beta} + 0.5\sigma_{\alpha\beta}$ for (a) and (b), $T_{\alpha\beta} = \mu_{\alpha\beta} + \sigma_{\alpha\beta}$ for (c) and (d), and $T_{\alpha\beta} = \mu_{\alpha\beta} + 2.0\sigma_{\alpha\beta}$ for (e) and (f). Increasing the threshold does reduce the number of noise edge points. However, the valid edge points whose intensity level is less than the threshold value will also be filtered out. Hence, simply increasing the threshold selection value will not produce improved results. Figures B.12 and B.13 illustrate the effect of variations of window size on statistical computation of different thresholds for Figure B.1 (c) and (d), respectively. In both figures, the parameters are 7 x 7 windows with (a) $T_{\alpha\beta} = \mu_{\alpha\beta}$, (c) $T_{\alpha\beta} = \mu_{\alpha\beta} + 0.5\sigma_{\alpha\beta}$, and (e) $T_{\alpha\beta} = \mu_{\alpha\beta} + \sigma_{\alpha\beta}$, and also 15 x 15 windows with (b) $T_{\alpha\beta} = \mu_{\alpha\beta}$, (d) $T_{\alpha\beta} = \mu_{\alpha\beta} + 0.5\sigma_{\alpha\beta}$, and (f) $T_{\alpha\beta} = \mu_{\alpha\beta} + \sigma_{\alpha\beta}$. Comparison of these figures with previous figures indicates that improved results are obtained using larger window sizes for the threshold selection calculations.

Combined Processors

Overlay, cascade, and parallel combinations of processors were investigated in an effort to improve performance in more than one quality measure (e.g., reduce noise, enhance contrast, and

improve resolution). The guiding rationale for various serial and parallel processor combinations was that processors which produce similar effects would be redundant if combined, and processors which produce opposite effects would be incompatible if combined.

It was anticipated that a potentially optimum edge output display would result from a combined original scene with edge or gradient images superimposed. Figure B.14 illustrates image (a) and sub-images (e) from Figure B.1 with Prewitt and Sobel operator gradient processed images added. In this figure, the images were summed on a pixel-by-pixel basis and then rescaled to fit within the display limits (0 to 255). Unfortunately, the original image gray levels were suppressed due to the much larger gradient values which biased the resultant image by setting the largest gradient value to the maximum display limit. This effect was corrected by using an edge replacement approach rather than simply summing the images. Figure B.15 demonstrates the edge replacement using the Prewitt local thresholded operator of $T_{\alpha\beta} = \mu_{\alpha\beta} + \sigma_{\alpha\beta}$ applied to images (c) and (d) from Figure B.1 with a window size of 3×3 for (a) and (b), a window size of 7×7 for (c) and (d), and a window size of 15×15 for (e) and (f).

A variety of serial combinations was considered. It was determined that the gross errors introduced by one method were generally carried over through subsequent processing steps. Examples of results from serial processors are provided in Figure B.16 with 5×5 windows, where (a) is LAGC followed by median filtering,

(b) is smoothing window followed by histogram equalization, and (c) and (d) are median filtering followed by LAGC.

Parallel combinations of selected processors appeared to result in better images. The selected processors were first applied individually to the original image. The resultant images were multiplied by a weighting factor applied to each pixel. The weighted images were then added together on a pixel-by-pixel basis. By this means, the parallel combination image is normalized to exactly the same intensity range as the original image. Examples are provided for image (a) from Figure B.1 in Figure B.17 of 5 x 5 windows with the weighting factors given in parentheses: (a) median filtering (1/3) with LAGC (1/3) with Prewitt gradient operator (1/3), (c) median filtering (1/4) with LAGC (3/4), with (e) median filtering (3/4) with LAGC (1/4). Figure B.17 also shows 5 x 5 windows for image (b) from Figure B.1 with the weighting factors given in parentheses: (b) median filtering (1/3) with LAGC (1/3) with Prewitt gradient operator (1/3), (d) median filtering (1/4) with LAGC (3/4), and (f) median filtering (3/4) with LAGC (1/4).

CHAPTER V

SUMMARY AND CONCLUSIONS

Result Comparisons

A comparison of results acquired from the simulation modeling of processor performance experiments can most effectively be presented in terms of the related effects upon the established processor performance categories. Experimental results generally tended to correlate well with the anticipated results predicted by way of previous efforts and preliminary analysis of processor performance. Processors were identified by means of experimental verification for optimal performance in the areas of noise reduction, contrast improvement, and clutter reduction. Furthermore, an effective configuration for the combination of processors was determined experimentally.

Of the noise reduction methods examined, the median filter approach offered the most improvement without significant image degradation. Investigation of the adaptive low pass filter revealed that a small specified filter error could only be maintained by restricting the smoothing window to the smallest practical size (3×3 pixels). This seriously limited the effectiveness of the adaptive filter as a smoothing technique, since resolution tended to degrade rapidly with increasing window size. The sliding convolutional window approach had less serious problems, although notable blurring of detail did arise with larger window sizes. The median filter was investigated with several different window sizes with

little variance of image quality observable. However, the larger window sizes did produce noticeably smoother images.

Of the contrast improvement techniques investigated, the local area gain control method showed the most effective performance. The histogram modification techniques as implemented did not improve contrast in such a manner as to enhance the extraction of small targets from background clutter. Both the equalization and hyperbolization techniques were applied under a global approach, and hence effectively enhanced the signatures only of the larger targets. The LAGC approach was quite effective in improving contrast, particularly for objects whose dimensions closely approximated those of the filter window. Simulation experiments with large window sizes (15 x 15 pixels) revealed a significant blurring of image detail for objects of less than window size. Experiments using a gain term of $G_{\alpha\beta} = 1/\sigma_{\alpha\beta}$ resulted in a problem of increased high frequency noise due to the non-linear processing effects and produced a confusingly cluttered scene. This problem was circumvented by using a gain term of $G_{\alpha\beta} = \mu_{\alpha\beta}/\sigma_{\alpha\beta}$, which greatly reduces the high frequency noise graininess and substantially improves contrast.

Of the clutter reduction techniques explored, local threshold edge detection showed greatest promise in improving the signatures for targets with weak edges. All gradient processors located strong edges easily. Little variance was observed between results from the Prewitt and the Sobel gradient operators. Gradient images are useful in identifying relatively distinct objects, but provided few cues in the detection of obscured, low-contrast targets without further

processing. Threshold edge detection does produce better target cues. Although global thresholding readily located strong gradients, unfortunately, weak gradients tended to be masked out. Local thresholding counteracted this tendency but introduced excessively noisy edges. Increasing the threshold value reduced noisy edge points, but also eliminated valid edge points.

Multiple combinations of processors were examined in an effort to accomplish more than one quality parameter improvement. Multiple processor combinations were developed under the guidelines that combining processors which have similar effects would be redundant and combining processors with contradictory effects would be counterproductive. A variety of serial combinations were investigated and generally produced results where gross errors of all processing steps tended to accumulate, so that the order of processing was, in many cases, significant. Parallel combinations produced less effective results, but without the problem of error aggregation, as with cascade processing. Additionally, the implementation of overlay combinations produced superior results when used in conjunction with the edge replacement approach. The most effective processor combinations and their optimal parameter settings are indicated by the results of the simulation modeling experiments.

Processor Recommendations

Based on the evidence collected from the simulation modeling experiments, a processor design is recommended as an effective filter for anticipated operational contexts. The final design incorporates elements from all three processor performance groups arranged so as to provide the operator with the maximum control flexibility. The following processor option recommended for implementation into a target acquisition/handoff system exhibits the widest possible range for operator selection of processor mixing and parametric setting. Figure 5.1 represents in block diagram format the proposed processor configuration.

The input image video signal will first pass through a median filter. This will reduce noise with minimum blurring of edges. The sliding window size will be operator selectable for subjective optimization of performance. The signal will then be split and routed to other processing components.

One of the additional processing elements is the local area gain control filter. The local gain term is computed as the ratio of the local mean to the local standard deviation. This will effectively improve the local contrast while suppressing the generation of high frequency clutter. As with the median filter, the sliding window dimension is operator selectable and generally will be precisely the same for all sliding window processors.

