

To the Graduate Council:

I am submitting herewith a dissertation written by William Bruce Jatko entitled "Application of a Human Visual Perception Paradigm for Automated Inspection of Monochromatic Security Documents." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Electrical Engineering.

Donald W. Bouldin

Donald W. Bouldin, Major Professor

We have read this dissertation
and recommend its acceptance:

Jm Googe

Michael G. Thomas

James B. [unclear]

Accepted for the Council:

Lew Minkel

Vice Provost
and Dean of The Graduate School

**Application of a Human Visual Perception Paradigm for
Automated Inspection of Monochromatic Security Documents**

**A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville**

William Bruce Jatko

May 1990

ACKNOWLEDGEMENTS

The author wishes to express his appreciation to the many individuals who have contributed to this research. The author is grateful to all the members of the advisory committee, Drs. D. Brzakovic, J. M. Googe, and M. G. Thomason for their assistance in preparing this dissertation, and especially to Committee Chairman Dr. D. W. Bouldin for his advice and encouragement.

The author would also like to acknowledge his colleagues at the Oak Ridge National Laboratory for their excellent ideas and suggestions. A special debt of gratitude goes to M. A. Hunt for his work in developing the physical realization. Drs. K. W. Tobin and C. K. Johnson are recognized for their contributions on correlation theory and flaw perception respectively. Finally, the author would like to thank D. W. McDonald and R. W. Tucker, Jr. for their support as project leaders at the Oak Ridge National Laboratory.

The following trademark names mentioned in the text are recognized:

Sun is a registered trademark of Sun Microsystems, Inc.

MaxVideo is a registered trademark of Datacube, Inc.

MegaPlus is a registered trademark of Videk, Inc.

The work reported here was performed at Oak Ridge National Laboratory, operated by Martin Marietta Energy Systems, Inc., for the U. S. Department of Energy under Contract No. DE-AC05-OR8421400.

ABSTRACT

A digital inspection machine has been developed to detect and evaluate printing flaws in U.S. currency using a methodology extensible to general graphical images. A flaw detection model was compiled from previous research by others, derived from a panel of experienced judges who rated a set of flawed exemplars from 1 to 10 according to the perceived noticeability of the flaws found on each note. The flaw model relates a numerical grade to the location, area and contrast of printing defects. The objective grading scale is a significant addition to previous currency inspection devices.

The inspection machine acquires a high-resolution image of a test note and subtracts a reference image from it to isolate the print flaws. There are two causes of large amplitude errors in the resulting difference image: (1) photometric errors caused by acceptable fluctuations in illumination and scene reflectance, and (2) spatial errors arising from normal variations in the printed pattern of the reference and test samples. Photometric errors magnify the flaw amplitude in the difference image, while spatial errors create topological artifacts related to surface structure. Photometric errors are mitigated by intensity normalization, which redistributes the grey levels in the test image to match a defined standard reflectance. (This technique does not change the feature distribution in the test image; the flaws are unchanged by normalization.) Spatial errors are caused by positional misalignment between the test and reference notes. A subpixel spatial normalization algorithm was devised to align the two images. The misalignment is complex because the samples may have subtle distortions, imperceptible to the eye, due to mechanical stresses from the printing process. The algorithm fits an elliptic paraboloid surface to the cross-correlation coefficients about a prominent topological feature common to both images. The fractional displacement of a feature in the test image relative to the reference is determined from the location of the surface peak. After the test image is normalized photometrically and spatially with the reference image, the absolute difference of the two images is taken. The difference image contains only those features of the test note not found on the reference.

To further reduce spatial errors, a structural filter is developed to control detection sensitivity in the image on a point-by-point basis. The sensitivity coefficients are weighting factors at each point and range from 0 to 1.0. The coefficients are determined during calibration from the measured variations in a set of known acceptable notes. In order to detect low-contrast flaws, the noise floor in the difference image must be less than the flaw magnitude. The registration and filter combination reduces the noise floor of the difference image to an acceptable level. Consequently, flaws isolated in the difference image are unaffected by normal variations in illumination, position, orientation, and printing conditions. Finally, the difference image is screened by size to separate actual printing flaws from any remaining artifacts using connectivity analysis. The size, contrast, and location of the flaws is measured, and the flaw severity grade representing the test note quality is calculated from the flaw parameters.

TABLE OF CONTENTS

CHAPTER	PAGE
1. INTRODUCTION.....	1
Background	1
The Bureau of Engraving and Printing	2
Evolution of Web Printing and Inspection	3
Research Objective	4
Narrative Organization	5
2. CURRENCY PRODUCTION AND INSPECTION.....	7
Domestic Currency Production.....	7
Currency Printing Flaws	7
Manual Currency Inspection	10
International Technology Assessment	10
Switzerland	11
Denmark	12
Japan.....	13
France	13
United States	14
3. FLAW PERCEPTION AND METROLOGY	17
Flaw Perception	17
Human Flaw Perception Model	20
Flaw Metrology.....	22
Local Flaw Severity Equation.....	24
Determination of Halftone Density	25
Global Flaw Equation	26
Composite Flaw Equation.....	28
Human Visual System	28
Machine Performance Factors	29
4. IMAGE ACQUISITION	33
Image Sensor	34
Vidicon.....	34
Silicon.....	34
Comparison of Sensor Characteristics.....	35
Image Retention.....	35
Photoresponse Nonuniformity	36
Dark Current.....	36
Geometric Nonlinearity.....	36
Light Bias.....	36
Gamma.....	37
Dynamic Range	37
Noise	37
Spectral Response.....	37
Array Geometry	38
Pixel Geometry	39

Sensor Selection	39
Sensor Resolution	39
Modulation Transfer Function	41
Imaging Optics	42
Thin Lens Model	43
Object Distance	44
Image Distance	44
Magnification	44
Focal Length	45
Field of View	46
Aperture	46
Depth of Field	47
Lens Resolution	49
Aberrations	51
Summary	52
Radiometric Terms	53
Radiant Intensity	54
Solid Angle	54
Irradiance	54
Radiance	54
Brightness	55
Scene Illumination	56
Image Brightness	56
Spectral Response	60
Image Digitizer	61
Quantization Uncertainty	61
5. IMAGE NORMALIZATION	63
Intensity Normalization	65
Gray Scale References	65
Photometric Transformation	67
Spatial Normalization	69
Coarse Correlation	70
Fine Correlation	72
Geometric Transformation	74
6. NOISE SUPPRESSION	77
Structural Filter	78
Weighting Function	83
Morphological Filter	85
Threshold Function	86
7. PHYSICAL IMPLEMENTATION MODEL	88
Hardware Architecture	88
Host CPU Modules	89
Image-Processing Modules	90
Data Storage System	91
Frame Buffer Format	92
Image Pipeline	93
Software Architecture	94
Data Structures	97

Initialization	97
Image Acquisition	97
Determining the Standard Reflectance	98
Image Normalization.....	99
Spatial Normalization.....	100
Flaw Isolation.....	101
Structural Filter.....	103
Morphological Filter	104
Flaw Threshold Calculation.....	104
Flaw Measurement.....	107
Connectivity Analysis	107
Flaw Evaluation.....	110
Global Flaw Evaluation.....	114
 8. EXPERIMENTAL VERIFICATION	 117
Sensor Characteristics	118
Procedure for Photometry Measurements	118
Spatial Resolution.....	119
Response Uniformity	120
Reflectance Accuracy.....	121
Intensity Normalization	122
Temporal Variation.....	123
Flaw Metrology.....	124
Spatial Normalization.....	124
Noise Suppression	125
Area Measurement.....	129
Density Measurement.....	130
Flaw Perception	131
Flaw Location.....	131
Comparison To Human Perception.....	131
 9. CONCLUSIONS	 136
Error Analysis.....	137
Strengths and Weaknesses of the Inspection System	141
VLSI Implementation	145
Limitations of Early Vision	146
VLSI Implementation Examples	148
Pattern Matching	148
Object Location and Tracking	149
Memory Access	149
Motion Detection.....	150
Edge Detection.....	150
Surface Orientation	150
 BIBLIOGRAPHY.....	 151
 APPENDICES.....	 158
 APPENDIX A	 159
Hardware Diagrams	159

APPENDIX B.....	163
Software	163
Data Structures	164
Flow Charts	170
APPENDIX C	190
Data Tables	190
VITA	227

LIST OF TABLES

TABLE	PAGE
3.1. Note Grading Scale Used in ORNL Flaw Survey.....	21
4.1. Depth-of-Field as a Function of Lens f-Number.	49
4.2. Lens Specifications.....	53
7.1. Frame Buffer Description.....	93
8.1. Pixel Response Uniformity.	120
9.1. Descriptive Statistics for Measurement Error.....	137
C.1. Grayscale Reflectance	191
C.2. Intensity Normalization in 100% Image Irradiance.....	192
C.3. Intensity Normalization in 50% Image Irradiance.....	193
C.4. Intensity Normalization in 25% Image Irradiance.....	194
C.5. Reflectance Variation Due to Intensity Normalization.	195
C.6. Shot to Shot Reflectance Variation.	196
C.7. Correlation Measurement.....	197
C.8. Correlation Measurement ($x = 0.0$ pixels, $y = 0.0$ pixels).	198
C.9. Correlation Measurement ($x = 0.0$ pixels, $y = 0.168$ pixels).	199
C.10. Correlation Measurement ($x = 0.0$ pixels, $y = 0.336$ pixels).	200
C.11. Correlation Measurement ($x = 0.0$ pixels, $y = 0.504$ pixels).	201
C.12. Correlation Measurement ($x = 0.168$ pixels, $y = 0.0$ pixels).	202
C.13. Correlation Measurement ($x = 0.336$ pixels, $y = 0.0$ pixels).	203
C.14. Correlation Measurement ($x = 0.504$ pixels, $y = 0.0$ pixels).	204
C.15. Correlation Measurement ($x = 0.168$ pixels, $y = 0.168$ pixels).	205
C.16. Correlation Measurement ($x = 0.336$ pixels, $y = 0.336$ pixels).	206
C.17. Correlation Measurement ($x = 0.504$ pixels, $y = 0.504$ pixels).	207
C.18. Effect of Noise Suppression Filter Without Registration.....	208
C.19. Effect of Noise Suppression Filter With Registration.....	209
C.20. Area Measurement.	210
C.21. Density Measurement.	211
C.22. Perceptual Comparison: Ink Spot on Open Substrate.....	212
C.23. Perceptual Comparison: Slywipe in Lathework.....	213
C.24. Perceptual Comparison: Slywipe in Portrait	214
C.25. Perceptual Comparison: Break.....	215
C.26. Perceptual Comparison: Portrait Coat Break.....	216
C.27. Perceptual Comparison: Portrait Background Break.	217
C.28. Perceptual Comparison: Lower Right Cracked Chrome.	218
C.29. Perceptual Comparison: Chip.....	219

C.30. Perceptual Comparison: Slywipe Smear.	220
C.31. Perceptual Comparison: Portrait Background Slywipe Streak.	221
C.32. Perceptual Comparison: Stain.	222
C.33. Perceptual Comparison: Substrate Flooding.	223
C.34. Perceptual Comparison: Right Side Ball-up Mark.	224
C.35. Perceptual Comparison: Light Print.	225
C.36. Perceptual Comparison: Mash.	226

LIST OF FIGURES

FIGURE	PAGE
2.1. Types of Printing Flaws.....	9
3.1. Representation of Currency Inspection Process.	18
3.2. Representation of Currency Noticeability Regions.....	23
3.3. Graph of Global Flaw Severity Equation.....	27
3.4. Note Reflectance as a Function of Wavelength.....	29
3.5. Currency Evaluation Model.	31
4.1. Image Acquisition System.....	33
4.2. Plot of Typical Modulation Transfer Function.....	41
4.3. Schematic Diagram of Thin Lens Optical Model.....	43
4.4. Geometry of Lens Depth of Field.....	47
4.5. Methods of Image Sampling.....	51
4.6. Illustration of Radiometric Terminology.....	55
4.7. Diffuse and Specular Reflection.	56
4.8. Image Irradiance Geometry.....	57
4.9. Digitizer Transfer Function.....	62
4.10. Quantization Probability Distribution.	62
5.1. Misregistration Error in an Uncorrected Difference Image.	64
5.2. Geometry of Gray Scale References.....	66
5.3. Intensity Mapping Function.	69
5.4. SSDA Correlation Windows.	70
5.5. SSDA Threshold.	72
6.1. Edge Noise after Subpixel Registration.	78
6.2. Probability Distribution Function of Edge Position.....	80
6.3. One-Dimensional Edge Noise Suppression.	82
6.4. Edge Extraction Kernels.	84
6.5. Morphological Filtering Operation on a Binary Image.	86
6.6. Perception Thresholds Based on Weber Ratio.	87
7.1. Block Diagram of the Physical Model.	88
7.2. Configuration of VME Chassis Modules.	89
7.3. Block Diagram of Data Storage System.	92
7.4. Image Pipeline.	95
7.5. Currency Evaluation Flowchart.....	96
7.6. Isolating Local Flaws from Global Flaws.....	106
7.7. Connectivity Analysis Windowing Algorithm.....	109
7.8. Flaw Grading Sequence.....	113

8.1.	Contrast Transfer Function.....	119
8.2.	Reflectance Accuracy.....	121
8.3.	Measured Reflectance After Intensity Normalization.....	122
8.4.	Gray Scale Histogram of Intensity Normalization.....	123
8.5.	Subpixel Correlation Accuracy.....	124
8.6.	Effect of Noise Suppression Filter.....	127
8.7.	Effect of Noise Suppression on Currency Edge Noise.....	128
8.8.	Measurement of Flaw Area.....	129
8.9.	Measurement of Flaw Density.....	130
8.10.	Process to Compare Human and Machine Perception of Flaw Severity.....	132
8.11.	Comparison of Measured Flaw Grade to Human Observations.....	135
9.1.	Measurement Error Distribution.....	139
9.2.	Measurement Error Probability Distribution Function.....	140
9.3.	Measurement Error by Flaw Type.....	142
9.4.	Human vs Machine Perception.....	143
9.5.	Computer Vision Operations.....	147
A.1.	Interconnection Diagram.....	160
A.2.	Front Panel Layout.....	161
A.3.	Image Pipeline.....	162
B.1.	Software Data Structures.....	164
B.2.	Frame Buffer Memory Map.....	168
B.3.	Frame Buffer Coordinates.....	169
B.4.	Main Flowchart.....	171
B.5.	AcquireImage Flowchart.....	172
B.6.	VmeStdRefl Flowchart.....	173
B.7.	NormIntens Flowchart.....	174
B.8.	ThreshFlaws Flowchart.....	175
B.9.	SysOpen Flowchart.....	176
B.10.	SysInit Flowchart.....	177
B.11.	GetNoteRefl Flowchart.....	178
B.12.	GetSubRefl Flowchart.....	179
B.13.	GetInkRefl Flowchart.....	180
B.14.	IsolateFlaws Flowchart.....	181
B.15.	ExtractFlaws Flowchart.....	182
B.16.	Canal Flowchart.....	183
B.17.	FindBlobs Flowchart.....	184
B.18.	GradeNote Flowchart.....	185
B.19.	Micrograde Flowchart.....	186
B.20.	CorrNote Flowchart.....	187

B.21.	SSDA Algorithm Flowchart.....	188
B.22.	WarpNote Flowchart.....	189

CHAPTER 1

INTRODUCTION

Background

As we near the 21st Century, global competitiveness has become the torch of American enterprise. Companies have accepted the challenge to increase productivity, improve quality, and reduce costs in order to remain competitive in a global market. Industrial automation has been instrumental in achieving these goals and has been aided by new tools such as automated inspection systems to replace humans for piece-by-piece inspection on the production line. The machine vision system is well suited for highly repetitive inspection tasks, which require application of a consistent evaluation standard.