Another of the processing elements is the gradient processor. This is also a local sliding window process whose size

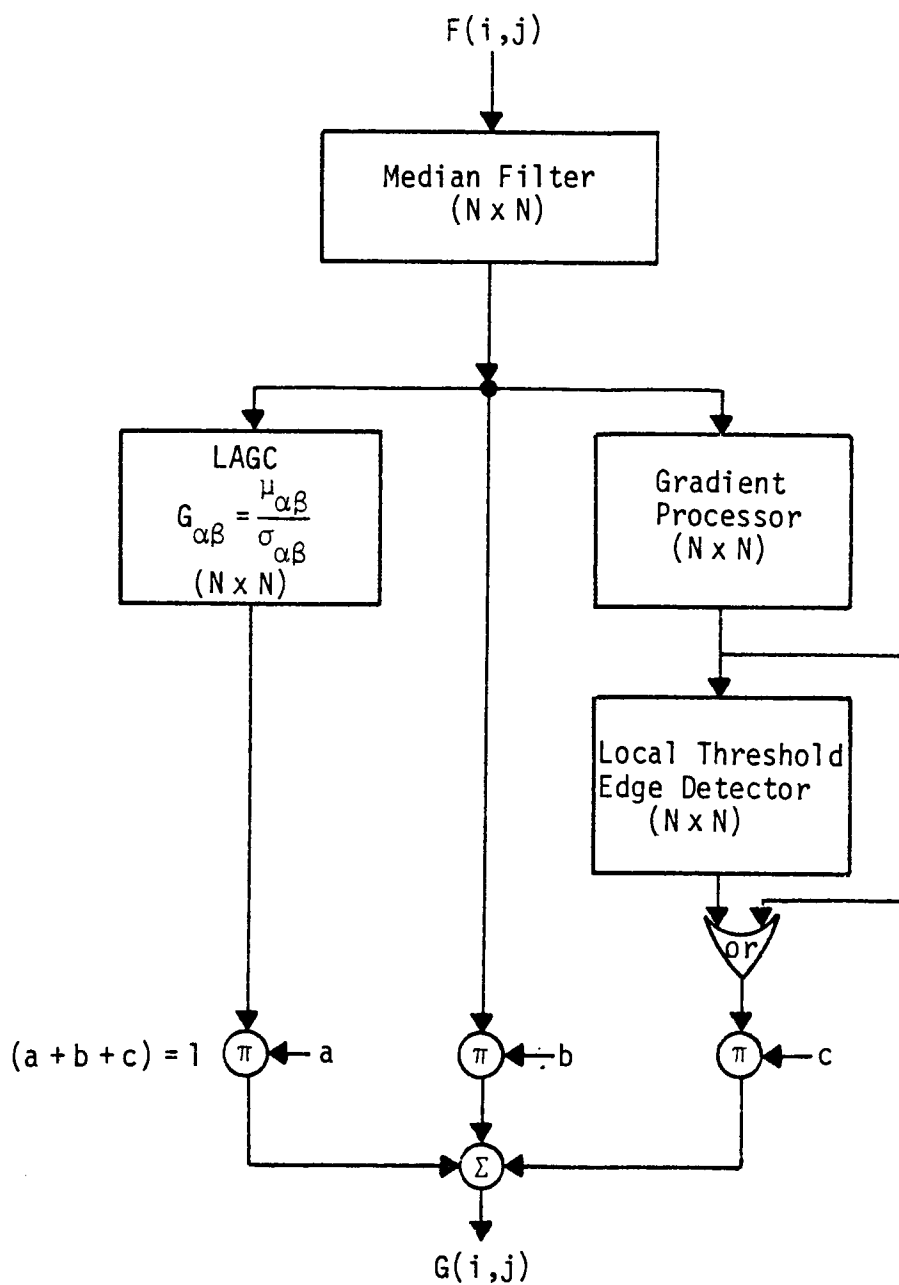


Figure 5.1. Recommended processor configuration.

is operator selectable. This will reduce scene clutter and initiate the process of boundary identification. The output signal is split and sent to additional processing elements.

Local threshold edge detection completes the process of locating distinct region signatures contained in the imagery. The window size of this operator corresponds to the other window sizes and is also operator adjustable.

The human operator may then elect to incorporate the gradient output or the edge detector output on the display console. The output of the median filter, the local area gain control filter, and the gradient/edge filter will then be combined in a parallel configuration such that the weighting of the various processors is operator adjustable. The weighting coefficients allow the operator to select for output display any processed image above or in any combination with other images.

This processor configuration exhibits two important operator adjustable options: processor mixing and parametric selection. In addition, the design specifically inhibits the accumulation of processing errors from one component to the next. Since scene content will vary within the prescribed limits of the scenario context, it is desirable that the processor be subjectively optimized by settings under operator control. The proposed design satisfies this condition.

Proposals

As a result of detailed investigation, several broad conclusions are inferred. Furthermore, suggestions for the application of results to areas of interest are made. In addition, proposals for the guidance of further research in related directions are made.

Image enhancement techniques, although applied successfully to many problems, suffer from the lack of a proven model for the human visual system. This hinders an analytical evaluation of image quality and processor performance. Moreover, analytical treatment is hampered by the non-linearity of almost all processing systems which produce subjectively useful results.

Although this research was oriented primarily toward target acquisition systems for airborne fire control, results are generally applicable to any real-time video display format imaging system. The recommended processor will be particularly effective as a front-end preprocessor for digital image change or motion detection. The processor is best applied to man-in-the-loop environments, but can be applied as a front-end processor for automated vehicle guidance systems or automated vision for industrial inspection.

Three avenues of further investigation can be proposed as direct consequences of the current effort. Local area processors produced results which were generally superior to those of global processors. Local area histogram modification should be pursued as a potentially effective real-time mechanism for contrast enhancement. Threshold edge detection proved to be one of the most effective

means of improving target signature. Although currently proposed algorithms are not realizable in real-time, the application of edge thinning or edge connection algorithms could potentially improve edge detection results. Additionally, further investigation involving the real-time optimization of operator selectable controls of the proposed processor configuration in the context of autonomous acquisition systems would doubtless prove a fertile field of research.

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APPENDICES

APPENDIX A

SIMULATION RESULTS--QUANTITATIVE CHARACTERIZATIONS

This appendix contains simulation results obtained as quantitative characterizations of the imagery (Tables A.1 through A.9).

Table A.1. Unprocessed Images

Fig.	Image	Statistics					R_{λ}	C_p
		Mean	Std	Skew	Kurtosis	SNR	SCR	
B.1	(a) B-TV (total)	206.4	57.2	-2.6	9.5	4.99	5.02	6 0.74
	(b) B-FLIR (total)	98.8	38.8	0.23	2.64	5.25	4.37	5 0.76
	(c) D-TV (total)	190.0	48.1	-1.97	8.61	5.02	4.96	6 0.75
	(d) D-FLIR (total)	55.5	37.1	1.78	9.90	5.30	4.31	5 0.75
	(e) B-TV (segments)							
	Target/Field	200.6	22.4	-2.2	9.7	4.8	5.99	7 0.72
	Target/Trees	190.8	25.3	-0.29	3.25	5.34	4.14	4 0.78
	Target/Field Trees	195.5	27.8	-0.48	2.64	5.98	4.17	4 0.79
	Tree Background	207.9	25.5	0.174	1.83	---	---	3 ---
	Field Background	237.9	7.37	8.0E-2	2.53	---	---	22 ---
	Large Target Board	180.1	53.8	-0.668	2.58	11.1	3.38	8 0.89

Table A.2. Processed Images--Noise Cleaned

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p
			Std	Skew	Kurtosis				
B.2	B-TV (segments)								
	(a) Median (3x3)								
	Target/Field	197.1	23.5	-2.25	10.2	9.3	6.12	7	0.66
	Target/Trees	189.6	26.4	-0.2	3.09	10.3	4.04	4	0.73
	Target/Field Trees	199.6	30.5	-0.48	2.5	10.9	3.8	3	0.79
	Tree Background	206.5	25.8	0.208	1.77	9.36	1.84	8	0.175
	Field Background	235.2	6.76	0.18	2.64	1.98	2.99	8	0.38
	Large Target Board	177.5	54.7	-0.69	2.6	20.6	3.4	8	0.82

Table A.2. (continued)

Fig.	Image	Statistics					R_{ℓ}	C_p
		Mean	Std	Skew	Kurtosis	SNR		
B.2	(b) Median (5x5)							
	Target/Field	193.3	24.3	-2.17	9.67	10.4	5	0.63
	Target/Trees	184.4	26.8	-0.18	2.85	12.1	4	0.67
	Target/Field Trees	193.4	30.8	-0.44	2.3	13.2	3	0.70
	Tree Background	206.6	25.7	0.231	1.74	9.59	3	0.163
	Field Background	235.1	6.43	0.34	2.83	2.15	6	0.268
	Large Target Board	172.1	57.5	-0.72	2.7	24.5	8	0.74

Table A.2. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_d	C_p
			Std	Skew	Kurtosis				
B.2	(c) Average (3x3)								
	Target/Field	196.7	23.0	-2.2	9.6	10.8	6.2	5	0.65
	Target/Trees	189.5	26.1	-0.23	2.99	12.0	4.09	4	0.73
	Target/Field Trees	189.8	31.6	-0.38	2.1	15.0	3.97	3	0.71
	Tree Background	206.2	25.6	0.227	1.75	10.4	1.87	3	0.167
	Field Background	235.3	6.40	0.14	2.77	2.14	3.17	7	0.37
	Large Target Board	177.1	53.0	-0.68	2.69	23.5	3.53	8	0.8

Table A.2. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.2	(d) Average (5x5)								
	Target/Field	191.0	24.2	-1.92	8.1	11.7	6.2	5	0.62
	Target/Trees	180.6	27.5	-0.12	2.69	13.6	4.17	4	0.66
	Target/Field Trees	199.3	30.2	-0.45	2.4	12.8	3.87	3	0.79
	Target Background	206.7	25.2	0.25	1.72	9.84	1.92	3	0.152
	Field Background	235.3	6.12	0.27	3.03	2.12	3.37	5	0.24
	Large Target Board	169.5	54.4	-0.66	2.8	23.4	3.6	8	0.68

Table A.2. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.3	Total Images								
	(a) Median (TV)(5x5)	206.7	56.6	-2.7	9.8	11.2	6.15	6	0.64
	(b) Average(TV)(5x5)	206.4	54.8	-2.6	9.5	12.1	6.12	6	0.63
	(c) Median(FLIR)(5x5)	93.8	38.1	0.21	2.6	11.3	6.23	5	0.66
	(d) Avg(FLIR)(5x5)	93.8	37.9	0.20	2.5	12.3	6.17	5	0.66
	D-TV and FLIR								
	(e) TV Median(5x5)	190.2	47.7	-2.0	8.8	11.3	6.17	6	0.65
	(f) FLIR Median(5x5)	55.3	36.2	1.8	10.4	12.4	6.14	5	0.60

Table A.3. Processed Images--Contrast Improved

Fig.	Image	Mean	Statistics			Kurtosis	SNR	SCR	R_ℓ	C_p
			Std	Skew						
B.4	B-TV and FLIR									
	(a) TV-HIST (Eq.)									
	Target/Field	152.3	48.4	-3.0E-2	1.8	4.7	3.8	5	0.77	
	Target/Trees	172.3	48.2	-2.4E-2	1.8	4.77	2.59	4	0.95	
	Target/Field Trees	168.8	46.5	-6.12E-2	1.8	4.57	3.2	3	0.89	
	Field Background	232.7	13.2	-7.3E-2	1.84	1.37	1.7	22	1.0	
	(b) TV-HIST (Hy.)									
	Target/Field	99.2	42.2	1.59	4.6	4.7	4.4	6	0.67	
	Target/Trees	118.2	40.9	1.6	4.7	4.7	4.1	4	0.4	
	Target/Field Trees	117.6	40.1	1.6	4.4	4.5	4.1	4	0.77	
	Field Background	217.9	11.6	1.5	4.4	1.31	3.4	22	1.0	

Table A.3. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.4	(c) TV-LAGC (3x3)								
	Target/Field	146.5	25.2	2.1E-2	3.3	5.2	5.0	4	0.59
	Target/Trees	167.8	25.7	3.85	3.04	5.32	3.69	7	0.81
	Target/Field Trees	164.9	23.6	0.12	3.11	5.02	4.28	4	0.67
	Field Background	231.7	7.9	8.0E-2	2.6	1.49	2.85	2	0.82
	Tree Background	204.2	14.9	9.6E-2	3.09	3.16	3.36	3	0.839
	(d) TV-LAGC (5x5)	152.2	25.4	5.2E-2	3.17	5.31	4.29	5	0.71
	(e) FLIR(unprocessed)	93.8	38.8	0.23	2.64	5.25	4.37	5	0.76
	(f) FLIR-LAGC (5x5)	109.7	21.8	0.71	4.19	5.18	4.35	5	0.74

Table A.3. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.5	D-LAGC ($1/\sigma$)								
	(a) TV-LAGC (5x5)	189.8	47.2	-1.9	8.55	5.09	4.94	7	0.77
	(b) FLIR-LAGC (5x5)	55.6	36.4	1.8	10.2	5.28	4.32	5	0.76
	(c) TV-LAGC (15x15)	187.9	45.8	-1.84	8.45	4.92	4.98	9	0.79
	(d) FLIR-LAGC (15x15)	56.1	35.7	1.86	11.2	5.19	4.27	8	0.78
B.6	D-LAGC (μ/σ)								
	(a) TV-LAGC (5x5)	187.6	49.5	-1.92	8.56	5.04	4.93	6	0.77
	(b) FLIR-LAGC (5x5)	55.0	36.0	1.9	10.3	5.28	4.37	6	0.77
	(c) TV-LAGC (15x15)	182.3	46.3	-1.89	8.51	4.99	4.97	10	0.79
	(d) FLIR-LAGC (15x15)	55.1	36.1	2.0	11.7	5.20	4.29	9	0.78

Table A.4. Processed Images--Gradients

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.7	B-TV Gradient								
	(a) Prewitt (3x3)								
	Target/Field	101.2	31.0	1.66	5.3	5.6	2.9	16	0.8
	Target/Trees	111.9	27.1	2.6	9.0	6.3	4.8	15	1.0
	Target/Field Trees	111.6	26.1	2.3	7.8	5.7	3.2	15	0.92
	Field Background	215.7	9.6	3.3	12.8	2.2	4.3	21	0.11
	Tree Background	173.2	20.1	2.7	9.9	4.3	4.5	17	0.77
	Large Target Background	64.1	40.8	1.57	5.2	7.39	4.9	14	0.67

Table A.4. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.7	(b) Sobel (3x3)								
	Target/Field	98.8	26.5	1.6	6.0	3.9	3.5	16	0.8
	Target/Trees	111.1	22.6	2.4	9.5	4.3	5.7	13	1.0
	Target/Field Trees	110.7	22.1	2.1	8.2	3.9	3.7	13	0.92
	Field Background	217.3	9.5	2.9	11.2	1.9	4.2	21	0.22
	Tree Background	175.2	18.5	2.24	7.59	3.05	4.79	17	0.217
	Large Target Background	60.5	38.0	1.74	6.1	6.37	5.33	14	0.61

Table A.4. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p	
			Std	Skew	Kurtosis					
B.7	(c) Unsharp Mask(3x3)									
	Target/Field	196.6	23.0	-2.1	9.6	10.8	6.2	5	0.65	
	Target/Tree	189.2	27.3	-6.7E-2	2.9	12.3	4.0	4	0.62	
	Target/Field Tree	199.3	30.2	-0.4	2.4	12.8	3.87	3	0.79	
	Field Background	253.4	6.39	0.14	2.76	2.14	3.17	7	0.36	
	Tree Background	207.8	25.3	0.15	1.79	5.5	1.8	3	0.21	
	Large Target Background	177.0	52.9	-0.67	2.69	23.5	3.52	8	0.81	

Table A.4. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.7	(d) Unsharp Mask(5x5)								
	Target/Field	199.8	21.6	-2.4	10.7	5.4	6.2	7	0.65
	Target/Tree	191.5	26.2	-0.2	3.2	6.7	3.9	4	0.58
	Target/Field Tree	198.1	28.1	-0.57	2.7	6.8	4.1	4	0.73
	Field Background	237.8	6.56	-0.3	2.7	1.56	2.69	8	0.83
	Tree Background	207.9	25.2	0.13	1.79	5.6	1.9	3	0.2