This latest industrial revolution has not been overlooked at the U. S. Bureau of Engraving and Printing in Washington, D.C. As the world's largest manufacturer of security documents, it has made a commitment to produce high-quality products for its customers at the lowest possible cost. This commitment is the first mission in the Bureau's Management Handbook (Bureau of Engraving and Printing, 1985).

The principal mission of the Bureau is to meet customer requirements for security products of the highest quality in the most cost-effective and safe manner possible. Most customer agencies are not required by law to purchase their products from the Bureau. Consequently, the Bureau's major objectives are high productivity, rigid quality control, and cost effectiveness. To accomplish these objectives, considerable emphasis continues to be placed on automation and the application of new or advanced technologies.

The Bureau is faced with limited room for expansion and an ever-increasing demand for more currency. Its challenge is to increase production capacity without increasing the equipment inventory. To fulfill its mission statement within the given physical constraints, a faster method of producing high-quality currency is necessary.

The Bureau of Engraving and Printing

The Bureau of Engraving and Printing (BEP) is the official printing agency for security documents of the U.S. Government. Each year more than 40 billion security documents are produced by the BEP. Federal reserve notes, or currency, and U.S. postage stamps account for ~ 93% of its production.

The BEP began in 1862 as a single room in the Treasury Building, with a staff of four women and two men. Their function at that time was to separate and seal currency printed by a private bank-note company. The U.S. Treasury Department began printing currency in about 1864, but the Bureau of Engraving and Printing did not receive status as a separate organization of the Treasury Department until March 3, 1869.

Gradually, currency printing functions were transferred from private bank-note companies to the Treasury, and by 1878 all currency was printed at what was then called the Engraving and Printing Bureau. From these modest beginnings, the BEP has grown to ~ 2300 employees. The BEP occupies two buildings in Washington, D.C., with more than 25 acres of floor space near the Nation's capitol.

The operation of BEP is financed by a revolving fund established on August 4, 1950. The fund is reimbursed by other governmental agencies that use BEP services. The cost to other agencies includes administrative expenses as well as the acquisition of capital equipment and modernization. The BEP tries to reduce costs to its customers by improving productivity and controlling labor expenses. Its success can be seen by its annual production increase of 9.6% while the number of full-time employees has been reduced by 26% since 1977. This has been accomplished by the aggressive and systematic infusion of new technologies and equipment. The BEP maintains an ongoing policy of replacing labor-intensive production practices with capital-intensive equipment.

Evolution of Web Printing and Inspection

Floor space at the BEP is limited and cannot accommodate major additions of production equipment. Also, the labor pool available to operate additional equipment is limited because of mandated restrictions in the number of full-time employees. The existing equipment is operated three shifts per day and cannot be expanded to meet the expected increase in demand. The present currency production rate is 10,000 sheets per press shift. Given the annual increase of 5% requested from the Federal Reserve Board, the production requirement is expected to increase by 400% (to 40,000 sheets per shift) by the year 2000 (Rogers, 1987; Regone, 1986).

Because of the space and manpower constraints, production needs for the 21st century must be met by advances in printing technology rather than through expansion of existing facilities. Web printing technology has been chosen to replace the existing sheet production line. In web printing format, the notes are printed on both sides at once on a continuous roll or web at 600 ft/min. The advantage of web printing is its higher press speed. It is estimated that web production will print 80,000 sheets per shift, which will meet the expected production requirements.

Equipment is being designed to print, inspect, and package currency in one operation. A single production line could replace several machines distributed in different areas. Consolidating production to a central location will alleviate the necessity of transporting the sheets to each station.

The inspection system should be an integral part of the press so that the examination can be performed without transporting the webs to another location. Combining the inspection with the press will require that the inspection system operate at web speeds. An automated inspection system that can operate at web speeds is crucial to the success of conversion to web technology. Encouraged by successful installations in other industries, the BEP plans to investigate converting its present manual inspection to an on-press automated inspection. The ultimate goal is a closed-loop system that enables the press to adjust its operating parameters to correct abnormalities detected by the inspection station.

The inspection system design is complicated by the lack of web currency because the web press is being developed concurrently with the inspection system. The performance of the press is unknown, and the product to be inspected is unavailable. As a result, many assumptions were made to begin design of the inspection system. Consequently, the uncertainty in the inspection system performance is higher than desired.

The inspection system will be developed in incremental phases to gain confidence that it can perform comparably to human examiners before being mounted on the press. The first phase is to develop an experimental prototype to test the efficacy of various inspection methods on static notes. The objective is to develop algorithms that meet the functional requirements but with reduced speed constraints. During the second phase, the prototype then will be extended to acquire dynamic images from a low-speed web transport mechanism. The third phase will begin when confidence has been established in the chosen approach for the prototype. A system that operates at production speed will be constructed and installed on an off-line inspection station for long-term evaluation. The final phase is to integrate the inspection and printing operations. When the web press becomes available, the fully developed inspection system will be mounted on the press.

Research Objective

The objective of this research is to demonstrate the feasibility of automated web inspection by developing the experimental prototype (phase one) inspection system. A literature survey will provide information on previous attempts. Published reports indicate that certain deficiencies are common to many other inspection methodologies. It is hoped that analyzing these machines will make it possible to mitigate inherent weaknesses.

One common problem is the lack of a quantitative method of rating the severity of print flaws. Previous attempts applied a decision threshold to a small sample of flawed notes to validate the performance of the inspection system. The data from such tests proved difficult to interpret. As a result, evaluations of machine performance were subjective. This method has been used to train human examiners, who can extrapolate these guidelines to arbitrary flaws. But it is unlikely that this perception and judgement can be implemented in a computer capable of operating at the required speeds.

Several critical yet contending requirements must be met if the inspection system is to be successful. Sensitivity must be high enough to detect small, low-contrast flaws and still ignore normal note-to-note variations caused by the printing process. The system must replicate the results (if not the reasoning) of human examiners from parameters measurable with a machine vision system. Moreover, it must be realizable with current technology.

The experimental prototype inspection system uses three models to implement currency inspection. Previous research of others was used to compile a flaw perception model describing the essential properties of currency inspection and an algorithmic model was developed from the mathematical description of the flaw perception model. A physical implementation model was then developed with hardware components and software architecture to realize the algorithmic model. Closure is achieved by evaluating the exemplars used to derive the flaw perception model and comparing the results with those of its human counterpart.

Narrative Organization

This report documents the research, design, and development process for the experimental prototype inspection system. Chapter 2 describes the present methods of currency production, and previous automated currency inspection machines are reviewed to compare the strengths and weaknesses of different methodologies.

Chapter 3 examines human perception of currency flaws. Two flaw-severity equations, derived empirically from human observations, relate a numerical value to the size, contrast, and location of printing flaws found on notes. The equations are a key component in the flaw perception model presented in this chapter.

Chapter 4 describes the image-formation process comprising the illumination, optics, and image sensor. Selection of a suitable sensor is given, along with the trade-offs of each candidate. An expression for image intensity as a function of physical parameters is derived.

Chapter 5 presents the three-dimensional normalization algorithm used to align a test note to a fixed reference image. The spatial normalization employs an unusual subpixel correlation scheme to locate topological features in the test note. The method of normalizing the photometric scale to a fixed reference is given also.

Chapter 6 presents the method of controlling the detection sensitivity over the image. A structural filter is used to reduce the adverse effects of normal printing variations by incorporating the statistical variances of real currency. The method of isolating, analyzing, and evaluating the flaws is described.

Chapter 7 describes the physical realization of the algorithmic model. The hardware components required to perform the image operations are shown, along with the software architecture required to realize the algorithmic model.

Chapter 8 presents the experimental data obtained with the prototype. The flaw perception model is validated from the experimental data.

Finally, Chapter 9 presents the conclusions of the study along with suggestions for future research. The experimental results are used to compare the prototype with evaluation of the human examiners in order to determine the strengths and weaknesses of the flaw models.

CHAPTER 2

CURRENCY PRODUCTION AND INSPECTION

Domestic Currency Production

U.S. currency is presently produced at the BEP on an intaglio press at the rate of 8000 sheets/h. It is printed on 100% rag paper interwoven with distinctive red and blue fibers. The paper is sized with animal glue and glycerine and has reflectance ranging from 0.65 to 0.73.

In intaglio printing, the engraver carves the desired image on the printing plate by cutting in the plate surface shallow grooves that will act as ink wells during printing. The engraved plate is wrapped around a steel cylinder, where an ink roller transfers ink to the plate, filling the engraved grooves. The plate then is wiped with a blade to remove excess ink from the raised areas. The plate is then pressed against the paper with up to 60 tons of pressure, forcing the ink onto the paper. When the plate is lifted from the paper, the ink is left on the paper giving the note its distinctive three-dimensional feel (Payne, 1986).

The sheets are printed backside first and are allowed to dry for 24 to 48 h before the portrait side is printed and dried. There are 32 notes on each sheet, four across and eight down. After inspection, the seals and serial numbers are added. The notes are then cut into single units, counted, and packaged for delivery to the Federal Reserve System.

Currency Printing Flaws

Ink transfer from the roller to the engraved plate is not precise; the ink grooves can be underfilled or overfilled. Also, a thin layer of ink can be left on the raised areas after wiping, causing an ink stain on the paper. In wide, deep engravings, ink splatter onto the paper during transfer can cause the ink lines to have ragged edges.

If the paper does not contact the ink in the engraving wells, the ink will not transfer to the paper, resulting in missing ink. A similar condition results from nicks or other mechanical damage to the engraving plates. Also, if the ink has not dried completely when the sheets are stacked, ink from the reverse side will transfer to the opposing surface.

Each plate used to print currency is slightly different. Additionally, environmental conditions during printing such as temperature, humidity, and moisture content of the paper contribute to normal variations in currency. Currency paper is made from a slurry consisting mostly of water. During the finishing process, the water is gradually removed until it is ~ 5%. Changes in the ambient relative humidity will cause the paper to expand or shrink. If an image has been printed, the image geometry changes along with the paper stretch. This is known to be less severe for web printing than sheets because the paper has a shorter exposure to the air due to the higher operating speeds (Reed, 1985).

At the highest level, currency flaws can be classified as either printing flaws or nonprinting flaws. Printing flaws occur as a result of the printing process and include (1) excess-of-ink flaw such as localized spots called slywipes, and (2) dearth-of-ink flaws such as areas of missing ink referred to as breaks. Nonprinting flaws are defects in the paper substrate and include oil stains and tears.

Printing flaws are considered to be either local or global depending on the coverage area. A global flaw is one that occurs over a large area of the note surface, typically affecting the entire note. A lightly-printed note in which the ink level was insufficient over the entire note is an example of a global flaw. Local flaws are confined to a finite subarea on the note. Examples of local flaws are slywipes and breaks.

In the sheet currency printing process, four prominent types of flaws can occur: (1) misregistration, (2) excess ink, (3) deficient ink, and (4) paper defects (Coggsall, 1981).

Misregistration: Recall that the front and back sides of the notes are printed separately. If the alignment of the second printing does not match the first, the front side is misaligned with the back.

Excess Ink: Excess-of-ink flaws fall into the following categories:

Mash • The ink tends to splatter at the edges of deep engraving lines such as on the corner denomination markers. The effect of mash is to render a clean, straight line as ragged and uneven.

Slywipe • If the excess ink on the plate is not wiped clean, it will be transferred to the paper as a localized inkspot.

Setoff • After the initial printing, the sheets are stacked for storage. If the ink has not dried sufficiently, it can transfer to the sheet above, leaving an image on the opposing surface.

Deficient Ink: Dearth-of-ink flaws can also occur, resulting in the following flaw conditions:

Breaks • Too little ink in certain engravings can fail to transfer, leaving a gap in the printed note.

Light Print • If the ink is uniformly insufficient over the entire plate, the printed image will be faint.

Paper Defects: Several defects arise from problems in the paper prior to printing; these include:

Creases • Paper sheets that have been creased or folded will cause the image to be distorted when the paper is unfolded.

Stains • Sometimes the oil from the press machinery can drip onto the threaded paper, leaving a transparent stain.

The most common printing flaws are illustrated in Figure 2.1.

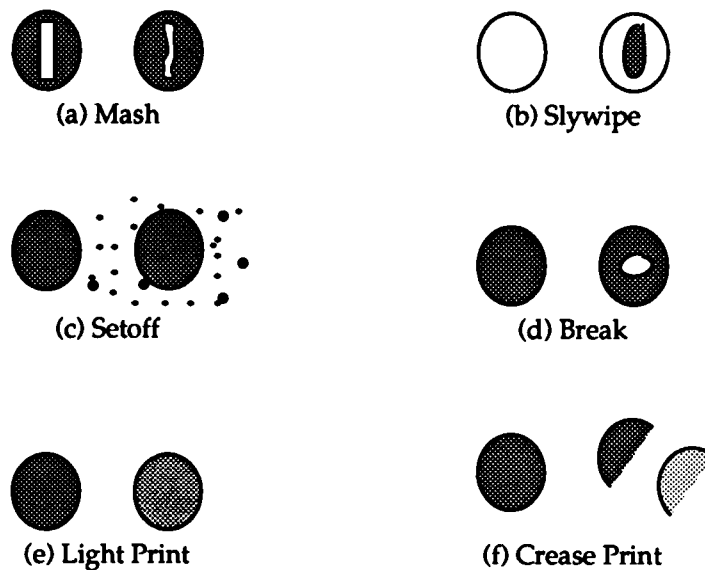


Figure 2.1. Types of Printing Flaws.