Table A.4. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p	
			Std	Skew	Kurtosis					
B.8 B-TV and FLIR Grad.										
	(a) TV-Prewitt(3x3)	11.1	23.8	6.4	51.7	5.07	5.0	7	0.77	
	(b) FLIR-Prewitt(3x3)	26.5	25.2	2.9	14.2	5.3	4.34	6	0.78	
	(c) TV-U. Mask(3x3)	112.6	7.3	0.44	58.6	5.16	4.97	8	0.67	
	(d) FLIR-U. Mask(3x3)	132.3	19.1	1.1E-2	3.7	5.34	4.28	6	0.65	
B.9 D-TV and FLIR Grad.										
	(a) TV-Prewitt(3x3)	11.5	20.5	6.5	53.9	5.08	4.91	7	0.73	
	(b) FLIR-Prewitt(3x3)	15.4	17.4	4.2	27.7	5.32	4.28	6	0.79	
	(c) TV-U. Mask(3x3)	116.8	7.4	-2.1	35.1	5.14	4.86	7	0.68	
	(d) FLIR-U. Mask(3x3)	125.4	15.5	8.2	6.1	5.39	4.22	5	0.71	

Table A.5. Processed Images--Edge Threshold

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p
			Std	Skew	Kurtosis				
B.10	Mean Threshold								
	(a) B-TV (Global) Prewitt								
	Target/Field	76.8	37.2	3.9	16.9	4.0	3.1	20	0.8
	Target/Tree	95.9	35.6	4.2	18.9	3.7	4.6	5	1.0
	Target/Field Tree	94.2	30.8	4.8	24.1	3.3	3.9	18	0.92
	Field Background	211.8	11.0	3.6	14.3	0.8	4.2	21	0.0
	Tree Background	160.8	21.3	41.8	18.5	2.1	4.0	10	0.0
	Large Target Background	60.4	85.4	1.84	4.39	8.0	2.52	18	1.0

Table A.5. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_Q	C_p
			Std	Skew	Kurtosis				
B.10	(b) B-TV (Global) Sobel								
	Target/Field	80.1	43.1	3.3	11.8	3.4	1.7	18	0.8
	Target/Tree	97.7	38.9	3.8	15.4	3.1	3.5	8	1.0
	Target/Field Tree	95.7	34.4	4.2	18.7	2.7	2.0	18	0.92
	Field Background	211.8	11.0	3.7	14.3	0.6	4.2	21	0.0
	Tree Background	160.8	21.3	41.8	18.5	1.6	4.6	10	0.0
	Large Target Background	70.2	96.2	1.35	2.82	6.41	2.11	14	1.0
	(c) D-TV (Local) Prewitt	125.2	127.6	3.5E-2	1.0	4.2	3.5	6	0.92
	(d) D-FLIR (Local) Prewitt	126.1	126.5	2.2E-2	1.0	4.15	3.6	6	0.92

Table A.5. (continued)

Fig.	Image	Mean	Statistics			Kurtosis	SNR	SCR	R_L	C_p
			Std	Skew						
B.11	D-TV and FLIR (Local) Prewitt (T in 3x3 window)									
	(a) TV-T = $\mu+0.5\sigma$	76.3	116.7	0.88	1.77	4.37	3.46	8	0.92	
	(b) FLIR-T = $\mu+0.5\sigma$	74.8	116.2	0.90	1.82	4.21	3.53	8	0.92	
	(c) TV-T = $\mu+\sigma$	199.2	51.4	-1.8	7.7	4.49	3.41	10	1.0	
	(d) FLIR-T = $\mu+\sigma$	84.0	77.9	1.4	3.7	4.29	3.47	12	1.0	
	(e) TV-T = $\mu+2\sigma$	190.4	48.2	-1.9	8.6	4.32	3.47	16	1.0	
	(f) FLIR-T = $\mu+2\sigma$	56.4	39.2	2.00	10.6	4.22	3.50	18	1.0	

Table A.5. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.12	D-TV (Local) Prewitt (T in 7x7 and 15x15 windows)								
	(a) T (7x7) = μ	217.6	51.7	-2.12	8.9	4.39	3.45	8	0.92
	(b) T (15x15) = μ	105.9	125.8	0.34	1.1	4.23	3.54	8	0.92
	(c) T (7x7) = $\mu+0.5\sigma$	208.1	51.1	-1.8	8.0	4.52	3.39	14	1.0
	(d) T (15x15) = $\mu+0.5\sigma$	66.7	112.1	1.1	2.2	4.31	3.44	16	1.0
	(e) T (7x7) = $\mu+\sigma$	200.8	49.7	-1.8	8.0	4.35	3.45	17	1.0
	(f) T (15x15) = $\mu+\sigma$	39.6	92.4	1.9	4.6	4.24	3.50	20	1.0

Table A.5. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p
			Std	Skew	Kurtosis				
B.13	D-FLIR (Local) Prewitt (T in 7x7 and 15x15 windows)								
	(a) T (7x7) = μ	143.6	103.8	5.1E-2	1.2	4.45	3.41	8	0.92
	(b) T (15x15) = μ	108.9	126.1	0.30	1.1	4.29	3.50	10	0.92
	(c) T (7x7) = $\mu+0.5\sigma$	110.9	95.3	0.7	1.8	4.36	3.49	14	1.0
	(d) T (15x15) = $\mu+0.5\sigma$	69.5	113.6	1.02	2.04	4.18	3.59	16	1.0
	(e) T (7x7) = $\mu+\sigma$	86.2	80.0	1.3	3.4	4.24	3.52	18	1.0
	(f) T (15x15) = $\mu+\sigma$	42.0	94.6	1.8	4.26	4.00	3.63	20	1.0

Table A.6. Rescale Sum Overlay

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p
			Std	Skew	Kurtosis				
B.14	B-TV								
	(a) Prewitt (segments)								
	Target/Field	161.1	15.1	-1.6	10.9	2.4	7.7	9	0.8
	Target/Tree	160.7	18.9	4.4E-2	3.5	2.7	6.5	5	1.0
	Target/Field Tree	160.2	18.9	-0.3	3.0	2.7	5.9	4	0.92
	Large Target Background	96.7	29.9	0.79	6.0	6.28	6.78	14	0.65

Table A.6. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.14	(b) Sobel (segments)								
	Target/Field	131.5	12.6	1.7	19.2	2.4	8.7	16	0.8
	Target/Tree	139.5	14.3	1.3	10.6	2.1	8.8	5	1.0
	Target/Field Tree	13.0	14.1	0.8	8.9	2.0	7.2	5	0.92
	Large Target Background	79.1	29.5	1.79	8.3	5.95	7.04	17	0.60
(c)	Prewitt	161.0	15.9	-1.1	8.1	2.5	7.3	8	0.8
(d)	Sobel	138.1	13.2	1.5	16.7	2.3	8.5	7	0.8

Table A.7. Edge Replacement Overlay

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p
			Std	Skew	Kurtosis				
B.15	D-TV and FLIR (Local) Prewitt								
	(a) TV-T (3x3) = $\mu+\sigma$	199.2	51.4	-1.8	7.7	5.54	6.47	8	0.8
	(b) FLIR-T (3x3) = $\mu+\sigma$	84.0	77.9	1.4	3.7	5.55	6.37	7	0.78
	(c) TV-T (7x7) = $\mu+\sigma$	200.8	49.7	-1.8	8.0	5.98	5.87	9	0.92
	(d) FLIR-T (7x7) = $\mu+\sigma$	86.2	80.1	1.3	3.4	5.92	5.80	9	0.91
	(e) TV-T (15x15) = $\mu+\sigma$	202.5	47.6	-1.8	8.7	6.31	5.49	11	1.0
	(f) FLIR-T (15x15) = $\mu+\sigma$	88.3	81.6	1.3	3.2	6.27	5.48	10	1.0

Table A.8. Serial Combinations

Fig.	Image	Mean	Statistics			SNR	SCR	R _ℓ	C _p
			Std	Skew	Kurtosis				
B.16	B-TV								
	(a) LAGC (5) Median (5)								
	Target/Field	159.5	26.6	-0.4	2.9	13.3	5.5	8	0.57
	Target/Tree	160.8	22.4	-8.5E-2	2.9	12.1	4.8	11	0.48
	Target/Field Tree	169.4	26.9	-9.8E-2	2.8	12.2	4.4	9	0.75
	Field Background	232.3	6.8	-7.9E-3	3.5	2.7	3.1	24	0.7
	Tree Background	202.5	13.9	-3.1E-2	3.4	6.9	3.1	10	0.47
	Large Target Background	126.4	50.4	-6.1E-2	2.2	23.0	4.22	8	0.645

Table A.8. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_ℓ	C_p
			Std	Skew	Kurtosis				
B.16	(b) AVG (5) HIST (Eq.)								
	Target/Field	152.1	48.4	-2.6E-2	1.8	4.7	3.8	5	0.62
	Target/Tree	172.0	48.2	-1.9E-2	1.8	4.8	3.2	4	0.64
	Target/Field Tree	168.6	46.5	-2.4E-3	1.8	4.6	3.3	3	0.74
	Field Background	217.9	11.7	1.6	4.5	1.3	3.6	5	0.16
	Tree Background	205.9	28.5	-2.4E-3	1.8	2.8	1.5	3	0.18
	Large Target Background	64.8	57.3	1.65	4.8	6.5	4.0	7	0.123

Table A.8. (continued)

Fig.	Image	Mean	Statistics			SNR	SCR	R_{ℓ}	C_p
			Std	Skew	Kurtosis				
B.16 (c)	MED (5)								
	LAGC (5)								
	Target/Field	128.9	16.6	3.1E-2	3.5	4.1	8.8	10	0.21
	Target/Tree	165.6	20.2	0.15	3.9	4.0	4.8	22	0.46
	Target/Field Tree	170.9	12.2	0.23	4.4	3.7	7.7	20	0.40
(d)	Field Background	231.4	4.5	0.1	4.5	1.3	4.8	6	0.5
	Tree Background	206.8	10.3	0.11	5.1	2.5	4.1	23	0.5
	Large Target Background	112.7	30.0	0.43	3.06	5.1	6.0	11	0.322
	MED (5)								
	LAGC (5)								
		145.2	19.5	0.15	3.51	4.15	4.74	12	0.42

Table A.9. Parallel Processing

Fig.	Image	Mean	Statistics			SNR	SCR	R_{λ}	C_p
			Std	Skew	Kurtosis				
B.17	Total Image B-TV								
	(a) MED+LAGC+GRAD	144.4	22.7	-2.1	8.3	4.10	5.31	8	0.49
	(c) MED (0.25) + LAGC (0.75)	193.4	45.0	-2.6	9.4	4.8	5.2	7	0.46
	(e) MED (0.75) + LAGC (0.25)	166.1	27.2	-0.76	3.9	4.6	5.4	7	0.47
	B-FLIR								
	(b) MED+LAGC+GRAD	76.0	20.2	0.77	4.20	4.0	5.34	7	0.50
	(d) MED (0.25) + LAGC (0.75)	97.5	31.7	0.30	2.72	3.95	5.27	6	0.49
	(f) MED (0.75) + LAGC (0.25)	105.4	22.6	0.80	3.50	3.90	5.43	6	0.50

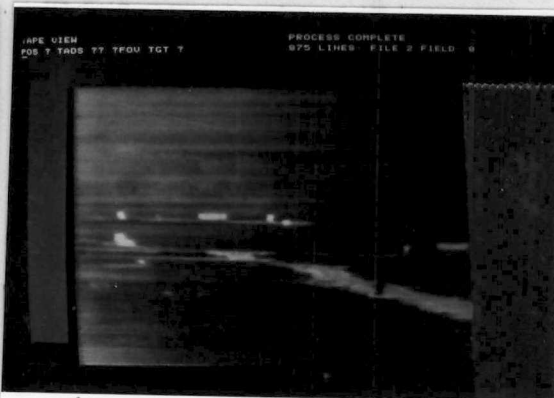
APPENDIX B

SIMULATION RESULTS--IMAGES

This appendix contains simulation results obtained as images (Figures B.1 through B.17).



(a)



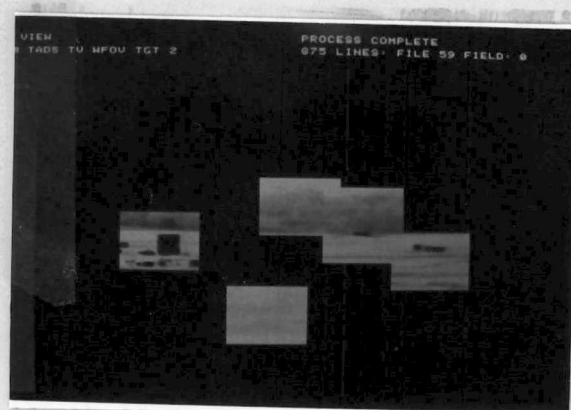
(b)



(c)



(d)



(e)

Figure B.1. Unprocessed original images.



(a)



(b)



(c)

(d)

Figure B.2. Noise cleaned images, series 1.

Figure B.3. Noise cleaned images, series 2.

Derived from full-frame images (a), (b), (c), and (d) from Figure B.1.



(a)



(b)



(c)



(d)



(e)



(f)

Figure B.3.

Figure B.4. Contrast improved images, series 1.

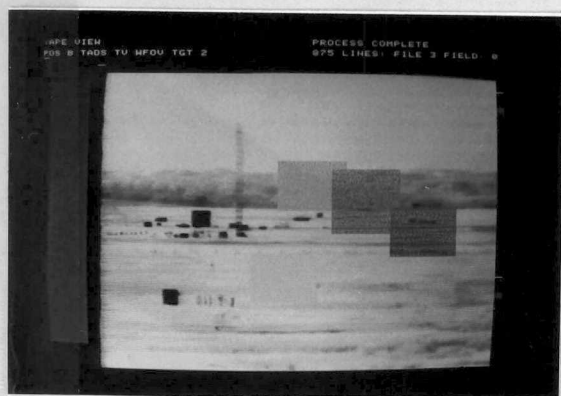
Derived from images (a) and (b) from Figure B.1.



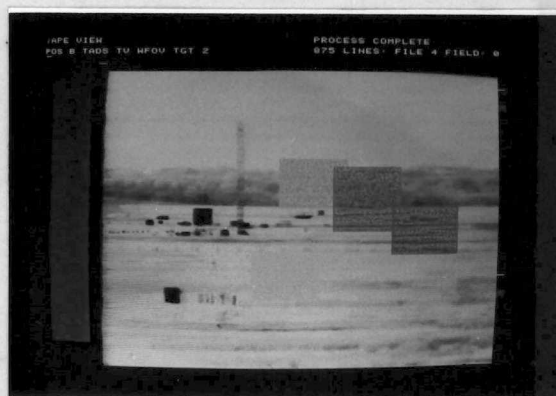
(a)



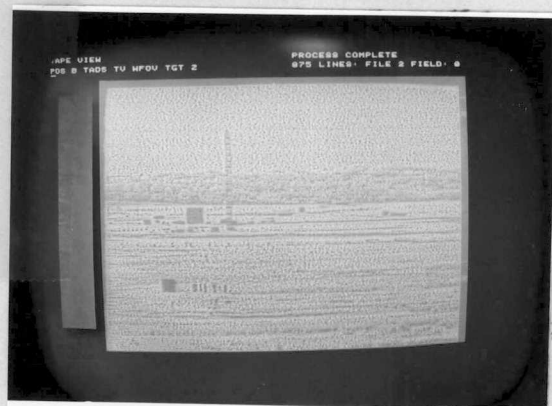
(b)



(c)



(d)

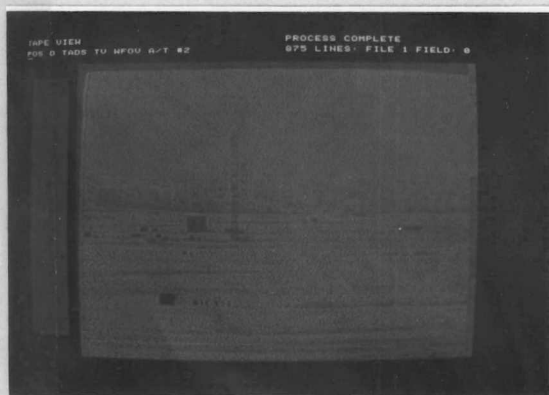


(e)



(f)

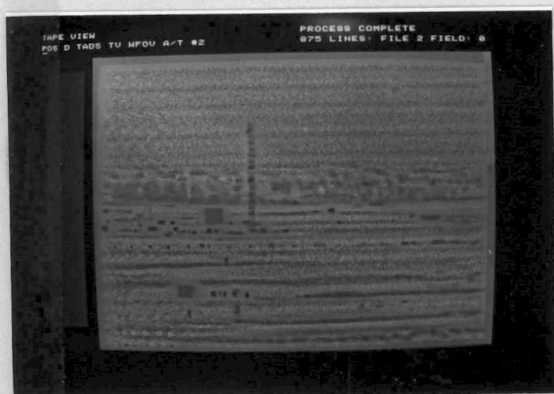
Figure B.4.