In each case (a-f), the normal image is shown on the left with the corresponding flaw on the right.

Manual Currency Inspection

Currency inspection is performed in a semiautomatic fashion by human examiners. After intaglio printing, an automatic sheet feeder cuts the partially printed sheets into half-sheets with two notes across and eight notes down. As the half-sheets move on a conveyor the portrait side is inspected by a human examiner. The sheets are then turned over and the reverse side is inspected by another inspector. Because the maximum inspection rate is 2 half-sheets/s, the examiner nominally has 30 ms to inspect each note. Consequently, the inspection is primarily to remove grossly defective sheets for destruction. Small flaws on individual notes are not easily detected with this inspection method.

The examiners use a set of flawed notes or exemplars as a reference. Representative samples of flaws such as slywipe, break, mash, or setoff are included in the set. Because the examiners use their individual judgement and experience to mentally extrapolate the acceptability of a flaw found on the inspection line to an exemplar, the potential for variation in evaluation standards among the examiners is high.

The sheet is removed whenever an unacceptable flaw is found and the entire sheet is eventually destroyed even if only one note is flawed. As a result, nearly \$3 million worth of acceptable notes are destroyed each year.

The acceptable half-sheets are stacked for use in the currency overprinting press. This is a two-color press that adds the serial numbers, the U.S. Treasury seal and the Federal Reserve Bank seal to the front side of the engraved notes. The sheets then are cut into individual notes and counted automatically. The finished currency is spot-checked by a human examiner before being packaged for delivery to Federal Reserve banks.

International Technology Assessment

The history of automated inspection dates back to the mid 1950's when the Bank of England attempted an analog method of comparing adjacent notes. Over the ensuing three decades, a variety of methods have been attempted by many currency-producing nations worldwide. This provides an excellent basis for evaluating the strengths and weaknesses of a variety of technology alternatives.

Switzerland

The Swiss National Bank began investigating automated inspection in 1974. An image-processing laboratory was built to experiment with various inspection methods. From 1979 to 1981, the algorithms conceived earlier were tested with actual and simulated flaws. The experimental work culminated in a prototype inspection system capable of inspecting full sheets of notes moving at 60 m/min (195 ft./min). Sensor exposure was 1/2000 s at an illumination of 3 million lux. By comparison, the illumination from the sun on a moderately bright day is 100,000 lux. The notes were spatially aligned using natural image features as reference points. The pixel size for the image was 0.52 mm (0.020 in) per side. Sensitivity near print edges was reduced to compensate for normal print deviations. The algorithm required 20 min to evaluate each note side using a minicomputer.

Several major obstacles to automated inspection were identified as a result of the Swiss experiment:

Paper Noise • Caused by the mottled texture and fiber content of the paper.

Print Variation • Normally acceptable variations in the location of engravings. Differences in reflectance of the ink and paper.

Digitization Noise • Errors arising from the quantization of the camera signal into discrete values.

Position Errors • Inconsistency of the note position caused by mechanical variations of the transport system.

Illumination Noise • Image noise introduced by variations in lighting intensity.

The researchers concluded that, although the quality of the inspection was deemed to be good by note printing specialists, the hardware available at that time (circa 1978), was inadequate to make their approach practical for an inspection system (Kuhl, 1986).

Denmark

In 1967 the Danmarks Nationalbank decided to switch from sheet printing of currency to continuous web printing. Since 1972 all Danish banknotes have been printed and cut from continuous web. In order to inspect the web, a wind-unwind stand with a viewing station was developed to manually inspect all notes on the web. The operator adjusted the web speed from 0 to 30 m/min with the average ~ 10 m/min. Because the work is so tedious, the operators must rest 15 of every 45 min.

An experimental automated inspection system was built in 1974 using a concept developed at the Bank of England in the 1950s. The Danish machine used two cameras to scan identical lines on adjacent notes on the web. The cameras used a 256-element linear array across the note, giving an image resolution of 0.6 mm (0.024 in.) per pixel. Because the web speed was 70 m/min (230 ft./min) and was not synchronized with the camera scan, the number of scan lines per note varied. The analog output of the two cameras was subtracted. If the difference signal exceeded a predetermined threshold level, the note was declared defective. The advantage of this method is that fast analog circuits can be used for the image subtraction rather than digital subtraction, which would have required a computer. At that time, computerized digital image subtraction was too slow to be practical. The disadvantage was that it required the adjacent notes to be perfectly aligned relative to each other and that no paper distortions be present.

One difficulty discovered during this experiment was the variation in sensitivity of individual pixels across the camera linear array. The problem was overcome by installing a look-up table to normalize each array element to a standard sensitivity. Vibrations on the web also caused problems in image alignment. After experiments with a floating mount were unsuccessful, the problem was solved by using a rigid mounting frame.

The normal note-to-note printing variation was also found to cause problems. In areas of large contrast change, the rejection threshold would have to be set very high in order to prevent false rejects due to print variation. The high threshold level would then allow low-density flaws to pass undetected.

The Danish experiment concluded that high-density flaws down to 0.7 mm (0.03 in.) could be found. The threshold level was set to permit 1% spoilage under normal conditions. Dark spots on dark parts of the paper were found to be more detectable than spots on light parts. The system easily identified high-density flaws but detection of low-density flaws was less reliable (Yde, 1986).

Japan

The Printing Bureau of Japan has been experimenting with automated currency inspection for more than 25 years. Although the initial prototype located spot defects down to 1 mm (0.040 in.) diam, the machine was considered inferior to human inspection due to several serious shortcomings. The most prominent difficulty was in selecting a flaw threshold. When the threshold was set low enough to detect small flaws, the noise of the electronic amplifiers caused excessive false rejects.

Building upon the knowledge gained from the initial system, the Printing Bureau continued to work on automated inspection. The result was a machine that could check currency sheets for color registration and other printing flaws. The system utilized an analog subtraction to compare notes from adjacent columns. The experiment indicated that the sheets must be very flat in order to prevent false rejects; any waviness or displacement in a sheet causes problems.

The Japanese concluded that automated inspection is possible but requires more development in order to detect the low-density flaws easily spotted by human observers (Matsukawa, 1986).

France

The Bank of France began an experimental program to inspect currency in 1971 when the digital computer became readily available. Their first system used three color image dissector tubes for the acquisition system. Image dissectors were selected over vidicon tubes because of their capability to address each pixel in the photosensitive plane. The tubes had a resolution of 1500 pixels but had very low light sensitivity. Consequently, an excessive amount of illumination was required to get a usable image.

This was deemed unacceptable, and a new detector head was designed to replace the image dissectors. The new detector was built in 1972 and consisted of 128 phototransistors in a linear array. The note was imaged onto the phototransistors through a fiber optic array. In 1973 the phototransistors were replaced with photodiodes to improve the temporal stability of the acquisition system. A He-Ne laser illumination system added in 1974 gave a resolution of 0.3 mm. They continued to work on this system until 1977, when it was deemed too expensive to achieve a practical inspection volume.

The difficulties of this method were due to the high false rejection rate caused by normal printing variations in notes. The program concluded that the technology had not matured sufficiently to support the inspection concepts developed to that point (Perron, 1986).

United States

The BEP has been investigating automated currency inspection since the early 1970s. The initial attempt used a laser to scan the sheets of currency but this method proved to be unreliable because mechanical vibrations disturbed the delicate optics required to maintain a precise scanning beam (Graminski, 1986).

In the mid-1970s an experimental system was built to determine the feasibility of detecting orientation faults in the Currency Overprinting Press which adds the serial numbers and seals to the 32-note sheets of engraved notes. The goal of this system was to detect sheets that were inverted, overturned, or completely blank prior to feeding into the press.

A charge injection device (CID) area array camera operating at 30 frames/s was used to scan each sheet. The camera frame could be partitioned into five rectangular windows of any size and position. Within each window, an adjustable threshold would clip the image to a one-bit binary representation. The number of pixels in each window was compared to an established acceptable value. If the pixel count was not in the acceptable range, the sheet was rejected.

While testing this prototype, it was observed that large, high-contrast printing flaws could also be detected (Bangs, 1986). Although this system ultimately proved unsuitable for determining sheet orientation due to excessive false alarms from sheet misalignment, it demonstrated the potential of automated currency inspection.

Several years later, the Bureau commissioned the Perkin-Elmer Corp. to develop and build a prototype system to inspect 32-note sheets of currency. The objectives of the inspection system were to examine 6000 sheets/h for front-to-back misregistration, printing flaws, folded corners, creases, and other defects. Defective notes were marked individually and the sheets were sorted according to the number of flaws on the sheet (Coggshall, 1981).

The Perkin-Elmer system used a commercially available, 1024-element charge coupled device (CCD) linear array camera. The array was oriented along the vertical axis of the note with 512 pixels per line. Adjacent array elements were summed together to form pixels 0.13 mm (0.005 in.) per side. The note was scanned at a resolution of 1200 lines per note as the sheet traveled past the stationary camera. The camera used an internal analog-to-digital converter to quantize the video signal to 16 gray levels. Eight cameras were required to examine the full sheet. Camera gain and offset was adjusted prior to each scan in order to compensate for changes in illumination.

The inspection was accomplished by a pixel-by-pixel comparison between the test note and a reference note image store in memory. Each successive line in the scan was spatially correlated to the reference image to ensure that the comparison was made between matching coordinates on both notes. The comparison was made by taking the difference of the two notes and algebraically summing a 2×2 pixel area in the difference image into a larger element called a patch. The 2×2 patches were then summed into 4×4 patches. This was repeated to form 16×16 and 32×32 patches. A histogram of the reflectance differences was accumulated from the patch intensities. If the two notes are properly aligned, a patch reflectance in the test image is equally likely to be higher or lower than the reference when the difference is due to random factors such as noise or quantization uncertainty. A histogram taken under these conditions produces a Gaussian distribution of the differences. If either the extent or symmetry of differences exceeded a threshold, the note was considered flawed (Blazek, 1986; Savarese, 1981). The smaller patches detected small, high-contrast flaws such as inkspots, setoff, breaks, and mash while the larger patches were for large, low-contrast flaws such as slywipes, blanket impressions, and stains.

This system performed as intended but could not reliably detect the low-contrast, excess ink flaws that occur in the printed parts of the notes. When the detection threshold was lowered to discern low-contrast flaws, it resulted in an increase in false alarms due to normally acceptable print variations. The lessons learned from these experiments will be included in the design of the experimental prototype inspection system described in the next chapter.

CHAPTER 3

FLAW PERCEPTION AND METROLOGY

Flaw Perception

Because human visual perception is done with such apparent ease, it is easy to underestimate the difficulty in automated perceptual evaluation of print defects until one attempts to solve the same problem with a computer algorithm. It should be remembered that image processing is not equivalent to image perception. Image processing is the enhancement and manipulation of images in order to produce a new image for human viewing. It can also be used to determine certain characteristics (such as average brightness) of an image.

Image perception is a higher level process of understanding what an image represents and the relationship of its contents. Often an image perception problem can be simplified by limiting the number of object classes under study. This is the situation in machine inspection tasks, where the relative goodness of a known class of objects is the primary concern. Therefore no attempt will be made here to formally relate currency inspection to human psychological models such as Gestalt theories. The goal of this research is to develop and demonstrate an automated currency inspection system that gives results similar to those of human inspectors. This is much akin to the way an airplane copies the behavior of a bird; they both fly, but the process is accomplished differently. In order to duplicate the performance of human examiners, a method of quantifying their standards of judgment must be found that can be implemented with machine vision equipment.

Image perception can be defined as the process of developing a description of an image in order to determine its contents. A hierarchy of perceptual models for a machine-based information processing task was suggested by Marr (1982). The three models can be summarized as follows:

Computational Theory • What is the goal of the computation and why is it necessary?

Representation and Algorithmic Model • How can the computational theory be implemented? In what form will the input and output be described? What are the rules of the operation?

Physical Model • How can the representation and algorithm be realized physically?

While true psychophysical perception is not the objective in this application, Marr's perceptual hierarchy is a useful tool to describe the currency inspection process. That process, illustrated in Figure 3.1, shows the three levels of abstraction and their relationship.

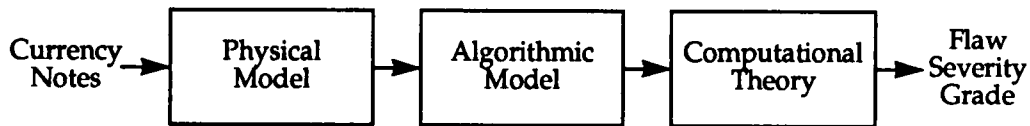


Figure 3.1. Representation of Currency Inspection Process.

In the inspection process, the notes are acquired according to the physical model into a two-dimensional image array. The image array is analyzed with the algorithmic model to locate any flaws on the note and to measure the flaw parameters. The flaw severity grade for the note is calculated from the flaw parameters using the flaw perception model described by the computational theory.

Computational theory is the highest level of abstraction for a task. In visual processing, the objective is to reliably extract or infer properties of the environment. The computational theory represents the link between human observation of flaw severity and machine perception of the same flaw. In this application, the computational theory represents the flaw perception model, which is closely coupled to the algorithmic model since the flaw detection algorithm will by definition be based on human perception. The next level is representation of the input and output of the process along with the algorithm by which the process operates. In machine vision systems, the representation is typically the two-dimensional array of intensities. The algorithmic model represents the numerical steps and calculations that isolate and measure the parameters of the printing flaws. It consists of the image formation and processing steps, which isolate and measure currency flaws. While computational theory describes the goals of the process, the algorithmic level describes how these goals will be achieved. The algorithmic model produces a numerical value

representing the print quality of the note. The lowest level is the physical model, which is the hardware required to implement the algorithmic model. The physical model interacts directly with the currency notes under inspection. It consists of the camera, image processing equipment, and computers used to perform the operations defined by the algorithmic model.