(a)



(b)



(c)



(d)

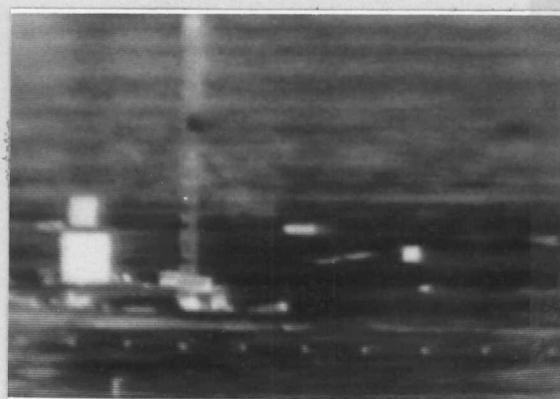
Figure B.5. Contrast improved images, series 2.

Derived from images (c) and (d) from Figure B.1 using LAGC gain parameter $G = 1/\sigma$.

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(a)



(b)



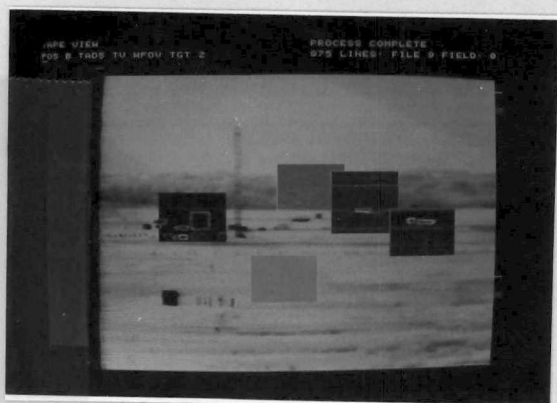
(c)



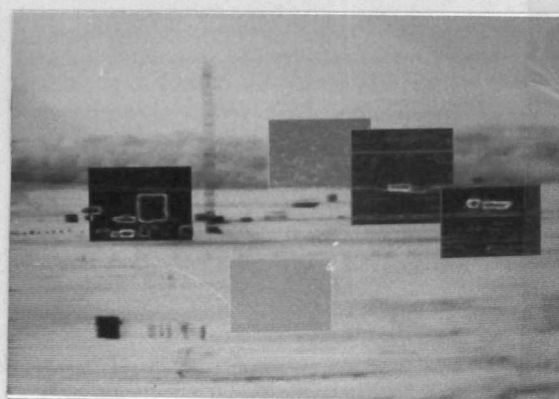
(d)

Figure B.6. Contrast improved images, series 3.

Derived from images (c) and (d) from Figure B.1 using LAGC gain parameter $G = \mu/\sigma$.



(a)



(b)



(c)



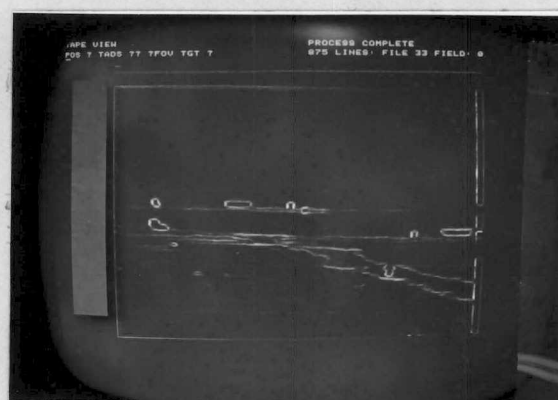
(d)

Figure B.7. Gradient images, series 1.

Derived from sub-image segment from Figure B.1 (e).



(a)



(b)



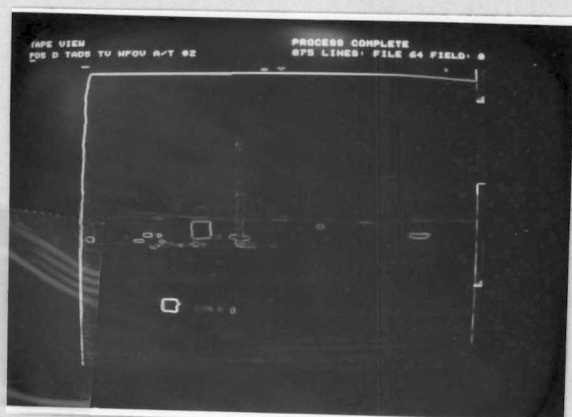
(c)



(d)

Figure B.8. Gradient images, series 2.

Derived from full-frame images (a) and (b) from Figure B.1.



(a)



(b)



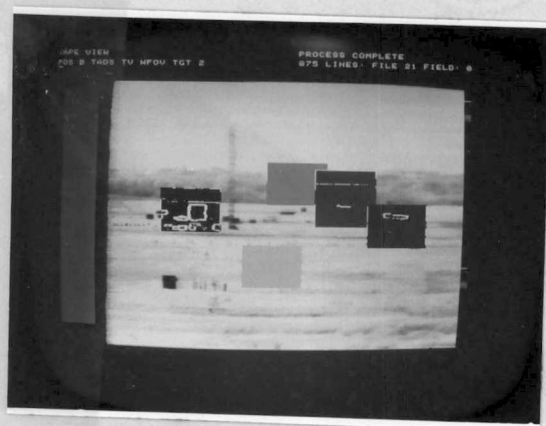
(c)



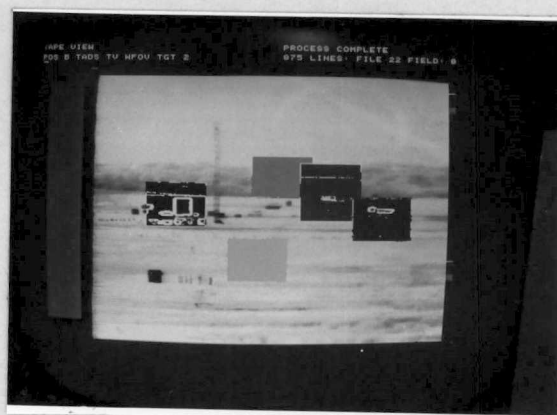
(d)

Figure B.9. Gradient images, series 3.

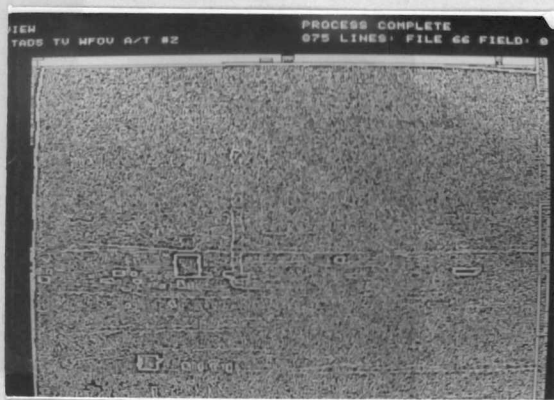
Derived from images (c) and (d) from Figure B.1.



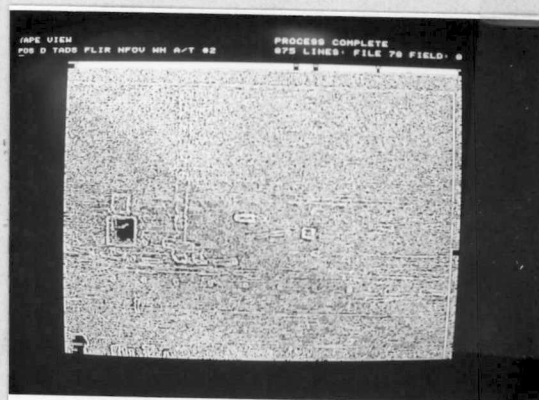
(a)



(b)



(c)



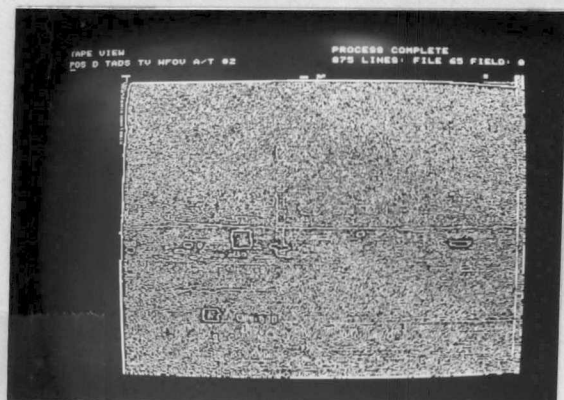
(d)

Figure B.10. Edge threshold images, series 1.