Machine vision operations are divided into low, mid, and high levels of computational complexity. The three levels differ in the data rates required to process the image and the complexity of the algorithms. Low-level processing treats the image as a set of data elements without regard to what the structure may represent. The image operations are performed on a pixel-by-pixel basis, scanning through the array until all elements have been processed. Examples of low-level processing are the simple filters for edge extraction and smoothing, zero-crossings, texture, motion, and depth. In mid-level processing, the structure and organization of the data are considered. Features extracted from the image at this level may be represented by intensity histograms, feature lists, connected components, and frequency domain transforms. High-level processing usually involves a knowledge-based system to describe the scene in more abstract terms through object and shape descriptors. Pattern matching, semantic nets, and inferences are examples of high-level processing.

The attributes of the three levels of processing are summarized below:

Low-level • 10- to 50- MHz processing speed, operates on image data, identical operation performed on each data element, 1D or 2D matrices, regular communication paths between processing elements, high parallelism.

Mid-level • 1- to 20- MHz processing speed, operates on low-level output, hierarchical data path, recursive operation. Data rates are slowed because some operations depend on the results of the previous operation. The data path is determined at execution time by a controller.

High-level • Less than 1- MHz processing speed, usually complex algorithms for decision functions, multiprocessor architecture, low parallelism. Custom multiprocessor architecture is desired.

The control of processing tasks can be either data-driven (bottom-up) or model-driven (top-down). In data-driven environments, image control moves from lower levels to higher levels along with the image data. Data at one level are used to direct the actions at the next higher level. If changes are perceived in a low-level image, this feature is passed up to the next level. In model-driven environments, the processing is goal-directed from the upper levels down to the

lower levels. The actions of one level are predicated upon the expectations of the level above. An image might be searched to see if it contains the expected object. In reality, the data-driven and model-driven approaches represent the ends of a continuum where most applications have a combination of control paths up and down the hierarchy (Luck, 1987).

The focus of an inspection task, as mentioned earlier, is on copying the perception of human inspection at the lowest level. Therefore, inspection system functions are necessarily concentrated in the physical and algorithmic models. These models correspond respectively to the low and mid-level processing associated with machine vision.

Human Flaw Perception Model

In a study by Collins *et al.* (1985), it was observed that the average person inspects currency by making a check of the corner denomination numeral along with a possible glance at the center portrait. Low-level visual processing occurs automatically and does not involve active cognition. It is related to edge detection and texture discrimination of features of high interest or noticeability. This usually occurs in response to changes in intensity, color, or texture patterns. The areas of high noticeability in currency are light features on a dark background such as the four corner numerals, portrait face, and lower center denomination title. The eye is instinctively drawn to the portrait region because of its central location on the note and because the shape and content are familiar. Thus it should be intuitively expected that the perception of flaws is highest in the portrait region. Conversely, the delicate scroll patterns in the outer lathework tend to blur together into complex and unpredictable patterns. The features in this region are so intricate that the average viewer cannot remember the pattern. In this region a flaw that matched the general intensity and texture of its surroundings would be difficult to detect.

The present inspection method requires human judgment to evaluate the relative noticeability of a given flaw. The test for acceptance or rejection of a note is based on a set of visual samples covering a limited number of flaw classifications. The noticeability in general depends on the contrast with the background, size, and location of the flaw. A flaw in the portrait area (particularly in the facial region) may be unacceptable, while the same flaw would be imperceptible elsewhere.

The failure of previous inspection systems can be attributed in large part to the lack of a quantitative flaw definition. The lack of a flaw metric makes comparison of machine performance with human examiners difficult. During an earlier BEP experiment (Karohl, 1989), a quantitative definition of a flaw could not be established, so a flaw was arbitrarily defined:

A printing flaw is any defect in the printing of currency which is obvious to a casual observer.

This definition has no provision for gradations in flaw severity and therefore gave inconsistent results when several observers rated an arbitrary flaw. Currency evaluation has not been an exact science; consequently, the grading tends to be subjective. There are variations in opinion even among experienced examiners. Further complicating the issue is the inherent pressures arising from production demands. An overly critical evaluation standard could reduce the production yield below needed levels.

To overcome these deficiencies, the BEP commissioned a study to incorporate visual flaw exemplars into a general definition of flaw standards (Johnson *et al.*, 1987). Thirty-seven judges were interviewed to determine their perception of observed print flaws in currency. The judges, recruited from the various ranks of BEP occupational categories, rated 300 exemplars of naturally occurring and simulated flaws. The exemplars were representative of the flaws found in sheet-currency, such as light print, slywipe, mash, blanket impression, setoff, and ink breaks. The judges assigned a numerical grade to each note to indicate their opinion of flaw severity based on the criteria given in Table 3.1.

Table 3.1. Note Grading Scale Used in ORNL Flaw Survey.

Grade	Note Condition
0	Ideal, Hypothetically Perfect Note
1	Always Acceptable
2	Good
3	Fair
4	Poor
5	Always Unacceptable

It was determined that the judges could be categorized as either liberal or conservative in grading, with the conservative judges being more critical in their evaluations. Liberal judges might find a flaw always acceptable, while the conservatives would rate the same flaw as always unacceptable. This bimodality seemed to be related to the occupational background of the judges. Those judges involved in production tended to be more liberal than those judges with a quality control background.

The data set was reduced to 245 notes and 31 judges after removing the outliers. A flaw severity grade ranging from 0 to 5 was calculated for each note by averaging the individual grades of the 31 remaining judges.

Flaw Metrology

The following definitions are useful in understanding the measurement of flaw severity.

Note Region • A bounded area within the note containing similar printed features.

Flaw Component • A flawed area within a note region delimited by a flaw boundary separating the flawed area from the unflawed area. If a flaw component crosses region boundaries, it is divided into multiple flaw components.

Flaw Component Reflectance ($R_{h,b}$) • The average reflectance of a flaw component.

Background Reflectance (R_b) - The average reflectance of an unflawed note in the same location as that of a flaw component.

Flaw Difference Reflectance ($|R_b - R_{h,b}|$) • The absolute value of the difference between the reference background reflectance and the flaw component reflectance.

Flaw Equivalent Halftone Density (H) • The fraction of area covered by dots in a halftone screen overlay that provides the same reflectance $R_{h,b}$ as a flaw component when the screen is positioned over the corresponding area of an unflawed note.

The note was divided into five regions based upon relative noticeability and texture of the note features in the surrounding area. The area comprising each note region for a \$1 note is illustrated in Figure 3.2.



Region	Note Areas Included
R_1	Portrait face and hair; portrait background; signatures and accompanying titles; other small lettering in the open substrate.
R_2	Scene vignette on note back including building or monument, shading, and the Great Seal; all-white lettering; portrait shirt; leafy and scroll-type patterns in the lathework; shaded area around letters in the bottom denomination panel.
R_3	Portrait coat; open substrate excluding white lettering; white space between adjacent note images on sheet.
R_4	Lathework and shrubbery patterns around note border.
R_5	Large, solidly inked areas including Federal Reserve Note panel and front U.S.A. titles.

Figure 3.2. Representation of Currency Noticeability Regions.

Local Flaw Severity Equation

The flaws on each survey note were measured to establish a correspondence between their area, contrast, and location and the flaw severity grade obtained in the opinion survey. The area was estimated by manually measuring the approximate width and length of a rectangle equivalent to the flaw coverage area. The contrast was visually estimated by comparing the flaw to a graduated halftone screen overlay. The patches on the overlay ranged in fractional dot coverage H from 0.10 to 0.90.

The flaws were categorized as either local or global in their coverage. Examples of local flaws are slywipes and breaks, while uniform light print is a global flaw. An equation for the severity of local flaws was derived by the method of nonlinear least squares using the observed flaw severity grades of 171 survey notes with slywipes and breaks.

The local flaw equation is given by

$$F_l = 3.93 \left[\sum_{j=1}^5 R_j \sum_{k=1}^m H_{jk}^{1.76} A_{jk}^{0.75} \right]^{0.2}, \quad (3.1)$$

where the calculated flaw severity grade F_l is a function of all flaws found on the note. The first summation is over the five regions in which the flaws are located. The second summation is over the m_j flaws within region j .

The region weighting factors have the following numerical values:

$$R_1 = 2.24$$

$$R_2 = 0.48$$

$$R_3 = 1.0$$

$$R_4 = 0.11$$

$$R_5 = 0.17$$

Note that Eq. (3.1) is shape-invariant since it was determined previously that circular flaws and rectangular flaws gave similar severity grades. Also, the area and density of each flaw component must be maintained separately during summation. This eliminates the commonly used machine vision technique of global thresholding and summing pixel over the entire note, since the area of individual flaws is lost.

The density parameter H is a transmissive factor and is not directly measurable with a machine vision camera, which measures the radiant energy reflected from the note surface. A flaw layer over a printed area produces an amplitude different from the same flaw over blank substrate. Therefore, a method of determining the equivalent H from image intensity is needed.

Determination of Halftone Density

In Eq. (3.1), H is given in units of halftone density, defined as the percentage dot coverage in an acetate overlay created for this survey. The overlay was made by printing small, uniform dots in a regular pattern over a prescribed rectangular patch.

The conversion from image intensity to halftone dot coverage is based on the theory of multilayer reflectance and transmittance (Kurtum, 1969). The total reflectance, R_{xy} , when homogenous layer x is covering layer y is given by:

$$R_{xy} = R_x + \frac{T_x^2 R_y}{1 - R_x R_y}, \quad (3.2)$$

where T_x, R_x is the transmittance and reflectance of the upper layer and T_y, R_y is the transmittance and reflectance of the lower layer. The transmittance is the amount of light that can pass through the patch and is inversely related the concentration or density of the dots in the patch. The transmittance can be increased by spacing the dots farther apart or decreased by reducing the dot spacing.

The concept was extended to cover the special case in which the upper layer is the halftone screen overlay rather than a laterally homogenous layer (Johnson *et al.*, 1987). If the blank acetate surrounding the dots is assumed to have transmittance of 1.0 and a reflectance of 0.0, the average transmittance and average reflectance of the overlay screen T_h and R_h can be expressed as:

$$T_h = (1 - H) + HT_d \quad (3.3)$$

and

$$R_h = HR_d, \quad (3.4)$$

where T_d and R_d are the transmittance and reflectance of the dots respectively. By substituting Eqs. (3.3) and (3.4) into Eq. (3.2), an expression is obtained for the reflectance of the halftone screen R_h over a reflective background R_b and is denoted R_{hb} in,

$$R_{hb} = HR_d + \frac{[(1-H) + HT_d]^2 R_b}{1 - HR_d R_b} . \quad (3.5)$$

This equation can be rearranged as a quadratic in the familiar form:

$$H(R) = \frac{b \pm \sqrt{b^2 - 4ac}}{2a} , \quad (3.6)$$

subject to the constraint $1.0 \geq H \geq 0.0$. The coefficients are determined by:

$$a = R_b \left\{ (1 - T_d)^2 - R_d^2 \right\} , \quad (3.7)$$

$$b = R_d + R_d R_b R_{hb} - 2R_b (1 - T_d) , \quad (3.8)$$

and

$$c = R_b - R_{hb} . \quad (3.9)$$

The parameters to be determined by the inspection system are the flaw coverage area A and the average density H of each flaw component k within region j . The calculated flaw severity grade is then obtained from Eq. (3.1). The reflectance and transmittance of the dots R_d and T_d are constants which were measured with the camera as, $R_d = 0.042$ and $T_d = 0.075$.

Global Flaw Equation

A second equation is used to determine global flaw severity such as when the flaw covers the entire note. In this case, the region and area have no meaning and are dropped. A new variable Δ was defined to be the difference in reflectance of the substrate and the print,

$$\Delta = R_s - R_p \quad (3.10)$$

where R_s and R_p are the average reflectance of the test note substrate and print respectively.

The global flaw equation was derived from the measured Δ at selected printed areas on a test note using a reflectance spectrometer. The experimental data were well approximated by a linear function of Δ , with slope m determined from the measured Δ and observed flaw grade F of any two survey notes i and j ,

$$m = \frac{F_i - F_j}{\Delta_i - \Delta_j} . \quad (3.11)$$

The global flaw severity grade F_g is calculated from slope m and constants Δ_o and F_o , which are the print-substrate reflectance difference and observed grade, respectively, of an arbitrary reference note:

$$F_g = \max \{ m\Delta + (F_o + m\Delta_o), 2 - [m\Delta + (F_o + m\Delta_o)] \} . \quad (3.12)$$

Notice that in the first term of Eq. (3.12), as Δ increases due to darker print the flaw grade can "improve" to values less than zero. The second term was added to ensure that $F \geq 1.0$ and is single-valued as well as to evaluate extremely dark print, such as mash. The resultant global flaw grade is the maximum value of the two terms of Eq. (3.12) shown graphically in Figure 3.3. Here the global flaw grade of arbitrary note F_i is shown along with the relationship to an "ideal" note with $F_s = 1$ and $\Delta = \Delta_s$ and an arbitrary reference note $F = F_o$ and $\Delta = \Delta_o$.

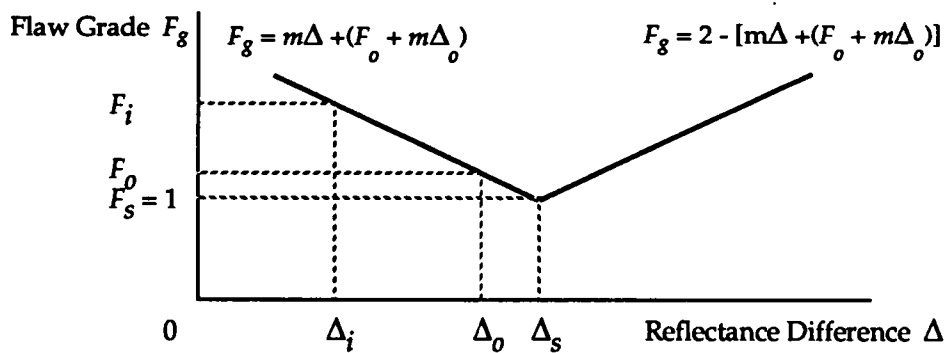


Figure 3.3. Graph of Global Flaw Severity Equation.

(Source: Johnson, 1987).

Composite Flaw Equation

Local and global flaw grades can be combined into a single numerical value for convenience in making an accept/reject decision. The composite flaw grade is obtained by considering the global flaw grade as an equivalent local flaw. The composite flaw grade is thus the geometric sum of the local and global grades according to

$$F = [F_g^5 + F_l^5]^{1/5} \quad (3.13)$$

Human Visual System

In order to construct a machine that can duplicate the ability of the human visual system (HVS), it is necessary to establish the limits of performance. For analysis purposes, the HVS is defined to be a hypothetical human inspector in an industrial, assembly-line environment. The inspector has normal vision (corresponding to a 20/20 Snellen rating), good lighting conditions, and a viewing distance of approximately arm's length (24 in.). The HVS field of view is limited to the currency note but is foveal in nature, resulting in the maximum resolution over the entire field.