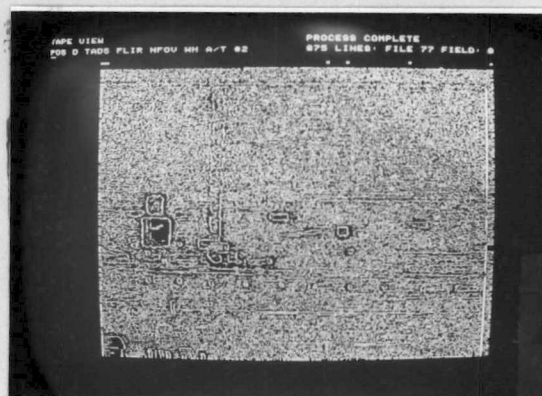
Derived from sub-scene image segments (e) and from full-frame images (c) and (d) from Figure B.1 using global and local threshold selection.

Figure B.11. Edge threshold images, series 2.

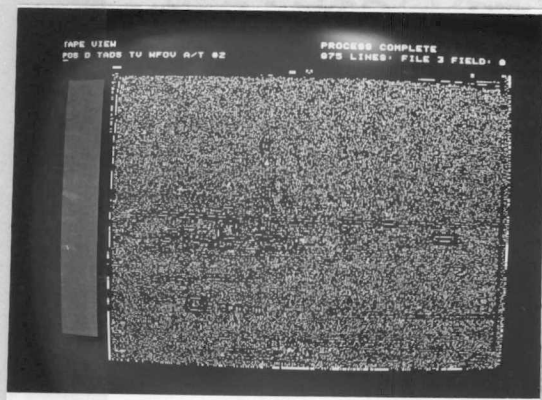
Derived from images (c) and (d) from Figure B.1 using local threshold selection.



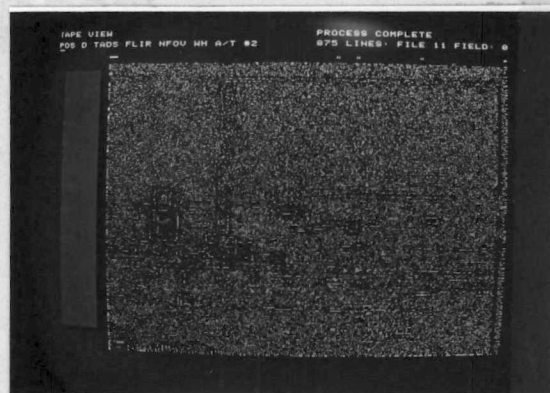
(a)



(b)



(c)



(d)



(e)

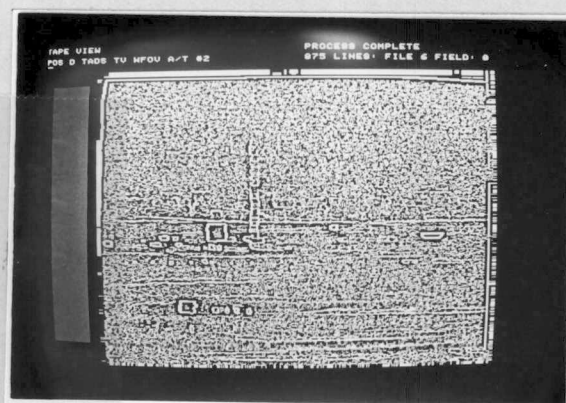


(f)

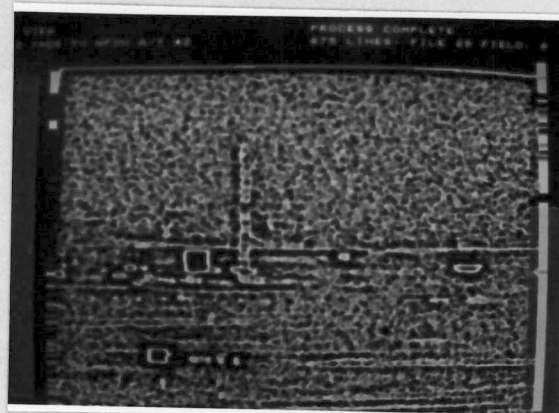
Figure B.11.

Figure B.12. Edge threshold images, series 3.

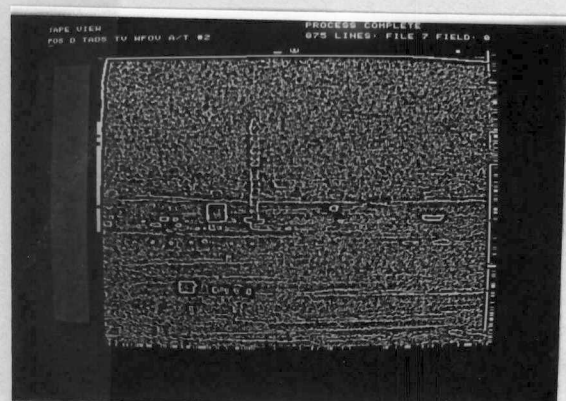
Derived from image (c) from Figure B.1 using local threshold selection with various window sizes.



(a)



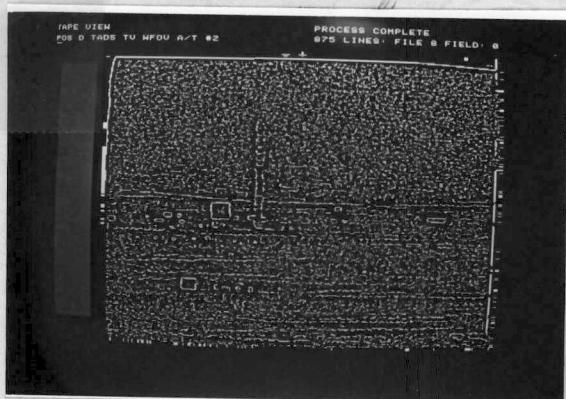
(b)



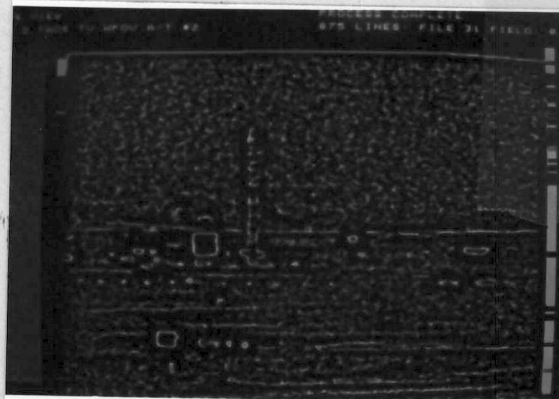
(c)



(d)



(e)



(f)

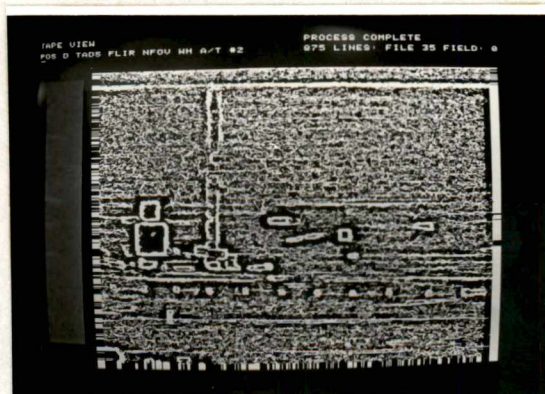
Figure B.12.

Figure B.13. Edge threshold images, series 4.

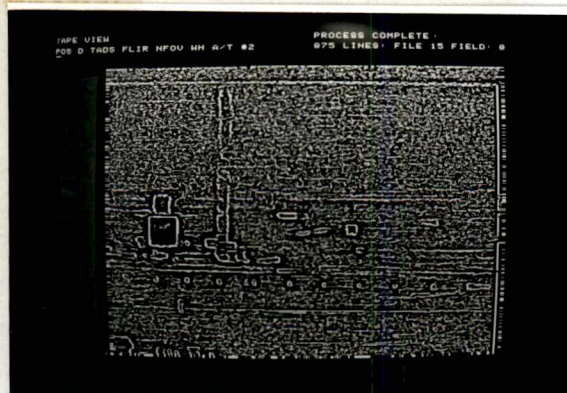
Derived from image (d) from Figure B.1 using local threshold selection with various window sizes.