The smallest observable black line on a white background for the HVS is 0.5 seconds of arc (Benson, 1986). Under the assumed conditions, the HVS can detect a minimum linewidth of 1.5 mm (0.06 mils). But observing a line is not the same as resolving it. Resolution is the ability to discriminate between two closely spaced objects. The minimum resolvable object size for the HVS is 1 minute of arc, which corresponds to 177.8 mm (7.0 mils).

The spectral response of the HVS is approximately Gaussian, ranging from 450 to 670 nm with the peak sensitivity in the green region near 550 nm. Previous experiments indicate that human visual acuity to currency is highest in yellow-green wavelengths (Carnes, 1979). The reflectance spectrum of a \$1 note shown in Figure 3.4 is relatively constant from 550 to 700 nm. This suggests that sensor amplitude would not be reduced by sampling in the 550-nm region.

The HVS excels in tasks that are qualitative, since it is insensitive to both global and absolute changes in intensity and color. This is in large part due to the adaptive ability of the HVS to compensate automatically for ambient lighting conditions. The MVS excels in quantitative tasks and can easily measure intensity changes down to 1 part in 256.

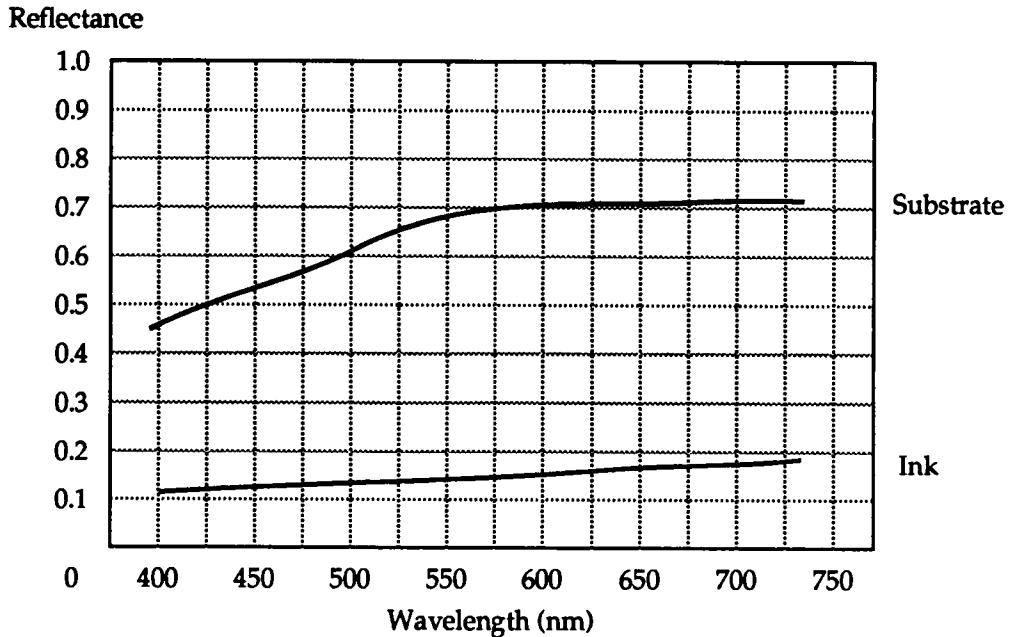


Figure 3.4. Note Reflectance as a Function of Wavelength.

The plot shows the reflectance of a typical \$1 note measured with a spectrophotometer. The upper trace gives the reflectance of the note substrate, and the lower trace is the ink in the portrait background.

Machine Performance Factors

Three factors could limit the performance of the inspection system, namely (1) process variability, (2) inherent flaws in the note, and (3) minimum detectable flaw size (Fitzpatrick, 1986). Process variability is the uncertainty in ink location and density that occurs normally in the printing process. Slight variations in print topology are imperceptible to humans but are easily identified by a high-resolution machine vision system. Inherent flaws are those features on a note that are expected but not predictable. The red and blue distinctive fibers and reflectance variations in the paper substrate are examples of inherent flaws. The minimum flaw size is related to the smallest ink feature on the note and represents the lower limit of flaw detectability.

The experiences of security producers worldwide were presented at a series of conferences sponsored by the BEP and the Oak Ridge National Laboratory. A committee of currency producers and machine vision developers collaborated to define the attributes of an ideal currency inspection system (Fridman, *et al.*, 1987; Smith *et al.*, 1987). The ideal automated currency inspection system should

- detect high-contrast flaws down to 0.8 mm (0.031 in) diam.

- have a variable flaw severity threshold that is a function of flaw position on the note.

- detect gross flaws with high contrast to the surrounding area.

- detect subtle flaws with low contrast to the surrounding area.

- detect thin streak flaws because they are very noticeable to the eye.

- accommodate normal note-to-note variations in print patterns. These are subtle variations in print geometry that are nearly imperceptible to the eye but are readily apparent to a machine.

- accommodate variations in note placement by registering the test image to a fixed reference.

- normalize note-image intensity to a fixed reference.

- evaluate notes based on a characterized set of flaw exemplars.

This information represents the accumulated experience of previous inspection efforts and, these recommendations will be incorporated in the design of the prototype inspection system.

A model of the image-processing sequence is shown in Figure 3.5. This shows the operations that will be applied to the currency inspection problem. It is desired to place an arbitrary note under the camera and to read the flaw severity grade indicating the relative worthiness of that note.

The acquired image of a test note $f(x, y)$ can be modeled as the sum of three components

$$f(x, y) = p(x, y) + e(x, y) + \eta[p(x, y), x, y] , \quad (3.14)$$

where $p(x, y)$ is the image created by the engraved plate impression on the paper, $e(x, y)$ is the ink excess and deficiency due to printing flaws, and $\eta[p(x, y), x, y]$ is the image caused from the acceptable variations in note topology correlated to $p(x, y)$. The flaws of a note are isolated from the other terms through a series of digital manipulations on the test image.

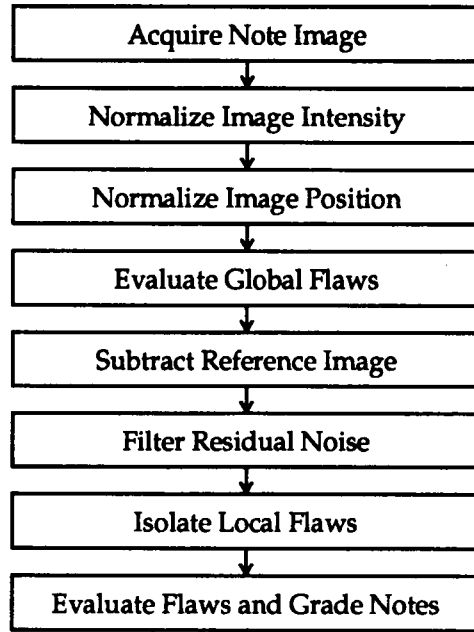


Figure 3.5. Currency Evaluation Model.

An image of a known good note is stored in memory and is used as the comparative reference image $f_r(x, y)$. The reference image is compiled from notes defined by the panel of judges as having “near perfect” quality. The reference image represents the image of the engraved plate

$$f_r(x, y) \equiv p(x, y) . \quad (3.15)$$

The engraved plate image is removed by subtracting the reference image from the test image according to

$$f_d(x, y) = |f(x, y) - f_r(x, y)| , \quad (3.16)$$

where $f_d(x, y)$ represents the absolute difference between the test and reference notes. After the subtraction, the components of the difference image are the flaws and noise artifacts

$$f_d(x, y) = e(x, y) + \eta(x, y) + \varepsilon(x, y) . \quad (3.17)$$

The term $\epsilon(x, y)$ is added to account for interpolation errors in the spatial alignment process. The spatial coordinate basis of the reference is imposed upon $f(x, y)$ by subpixel registration to align the two images prior to subtraction. The noise term is minimized by a novel noise suppression algorithm that reduces spatially-correlated topology variations in $f(x, y)$. The noise suppression algorithm is applied to the difference image by

$$f_t(x, y) = \tilde{W}[f_r(x, y), x, y] f_d(x, y) , \quad (3.18)$$

where $f_t(x, y)$ is the final image and $\tilde{W}[f_r(x, y), x, y]$ is a spatially dependent filter function.

The noise suppression filter is intended to reduce the amplitude of spatial variations without affecting the actual printing flaws by

$$f_t(x, y) = Ae(x, y) + B[\eta(x, y) + \epsilon(x, y)] . \quad (3.19)$$

The filtering algorithm attempts to maximize B/A so that attenuation of the artifact terms is large is compared to that of the true flaws, thus increasing the signal-to-noise ratio

$$SNR = \frac{e(x, y)}{\eta(x, y) + \epsilon(x, y)} . \quad (3.20)$$

The features of $f_t(x, y)$ are measured using connectivity analysis to determine the location of distinct flaw components. The flaw severity grade in Eqs. (3.1), (3.12), and (3.13) is calculated from the location, area, and density of the individual flaw components. The following chapters will describe the theory underlying each block in the model.

CHAPTER 4

IMAGE ACQUISITION

One very important function, yet usually taken for granted, is image acquisition. Image-processing algorithms have been developed with excellent methods of separating and analyzing image information. However, if the image presented is of poor quality, the likelihood of successfully extracting the desired information from the image is greatly reduced. The image of the desired scene is formed, collected, and quantized by the (1) image sensor, (2) imaging optics, (3) scene illumination, and (4) image digitizer, which constitutes the image acquisition system as typified in Figure 4.1. Each of the four elements must be optimized in order to acquire an image with low noise content, high spatial resolution, specific spectral response, and low geometric distortion. A high-quality image is necessary in order for the subsequent flaw detection algorithms to be effective.

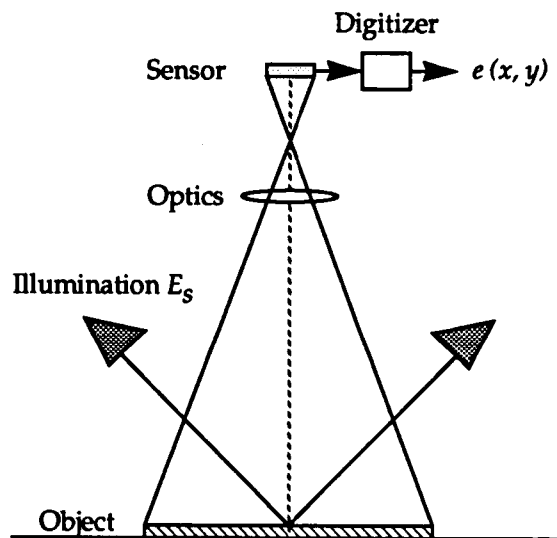


Figure 4.1. Image Acquisition System.

Image Sensor

Traditionally, video cameras are designed to produce pictures that are pleasing to the eye. These cameras take advantage of the eye's insensitivity to global intensity gradients, absolute intensity levels, and spatial coordinates by reducing the performance requirements. The inspection system, on the other hand, must accurately measure spatial and intensity features. Therefore an image sensor with superior capability must be selected for this application.

The two predominant sensor types at present are the photoconductive vacuum tube and the photosensitive silicon semiconductor. If a silicon sensor is selected, the array geometry also must be determined. Both sensors have characteristic distortions that should be considered when selecting the sensor.

Vidicon

Until recently, the most widely used sensor for industrial applications was the photoconductive vacuum tube, typically a vidicon. The vidicon develops an electric charge proportional to the light intensity on a photoconductive layer of antimony trisulfide. The charge is collected through an electron beam scanning the rear of the layer to form the video signal (Neuhauser, 1987). The disadvantages of the vidicon are similar to those for all vacuum tubes. It requires significantly more power than silicon sensors, is less rugged, and requires additional circuitry to control the scanning electron beam. The vidicon resolution is limited by the diameter of electron beam. A premium vidicon can reproduce 2000 lines of resolution.

Silicon

Silicon sensors are available in three types, (1) charge coupled devices (CCD), (2) charge injection devices (CID), and (3) metal oxide semiconductor (MOS) devices. The major differences between them are related to their internal organization (Harold, 1986). Therefore they are considered collectively for this discussion.

The basic element of the silicon sensor is the photosensitive cell called a picture element or pixel. The cell converts incident photons into a charge proportional to the light intensity on the cell window. The image is obtained by sequentially reading the charges stored in the cells. The cells can be connected together to form a line of cells called a linear array. Linear arrays can also be combined to form an area or matrix array.

The resolution of the silicon sensor is determined by the number of individual photosites. Silicon sensors are available with spatial resolutions of 2048×2048 , which is comparable to the vidicon (Holt, 1985). Silicon sensors will likely become the dominant technology in the future because of the inherent advantages of semiconductors over vacuum tubes.

Comparison of Sensor Characteristics

The decision criteria for the image sensor is to maximize the image quality while minimizing characteristic distortions. Image sensors are subject to a number of deficiencies that can limit their performance in analytical applications. Their deficiencies will be analyzed to compare and contrast the relative merits of each sensor (Newitt, 1985; Spidell, 1987; Martins, 1988; Lake, 1984; Jatko, 1989).

Image Retention

The vidicon is subject to image retention due to the high capacitance of the photoconductive layers. Retention occurs when the charge collected during one frame remains over several succeeding frames. Retention can be lessened with a lead sulfide photoconductive layer, but the sensitivity is reduced. Retention in the silicon sensor is related to the integration time of the semiconductor. Image retention in the vidicon is similar to the silicon sensor at high illumination levels. Below this intensity, retention in the vidicon increases inversely to the square root of the intensity.

Photoresponse Nonuniformity

The output amplitude of all photosites across the sensor should be uniform. Deviation from this ideal behavior is called photoresponse nonuniformity, sometimes referred to as shading. Photoresponse nonuniformity is a spatial gradient of brightness in response to a uniformly illuminated matte surface. It is more severe in vidicon sensors but can be compensated electronically.

Dark Current

Dark current is the leakage current from the sensor when no light is present. Dark current arises from internally generated electrons caused by surface states, crystal imperfections, lattice defects, and general impurities in the photoconductive material. It increases with temperature, photoconductor voltage, and integration time. Both sensor types employ methods to minimize dark current.