(a)



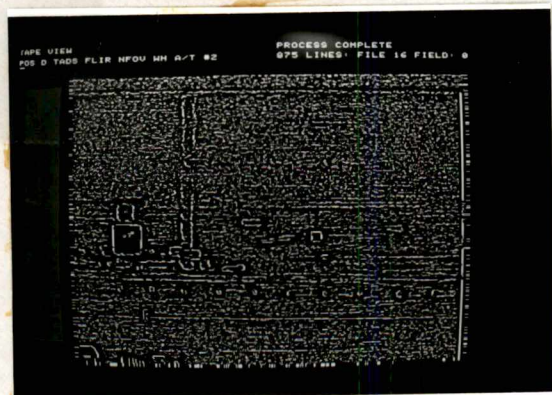
(b)



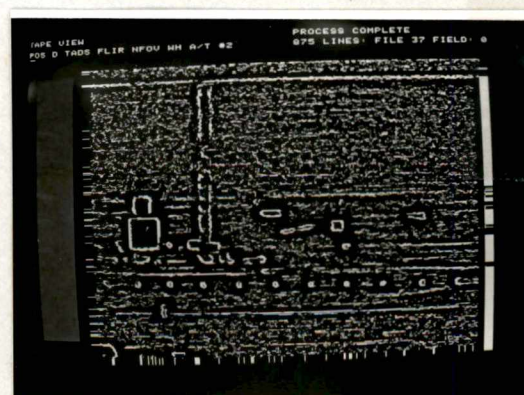
(c)



(d)



(e)

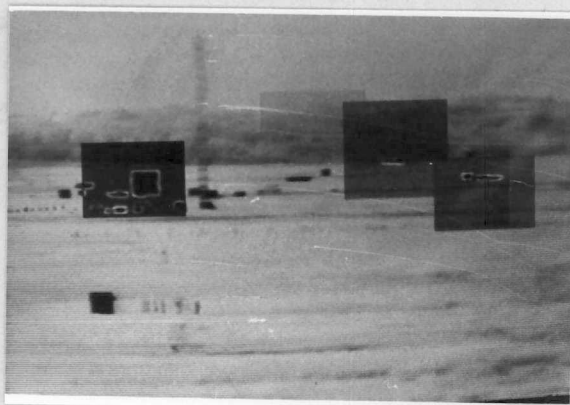


(f)

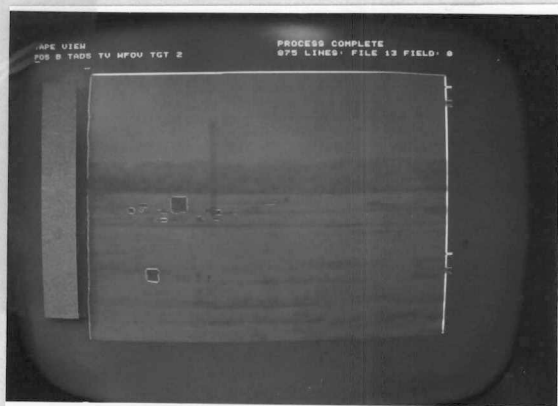
Figure B.13.



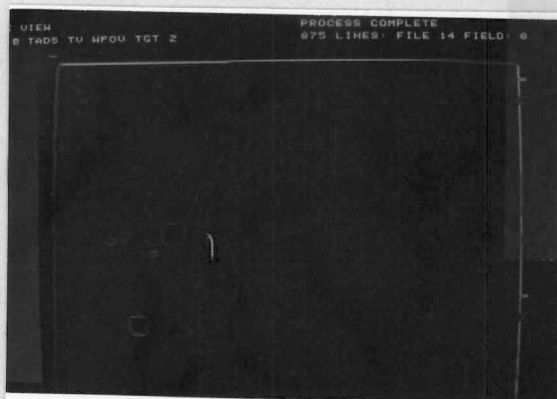
(a)



(b)



(c)



(d)

Figure B.14. Rescale sum overlay images.

Derived from sub-scene image segments (e) and from full-frame image (a) from Figure B.1.

Figure B.15. Edge replacement overlay images.

Derived from images (c) and (d) from Figure B.1.



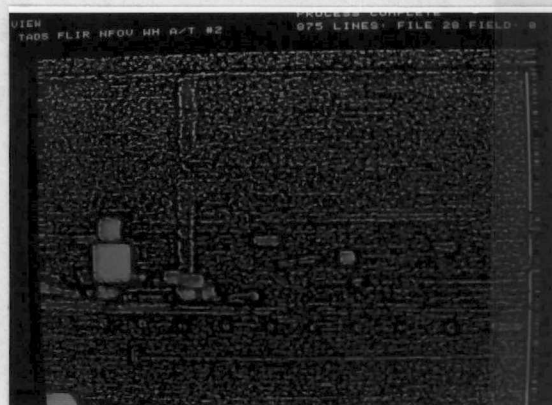
(a)



(b)



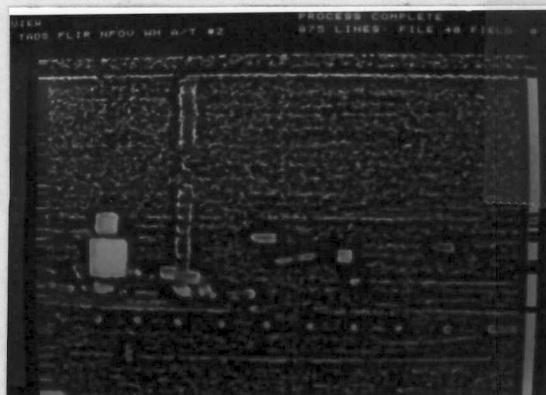
(c)



(d)



(e)



(f)

Figure B.15.



(a)



(b)



(c)



(d)

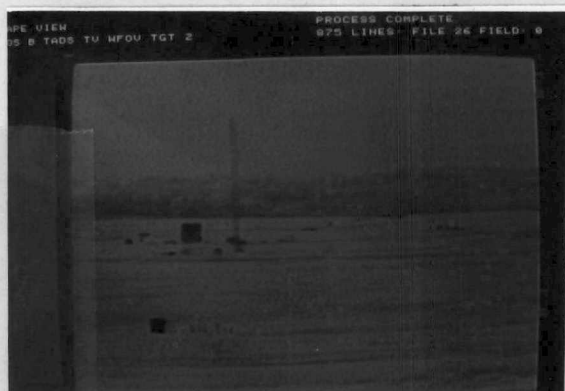
Figure B.16. Serial combination images.

Derived from sub-scene image segments (e) and full-frame image (a) from Figure B.1.

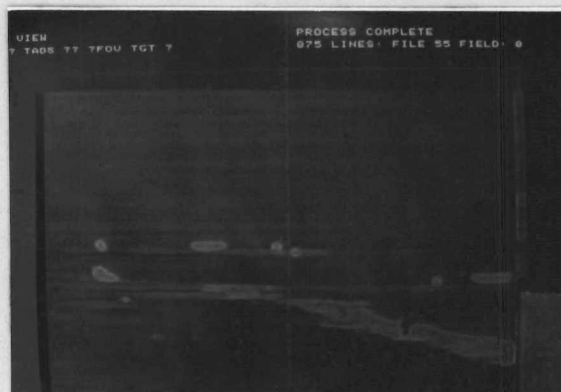
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Figure B.17. Parallel combination images.

Derived from images (a) and (b) from Figure B.1.



(a)



(b)



(c)



(d)



(e)



(f)

Figure B.17.

VITA

Jeffrey Paul Lankford was born May 24, 1957 in Riverside, California. As the son of a career United States Air Force officer, his youth was misspent in various locations around the globe.

In May 1980, the degree of Bachelor of Science in Computer Science was conferred magna cum laude by Old Dominion University, Norfolk, Virginia. The degree of Master of Science in Engineering Science was awarded in March 1982, by The University of Tennessee, Knoxville.

Mr. Lankford is a member of the Association for Computing Machinery and the Institute of Electrical and Electronics Engineers.