Geometric Nonlinearity

Image geometry in the vidicon is determined by the linearity of the electron beam scan, which can drift over time. Geometric distortions occur largely in the outer 10% circle of the picture area. A typical value of geometric distortion is 3% in the outermost picture region, which can be reduced to less than 0.5% with compensation. Solid state sensors have fixed photosites and are immune to geometry distortions.

Light Bias

Light bias is a shift in the absolute gray scale caused by changes in average scene illumination. Light bias causes the amplitude of an individual point in the image to be a function of the average illumination of the scene. For measurement purposes, the intensity of an image point should be independent of the surrounding points.

Gamma

The photosensitive material of certain sensors has a nonlinear response to light. The linearity factor is called the gamma (γ) in the illumination transfer function $v \propto I^\gamma$, where v is the output amplitude and I is the light intensity. For $\gamma < 1$, white levels are compressed; for $\gamma > 1$, the dark levels of the scene are compressed. Vidicons have a $\gamma = 0.65$ while silicon sensors have a $\gamma = 1.0$. For machine vision systems, the sensor should have a linear response.

Dynamic Range

When the incident light generates charges faster than they can be collected, the sensor becomes saturated, resulting in a loss of dynamic range. This occurs when excessive illumination is used or if the lens aperture is opened too wide. It is important to operate the image sensor within its dynamic range in order to preserve the integrity of the sensor data.

Noise

Both sensors are subject to a variety of noise sources. Thermal noise arises from temperature agitation of electrons within a resistance and increases with temperature. Shot noise occurs when discrete, charged carriers cross a semiconductor junction. Contact or $1/f$ noise comes from conductivity differences between dissimilar materials when two conductors are joined together and is referred to as $1/f$ because of its inverse frequency power density spectrum. Popcorn noise is caused by imperfections and impurities in semiconductor devices. Its power density has a $1/f^n$ characteristic with n typically 2. All of these noise sources can contribute to the total signal uncertainty in electronic image sensors. Additionally, certain silicon sensors exhibit a fixed pattern of sensitivity nonuniformity over the surface (Ott, 1976).

Spectral Response

In a silicon sensor, infrared light penetrates more deeply into the bulk material than visible light. Carriers generated in these deep regions where the capturing electric fields are weak can drift into adjacent photosites before being collected. This crosstalk of electron carriers causes the intensity levels to be misrepresented, resulting in measurement errors. Silicon sensors have a higher sensitivity to infrared radiation compared to the eye. Because of both factors, an infrared cutoff filter such as a BG-38 may be necessary with a silicon sensor.

Array Geometry

In the silicon sensor, the geometry of the photocell array can be oriented in either a one or two-dimensional format. A linear array is a one-dimensional configuration which acquires the image one line at a time. The scene must be transported past the camera in order to scan the object field. The sensor scan must be precisely synchronized with the motion of the object in order to preserve the scene geometry. This requires a mechanical device to move the scene past the camera and synchronization circuitry to control the array scan rate. The area array allows a two-dimensional image to be acquired. The scan is internally synchronized in the area array. The entire field of view is available immediately after the single acquisition. Thus the area array offers an advantage in a development environment.

Because the field of view is one line wide in the linear array, the image plane needs to be constrained over a very small area. It is important to prevent image blurring if the object moves out of the plane of best focus. In the area array, the image plane extends over a larger surface and the planarity constraints are greater.

An important consideration in both arrays is the fill factor, the percentage of the photocell that is actually light sensitive. A fraction of the cell area is occupied by the circuitry which transfers the collected charge. This area does not collect light and reduces image resolution. Points of light in the scene that strike the insensitive areas go undetected. For this reason it is desirable to maximize the light-sensitive area.

The same argument holds for blemishes or defects in the array. Because light rays striking a defective cell cannot be collected, flaws projected onto a defective cell would go undetected. The error caused by a sensor blemish can be bounded by considering a worst-case condition. Assume a single flaw, exactly the size of one pixel, in the most critical note region, with the maximum contrast of 1.0. If the flaw is undetected, the flaw severity grade will be understated by 1.5. To prevent flaw grading errors, the sensor should have a unity fill factor and be free of photosite defects.

Pixel Geometry

Many cameras use the RS-170 video standard, which defines a 4:3 horizontal-to-vertical aspect ratio. This means that the image of a square is 4/3 longer in the horizontal direction than in the vertical direction. Unless the aspect ratio is corrected, object dimensions cannot be measured accurately. Cameras for machine vision applications should have square pixels, which gives a unity aspect ratio.

Sensor Selection

Silicon sensors are more rugged and have linear response and fixed geometry. They are also more linear in their dynamic range than vidicons and are available with square pixels. Because of the numerous advantages described earlier, the MegaPlus™ sensor was selected for this application. The MegaPlus is an area array, CCD sensor with a spatial resolution of 1320 x 1035 pixels across a 9 x 7-mm area. The pixels are 6.8 μm square with a center-to-center spacing or pitch of 6.8 μm in both directions for a unity fill factor.

An internal cover glass over the sensor attenuates the infrared energy above 700 nm. The dark current is monitored by sampling the cells beneath an opaque section of the sensor. This is used to compensate for temperature-induced changes in the output (Martin *et al.*, 1987).

Sensor Resolution

The lens should be matched for the CCD sensor, which will convert the optical image to an electrical signal. For maximum performance the lens resolution should exceed the sensor resolution. In order to properly specify the lens, it is necessary to compare the lens resolution with the CCD. The resolution of a CCD is measured differently than the optical components. The CCD comprises discrete, light-sensitive elements called pixels, arranged in either a linear or area array. The resolution of the CCD is given by the pitch ρ of the array

$$R_{ccd} = \rho \text{ (mm/pixel)} . \quad (4.1)$$

Lens resolution is specified in line pairs per millimeter (lp/mm) where a line pair is the equivalent of two pixels in the array. A minimum of two pixels is required to capture a complete cycle of a spatial distribution (e.g., a sinusoidal illumination pattern imaged on the sensor). The equivalent optical resolution of a CCD is the inverse of twice the R_{ccd} ,

$$R_{lens} = \frac{1}{2p} \text{ (line pairs/mm) .} \quad (4.2)$$

The 6.8- μm pitch of the selected sensor gives a Nyquist limited resolution of 73.5 cycles/mm.

The signal from the CCD sensor can be modeled as follows. Each pixel blurs the image over the pixel boundaries, then samples the blurred image. For the case of square pixels of length w on a side, the sampled image distribution Q is given by

$$Q(x, y) = \left(\frac{1}{w^2}\right) \left[E(mx, my) \oplus \text{rect}\left(\frac{x}{w}, \frac{y}{w}\right) \right] \text{comb}\left(\frac{x}{w}, \frac{y}{w}\right) , \quad (4.3)$$

where $\text{rect}()$ and $\text{comb}()$ are the rectangle and comb functions represented by

$$\text{rect}(x, y) = \begin{cases} 1, & \text{if } \left[\left(-\frac{w}{2}\right) \leq x \leq \left(\frac{w}{2}\right), \left(-\frac{w}{2}\right) \leq y \leq \left(\frac{w}{2}\right) \right] \\ 0, & \text{otherwise} \end{cases} \quad (4.4)$$

and

$$\text{comb}(x, y) = \begin{cases} \infty, & \text{for } (x = x_o); (y = y_o) \\ 0, & \text{otherwise} \end{cases} \quad (4.5)$$

The ordered pair x_o, y_o is the coordinate of the pixel center. E is the irradiance distribution of the object, m is the optical magnification, and $\oplus$ denotes the convolution operation (Zisk *et al.*, 1987).

Modulation Transfer Function

The image quality is specified by the resolution and contrast of the image. Resolution is the ability to distinguish between fine details in the scene. The contrast is the ratio of output intensity to input intensity specified for a given spatial frequency. The relationship between image resolution and contrast is established with the modulation transfer function (*MTF*). The *MTF* provides a metric for the relative contrast of a sinusoidal intensity distribution. The *MTF* is the amplitude response as a function of spatial frequency,

$$MTF = |\mathcal{H}(w_x, w_y)| \quad , \quad (4.6)$$

where $\mathcal{H}$ represents the Fourier transform of the normalized impulse response $H(x, y)$ of the lens. The sample *MTF* plot in Figure 4.2 shows the relative amplitude response as a function of spatial frequency.

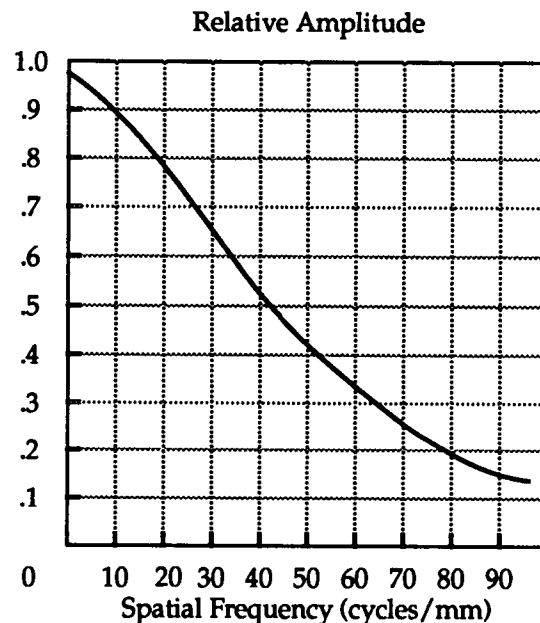


Figure 4.2. Plot of Typical Modulation Transfer Function.

The *MTF* plot is analogous to the frequency response chart used by electrical engineers to describe the output of a linear system to a sinusoidal input. One key advantage of the *MTF* is that it permits the lens to be treated as a linear system. Thus, the response of a multi-element lens is the product of the individual *MTFs*.

The *MTF* is given as a relative contrast at a particular spatial frequency. For example, a *MTF* of 80% at 40 lp/mm indicates that the output amplitude of a 40-lp/mm sine wave is 80% of the input amplitude. By convention, the maximum lens resolution specified by the manufacturer is 20% *MTF*. This contrast is usually inadequate for machine inspection applications. A better figure of merit for machine vision is the resolution specified at 50% *MTF* (Harding, 1988). The *MTF* of the MegaPlus sensor is 50% at the Nyquist frequency of 73.5 lp/mm.

The illumination striking a pixel can be considered uniform over the small area of the pixel. The theoretical *MTF* of a CCD sensor is the Fourier transform of Eq. (4.3),

$$MTF(\text{ideal}) = \frac{\sin(x)}{x}, \quad (4.7)$$

where x represents the product of the relative spatial frequency and the pixel fill factor (Gurley *et al.*, 1985). The fill factor is the ratio of the pixel sampling area to the total area,

$$x = \frac{wf}{W}. \quad (4.8)$$

Imaging Optics

The function of imaging optics is to form the incoming light rays from the scene into an image on the sensor face. A commercial camera lens is adequate for this purpose. Commercial lenses usually are designed with a specific purpose in mind. A lens intended for surveillance will be vastly different from a lens needed for high-quality inspection applications (Lindsey, 1989). A lens well-suited for machine vision will likely have (1) high resolution, (2) short working distance, and (3) low distortion.

Thin Lens Model

The typical lens comprises several glass elements held together in a mechanical housing. Complex equations are generally needed to characterize the optical behavior of a compound lens, but it can be approximated with the thin lens model shown pictorially in Figure 4.3. In the thin lens model, the compound lens is considered to be a single, ideal lens in free air. For initial design purposes, the thin lens model gives reasonable estimates of the key lens parameters such as the following:

- object distance
- image distance
- magnification (reduction)
- focal length
- field of view
- aperture
- depth of field

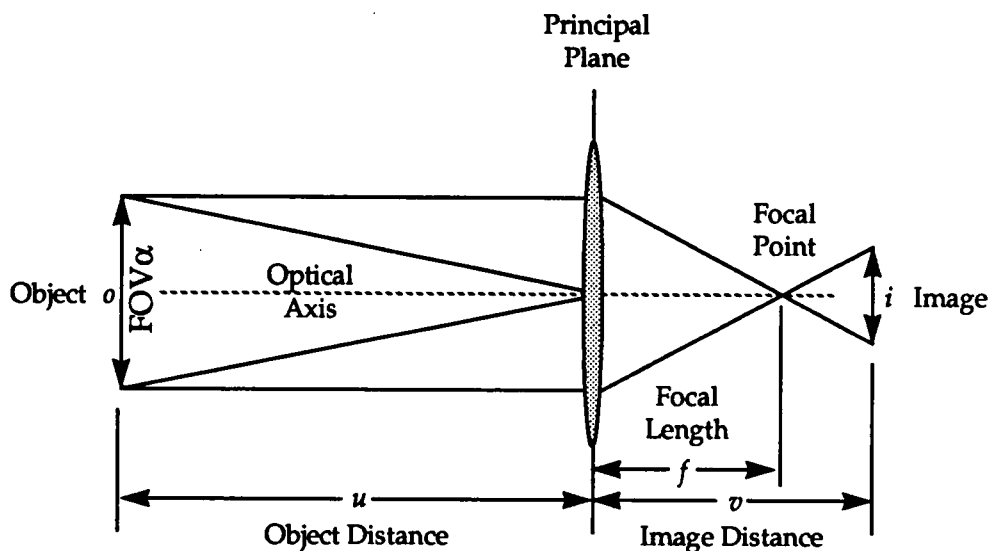


Figure 4.3. Schematic Diagram of Thin Lens Optical Model.

The optical axis is the line through the center of the lens along which a light ray would pass unchanged because it is normal to all surfaces. The focal point of the lens is the location on the optical axis at which parallel light rays will converge. The plane at which these parallel rays appear to bend is called the principal plane. The distance from the final principal plane to the focal point is the focal length of the lens.

Object Distance

The object distance, or conjugate u , is the distance from the principal plane to the object o along the optical axis. In many machine vision applications, the object distance is constrained by the environment, which may limit the maximum or minimum height the camera can be mounted above the inspection surface. The physical mounting apparatus for the camera is such that the object distance u is limited to 1220 mm or less. An initial design choice was made to use half of the available distance and set $u = 610$ mm.

Image Distance

The image distance, or conjugate v , is similarly the distance from the principal plane to the image i along the optical axis. If the image is located behind the lens, it is said to be a "real" image. For a concave lens, the image is located in front of the lens and is called a "virtual" image. Virtual images are not useful for machine vision work and will not be considered further. Therefore, the negative sign usually given to coordinates on one side of the lens is dropped.

Magnification

Due to the short object distances necessary in machine vision, the object is typically larger than its corresponding image. The lens must reduce the image of the object to fit within the boundaries of the sensor. The magnitude of this reduction is called the lateral or transverse magnification and is determined from the ratio of the image size to the object size,

$$m_t = \frac{i}{o}. \quad (4.9)$$

The ratio of the object distance to the image distance is known as the image conjugate. A magnification of 1/10 is equivalent to a 10:1 image conjugate. It is clear from Figure 4.3 that the magnification can also be given by the ratio of the image distance to the object distance,

$$m_t = \frac{v}{u} . \quad (4.10)$$

Recall that the sensor width is 9 mm in the horizontal direction. It is desirable to use a reduced area in order to minimize the off-axis optical distortions introduced by lens aberrations. A reduction of 0.8 gives an effective sensor width of 1056 elements out of the 1320 possible elements. The image width is arbitrarily chosen to be 1024 in order to maximize utilization of the digital memory available. Because the sensor has 1024 elements, each one 6.8 μm wide, the available image size is $i = 7$ mm. The object width of a standard currency note including borders is $o = 157$ mm. Using these values in Eq. (4.9) gives the magnification needed for the lens, $m = 1/22.4$.

Focal Length

The point on the optical axis where the light rays converge is the focal point. The thin lens has a focal point both in front and in back of the principal plane. The focal length f is the distance from the principal plane to the focal point, and is given by the Gaussian lens equation (Hecht, 1987),

$$\frac{1}{f} = \frac{1}{u} + \frac{1}{v} . \quad (4.11)$$

It is inconvenient to measure the image distance since it is inside the camera body. The focal length can be given in terms of the magnification and object distance by substituting Eq. (4.10) into Eq. (4.11) and rearranging terms,

$$f = \frac{mu}{m+1} . \quad (4.12)$$

Also, Eq. (4.12) can be rearranged to give the object distance for a specified m and f ,

$$u = \frac{f(m+1)}{m} . \quad (4.13)$$

Commercial lenses are available in fixed focal lengths such as 20, 28, 35, and 55-mm sizes. The image distance for a particular camera is also fixed by the mounting flanges and sensor position. The lens focal length is then determined from Eq. (4.9) and Eq. (4.12). From Eq. (4.12), if $u = 610$ mm then $f = 26$ mm. The nearest standard value lens is $f = 28$ mm. The object distance is determined for the standard focal length lens by substituting $f = 28$ mm, and $m = 1/22.4$ into Eq. (4.13), which gives the required object distance $u = 655$ mm (25.8 in.).

Field of View

The field of view (FOV) is another measure of the lens magnification. A wide-angle lens will have a large field of view, while a telephoto lens will have a small field of view. The FOV is the angle α formed by the object and the intersection of the optical axis and the principal plane,

$$FOV = 2 \operatorname{atan} \left(\frac{o}{2u} \right) . \quad (4.14)$$

Recalling that $o = 157$ mm and $u = 655$ mm, then the $FOV = 13.7^\circ$.

Aperture

The lens aperture a is the diameter of the mechanical stop, which limits the amount of light passing through the lens. The lens aperture is specified by the ratio of the focal length to the lens f -number,

$$a = \frac{f}{\phi} , \quad (4.15)$$

where ϕ is the f -number representing the relative transmission efficiency of the lens. The amount of light admitted through the lens is inversely proportional to the square of the lens f -number. A change of one f -stop results in a 2:1 change in image illumination. In order to optimize the lens performance between diffraction effects and lens aberrations, an f -number of $f/5.6$ is chosen. The aperture is $a = 5$ mm when $\phi = f/5.6$ and $f = 28$ mm.

Depth of Field

The depth of field (*DOF*) is the loci of points along the optical axis through which the object can move and still remain in focus at the image plane as shown in Figure 4.4. The closest the object can be to the lens and remain in focus is the near depth-of-field. Similarly, the farthest the object can be is the far depth-of-field. The sum of the near and far depth-of-field is the total usable depth-of-field.

The limit of focus occurs where the image blur due to defocus is the highest that can be tolerated without degrading the image. The blurred area is called the circle of confusion because it represents an area of image uncertainty. To maintain high image quality and resolution, the circle of confusion should be less than the equivalent of one pixel at the object plane. The blur circle c at the object plane is given by

$$c = \frac{\rho}{m} , \quad (4.16)$$

where ρ is the pixel pitch and m is the lateral magnification.

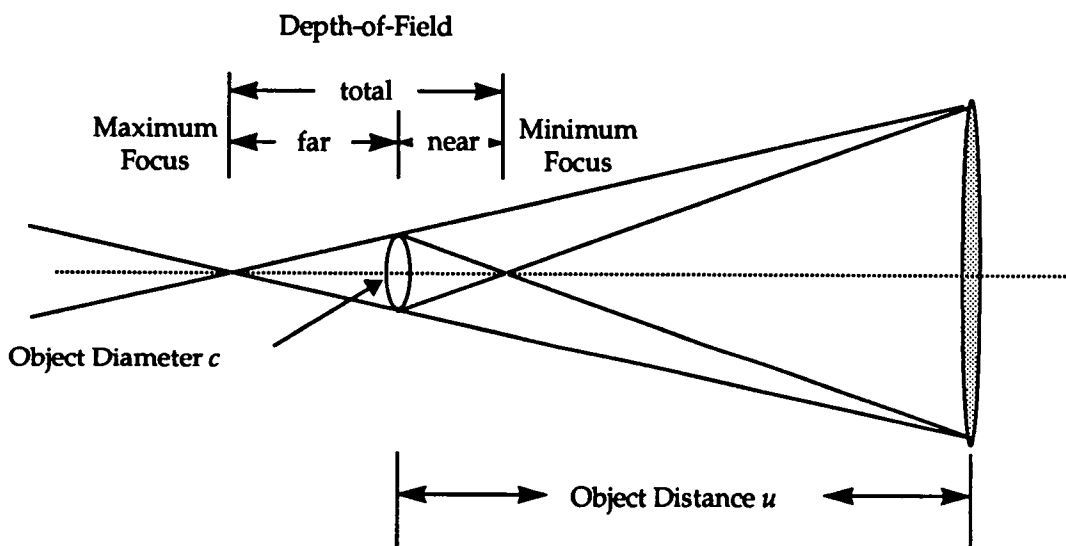


Figure 4.4. Geometry of Lens Depth of Field.

The near depth-of-field is a function of the blur circle, object distance, and lens aperture,

$$DOF_{near} = \frac{cu}{a+c} \quad , \quad (4.17)$$

and likewise, the far depth-of-field is

$$DOF_{far} = \frac{cu}{a-c} \quad . \quad (4.18)$$

The depth-of-focus (*dof*) is the distance along the optical axis in which the image will be in focus and is the depth-of-field divided by the longitudinal magnification. Recall that the longitudinal magnification is the square of the transverse magnification,

$$dof = \frac{DOF}{m_t^2} \quad . \quad (4.19)$$

For this application, the equivalent pixel size at the object plane is $c = 0.015$ mm. Substituting the values determined previously, $u = 655$ mm, $f = 28$ mm, $a = 5$ mm into Eqs. (4.17) and (4.18), the depth-of-field is calculated to be $DOF_{near} = 19.1$ mm and $DOF_{far} = 20.3$ mm. The total distance an object can vary along the optical axis and still remain in focus is the sum of the near and far DOF or 39.4 mm (1.55 in.). The depth-of-field can be increased by stopping down the lens (decreasing a). However, this will also reduce the light and resolution for a given lens. Notice that the depth-of-field is not symmetrical, and as $a \rightarrow c$, the $DOF \rightarrow \infty$. This allows the lens to focus objects from a point near the lens out to infinity. Table 4.1 shows the effect of reducing the aperture on depth-of-field for this example.

Table 4.1. Depth-of-Field as a Function of Lens f -Number.

$f/\#$	DOF_{near}	DOF_{far}	DOF_{total}	
	(mm)	(mm)	(mm)	(in)
4	13.8	14.4	28.2	1.1
5.6	19.1	20.3	39.4	1.6
8	27.0	29.4	56.4	2.2
11	36.5	41.1	77.6	3.1
16	51.8	61.5	113.3	4.5

Lens Resolution

It is difficult to determine analytically the lens resolution as it requires knowledge of the specific lens properties. Typical values of resolution for commercial lenses range from 20 to 100 lp/mm. However, because the maximum resolution is limited by the physical dimensions, the diffraction limitation of the lens aperture can be used to estimate the minimum detectable object size.

When the incoming light rays strike the edges of the lens aperture, points in the object space are rendered as a diffraction disk in the image. The diffraction disk, also known as the Airy disk, consists of a series of concentric, light and dark alternating rings. Mathematically, the Airy disk is represented by a first-order Bessel function about the point. An object field consisting of two points will result in two Airy disks in the image. If the disks are brought close enough together, they will appear to merge into one disk and cannot be distinguished (Longhurst, 1967). The distance d at which two closely spaced points can just be distinguished is given by the Rayleigh criterion,

$$d = 1.22\lambda\phi, \quad (4.20)$$

where λ is the wavelength of the light and ϕ is the lens f -number. It is important to remember that ϕ is the effective f -number seen from the plane in which d is measured. By applying Eq. (4.15) at the object plane, the effective f -number is

$$\phi_{eff} = \frac{u}{a}, \quad (4.21)$$

where u and a are the object distance and the lens aperture respectively. The minimum resolvable object diameter is given by d .

This result is for a distortion-free lens. In practice, this limit is rarely met due to lens aberrations. A more realistic estimate of the minimum object size is 3 to 4 times the diffraction-limited resolution. Applying this criterion, the minimum resolvable object diameter is given as $d = 0.26 \text{ mm}$ (0.010 in.).

It should be noted that it is possible to detect an object without resolving it. For an inspection system, the task is more often to detect an isolated spot in the field of view. In this situation, the minimum detectable single object size can be less than predicted by the Nyquist limit. Consider the behavior of an ideal sensor which samples the projected image shown in Figure 4.5a. When the projected image is a regular pattern of light and dark bars at the same size as the pixel width, the image can be reproduced reliably. When the pattern is translated so that the image is out of phase with the detector elements, the signal is completely cancelled.

Now consider Figure 4.5b where the image consists of a single dark circle with diameter equal to the pixel width. When the spot is aligned with the pixel, the output is maximum. But when the spot is translated to be out-of-phase, the output remains at 25% of the maximum level. Thus it is possible to detect defects smaller than the sensor element if the detection threshold were low enough. The exact of size and contrast of such defects cannot be determined however.

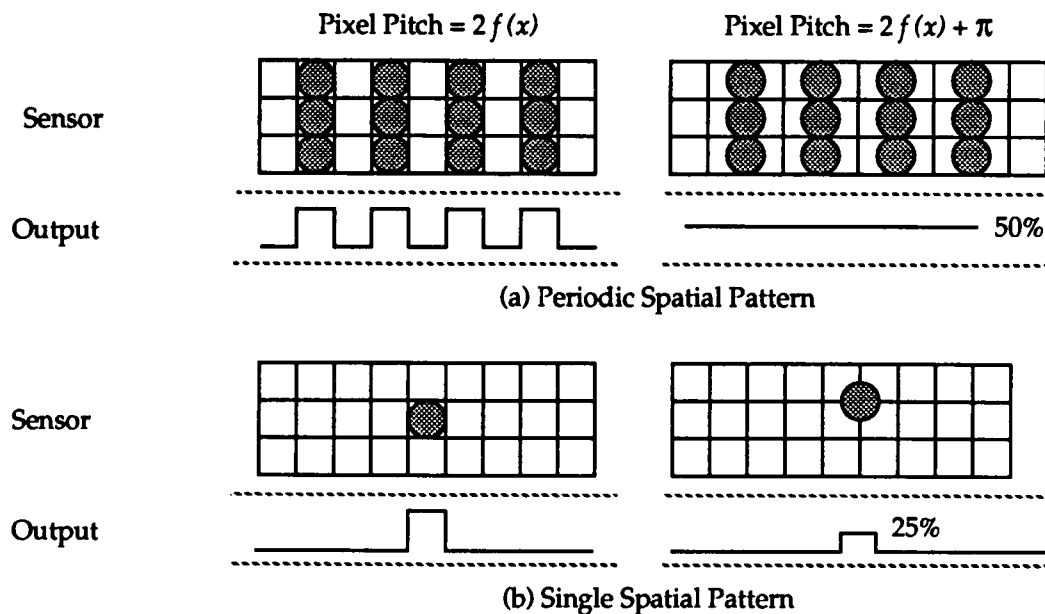


Figure 4.5. Methods of Image Sampling.

Illustration of the sampling process for (a) a periodic spatial pattern of light and (b) a single spot typical of defect patterns in inspection.

Aberrations

Lens aberrations are deviations in the path of a light ray from the ideal path. Aberrations degrade image quality by blurring sharp points and edges in the reproduced image. Aberrations can be caused by a poor-quality lens or by improper use of a high-quality lens. Lenses are designed for best performance within a given operating range. Attempts to use a lens outside this range (such as object distance), will degrade the image (Harding, 1988; Batchelor *et al.*, 1985). A brief description of the common lens aberrations is given below.

Chromatic • Different wavelengths are focused at different distances from the lens, causing colored fringes at image points. This is important when color is being inspected.

Spherical • Uniform enlargement of points in the image. The enlargement decreases with the cube of the increase in f -number (smaller aperture). Spherical aberrations are important when inspecting fine detail or small objects.

Coma • Image points are blurred proportional to their distance from the optical axis. Coma decreases with the square of the increase in f -number. Coma is important when constant resolution over the field of view is desired.

Field Curvature • The surface of best focus is spherical, causing the focus of points in the image to vary with the square of the distance from the optical axis. Field curvature decreases linearly with the increase in f -number. This is important when position invariance is required.

Distortion • Changes in the image geometry proportional to the cube of the distance from the optical axis. This causes a square to appear stretched or flattened in the image. Distortion is important when object morphology is needed.

Vignetting • The falloff in light intensity of a uniformly illuminated field. The intensity decreases with the distance from the optical axis. This is important when using a global detection threshold.

The lens aberrations are proportional to aperture size, and most are more severe off-axis. General practice is to select a lens aperture setting near $f/5.6$ to reduce aberrations while maintaining high resolution. The intensity of illumination is then adjusted for an acceptable image at the camera.

The resolution of many lenses can be diffraction-limited if operated within a narrow spectral bandwidth, at small aperture, and over the central portion of the image. This means that the aberrations will be negligible when compared to the diffraction effects of the lens. The resolution is then a function of the physical dimensions of the lens elements.

Summary

The thin lens model should not be taken as a complete measure of optical performance; it is merely a tool to assist in early design estimates. If the exact measurements of a particular lens is sought, the manufacturer's data sheet should be consulted. The specifications for the imaging optics system are summarized in Table 4.2.

Table 4.2. Lens Specifications.

Symbol	Parameter	Value	
		(mm)	(in.)
m	Magnification	1/22.4	
u	Object distance	655	25.8
v	Image distance	29.3	1.2
f	Focal length	28	1.1
FOV	Field of view	13.7°	
a	Lens aperture	5	0.3
ϕ	f -Number	$f/5.6$	
DOF	Depth of field	28.5	1.1
c	Blur diameter	0.15	0.006
o	Object width	157	6.2
i	Image width	7	0.03

Radiometric Terms

There can be some confusion when discussing brightness due to the overlap between radiometric and photometric units. The power output of sources is sometimes measured in luminous flux, which is the power weighted by the spectral response of the human eye. Photometric measurements are derived from this spectral sensitivity in units of lumens. Radiometric measurements are derived from the radiant flux, which is the total energy integrated over the entire spectrum and is given in watts.

We desire an expression for the reflectance at an arbitrary point on the object from the output of the corresponding pixel in the sensor. The sensor output is proportional to the object brightness, which depends upon the object's inherent characteristics and the physical geometry and energy of the illumination.

In order to determine the image brightness, is useful to define the units of radiometry. The radiometric terms used to develop the image brightness equations are illustrated in Figure 4.6 and defined in the following paragraphs.

Radiant Intensity

The light energy emitted by an object is the flux ϕ measured in watts (Ballard and Brown, 1982). A point source emits flux uniformly in all directions. The radiant intensity I is the flux emitted in the direction of a solid angle ω ,

$$I = \frac{d\phi}{d\omega} \text{ (watts/steradian) .} \quad (4.22)$$

Solid Angle

The solid angle is the cone subtended by an area A and a point located a distance R from A . It is the ratio of the apparent area seen by the flux to the distance squared,

$$\omega = \frac{A \cos \theta}{R^2} \text{ (steradians) .} \quad (4.23)$$

Irradiance

The irradiance E is the flux incident upon an incremental area dA ,

$$E = \frac{d\phi}{dA} \text{ (watts/meter}^2\text{) .} \quad (4.24)$$

Radiance

The radiance L from an incremental surface area dA is the emitted flux per apparent area per solid angle,

$$L = \frac{d^2\phi}{\cos \theta dA d\omega} \text{ (watts/meter}^2\text{ steradian) ,} \quad (4.25)$$

where θ is the angle between the surface normal and the direction of emission.

Brightness

If a source is too large to be considered a point source, brightness is used instead of intensity. The brightness B of an extended source is the ratio of the intensity of an incremental area to its apparent area,

$$B = \frac{dI}{\cos \theta dA} . \quad (4.26)$$

The apparent brightness of an object is unaffected by distance because increasing the distance also increases the source area.

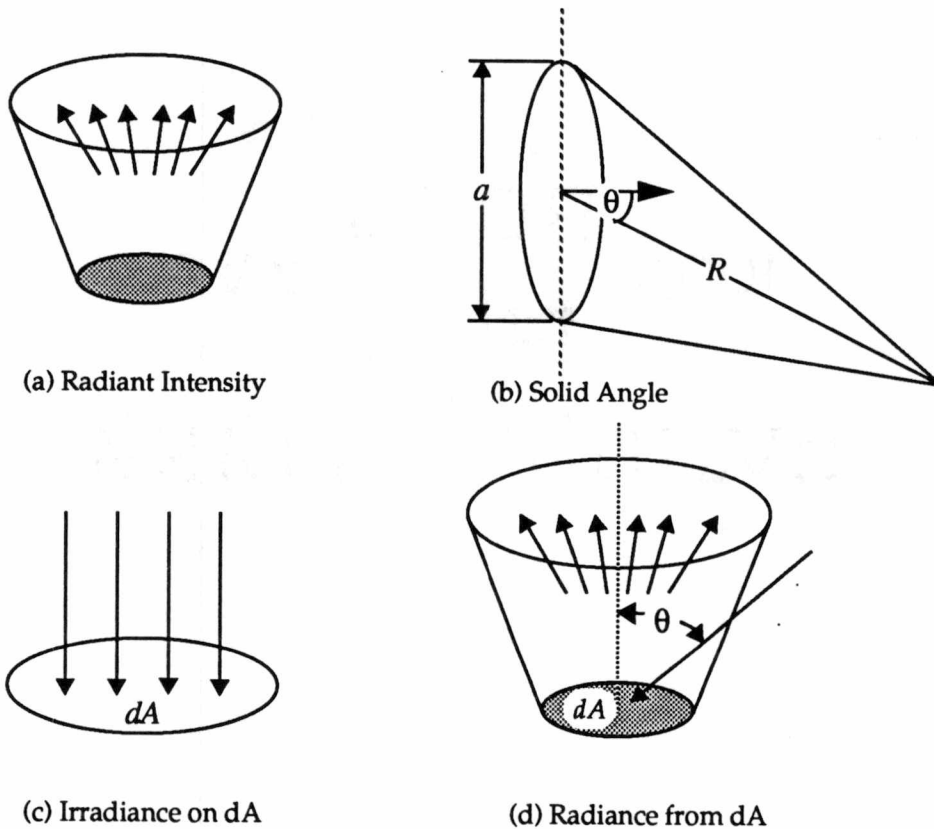


Figure 4.6. Illustration of Radiometric Terminology.

Scene Illumination

The illumination system is used to increase the intensity of the desired image features. The criteria for optimization are to maximize the contrast and energy of the desired features while minimizing variations due to object geometry, lighting geometry, and the environment by maximizing the signal-to-noise ratio. The illumination spectrum should be maximum in the region of highest sensor sensitivity. In this application, the desired features are currency ink and the background is the paper substrate. The illumination should be uniform over the scene. The geometry of the illumination should reduce the glare caused by specular reflections. Finally, the illumination should be constant over time and temperature.

Image Brightness

The world we see is composed of reflected light. We do not see objects, but rather that part of the energy spectrum reflected by those objects. When a ray of light hits an object, the ray can be absorbed, reflected, or transmitted. For surfaces which are flat and homogeneous, the reflected ray will be at the same angle to the surface normal as the incident ray as shown in Figure 4.7. This is referred to as specular reflection and is exemplified by the reflective glare of polished metals. If the surface microstructure is irregular, causing the light to be reflected in multiple paths, the surface reflectance is said to be diffuse. An ideally diffuse or Lambertian surface reflects and scatters the incident light equally in all directions. Most objects have components of both specular and diffuse reflection.

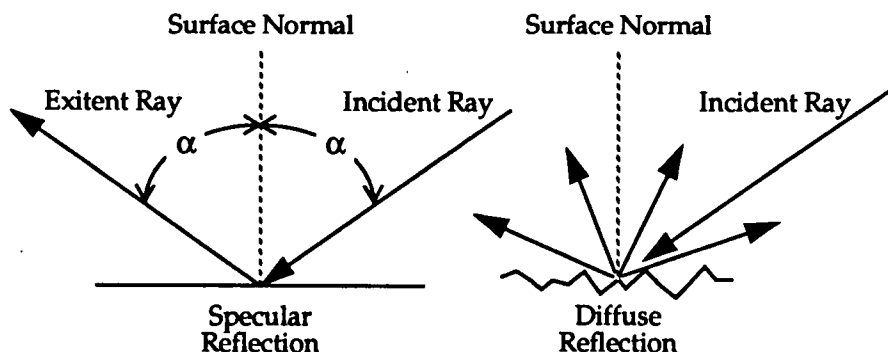


Figure 4.7. Diffuse and Specular Reflection.

We desire to relate the sensor output to scene variables such as illumination intensity. The development of a model for image brightness generally follows Horn (Horn, 1986). The optical components are assumed collimated such that the surface normal is parallel to the optical axis shown in Figure 4.8. Consider the simple model of an object area dA_o in the scene, which projects an image onto area dA_i through a simple lens of diameter d . Then dA_o subtends a solid angle ω_o with the optical axis at angle α .

From the geometry and Eq. (4.23), ω_o can be written as

$$d\omega_o = \frac{dA_o \cos \alpha}{\left(\frac{u}{\cos \alpha}\right)^2}, \quad (4.27)$$

where u is the object distance. Similarly, the solid angle ω_i formed by the lens is

$$d\omega_i = \frac{dA_i \cos \alpha}{\left(\frac{v}{\cos \alpha}\right)^2}, \quad (4.28)$$

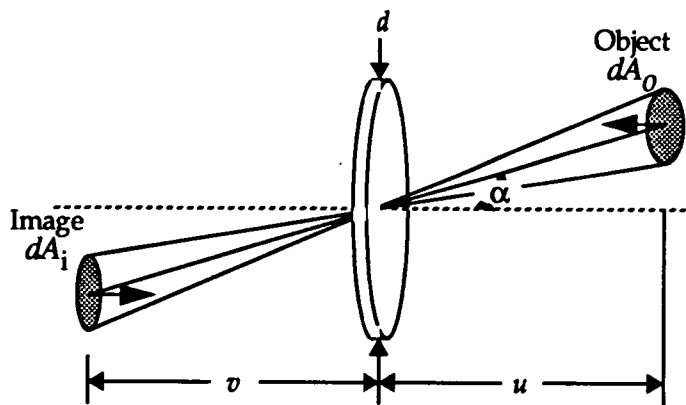


Figure 4.8. Image Irradiance Geometry.

The image irradiance is related to the scene radiance by the geometry of incremental areas dA_o and dA_i through the thin lens approximation.

where v is the image distance. Since the rays through the lens center are not deflected, then $\omega_i = \omega_o$. Combining Eqs. (4.27) and (4.28),

$$dA_i = \left(\frac{v}{u}\right)^2 dA_o. \quad (4.29)$$

The irradiance on dA_i is given by Eq. (4.24),

$$E_i = \frac{d\phi_i}{dA_i}. \quad (4.30)$$

If the losses in the lens are neglected, the flux incident on dA_i is equal to the flux emitted by dA_o , and $d\phi_i = d\phi_o$. Rearranging Eq. (4.25) gives an expression for the flux emitted by dA_o and equivalently the flux incident on dA_i :

$$d\phi_i = dA_o \int L \cos \alpha d\omega_o, \quad (4.31)$$

where L is the scene radiance. Substituting Eqs. (4.29) and (4.31) into Eq. (4.30),

$$E_i = \left(\frac{u}{v}\right)^2 \cos \alpha \int L d\omega_o. \quad (4.32)$$

The radiance from a small diffuse reflector such as paper can be assumed to be constant over $d\omega$. Therefore, L can be brought out from the integral in Eq. (4.32). Also, the integral over $d\omega_o$ can be approximated by the angle subtended by a point in dA_o with the lens. The solid angle seen by dA_o looking back toward the lens can be written as

$$\Omega_o = \left(\frac{\pi}{4}\right) \left(\frac{d}{u}\right)^2 (\cos \alpha)^3. \quad (4.33)$$

Substituting Eq. (4.33) for $d\omega_o$ in Eq. (4.32) gives

$$E_i = \left(\frac{\pi}{4}\right) \left(\frac{d}{v}\right)^2 L (\cos \alpha)^4, \quad (4.34)$$

where v/d is approximately the f -number ϕ of the lens from Eq. (4.15). The $\cos^4$ term indicates the intensity falloff due to off-axis emanations.

The radiance of a matte surface is proportional to that for a perfect (Lambertian) reflector. The proportionality factor is the albedo or reflectance of the surface material. The radiance of such a surface is obtained by integrating an incremental radiance dL over the hemisphere surrounding the surface. The radiance of such a surface, illuminated by source E_s is given by

$$L = \left(\frac{r}{\pi} \right) E_s \cos \theta_i, \quad (4.35)$$

where θ_i is the angle of incident illumination and r is the surface reflectance. Substituting Eq. (4.35) into Eq. (4.34) and simplifying,

$$E_i = \left(\frac{r}{4} \right) \left(\frac{d}{f} \right)^2 (\cos \alpha)^4 \cos \theta_s E_s. \quad (4.36)$$

If the geometry is fixed and E_s is constant, then Eq. (4.36) can be rewritten as

$$E_i = krE_s, \quad (4.37)$$

where k is a proportionality constant defined by

$$k = \left(\frac{1}{4} \right) \left(\frac{d}{f} \right)^2 (\cos \alpha)^4 \cos \theta_s. \quad (4.38)$$

E_i is the illumination level at the sensor. The dependencies due to geometry have now been eliminated, leaving an expression for the sensor output in terms of the source illumination and the surface reflectance. The image model is based on the surface reflectance found by rearranging Eq. (4.37),

$$r = \frac{E_i}{kE_s}. \quad (4.39)$$

Spectral Response

The sensor output $e(\lambda)$ is the product of the image irradiance E_i , the spectral response of the lens H , and sensor response S integrated over the spectrum (Chapelle, 1988):

$$e(\lambda) = \int E_i(\lambda) H(\lambda) S(\lambda) d\lambda \quad . \quad (4.40)$$

The spectral response is constrained by placing a narrowband filter in the optical path. If the filter passband is centered at Λ , then the lens spectral response $H(\lambda)$ can be approximated by the impulse function

$$H(\lambda) = \delta(\lambda - \Lambda) \quad . \quad (4.41)$$

By the sifting theorem, Eq. (4.40) is equivalently

$$e(\lambda) = E_i(\Lambda) S(\Lambda) \quad . \quad (4.42)$$

Substituting Eq. (4.42) into Eq. (4.39) completes the expression for the surface reflectance,

$$r = k(\alpha, \theta_s, d, f) \frac{e_i(\Lambda)}{e_s(\Lambda)} \quad . \quad (4.43)$$

Note that the dependencies on the sensor are cancelled by the relative nature of the reflectance. In the next chapter, the intensity normalization method of determining the component of the sensor signal to due the source illumination e_s will be described.

Image Digitizer

The output of the sensor is a continuous signal representing the image irradiance after spatial sampling. The image must be converted to digital information in order to be useful for manipulation by a digital computer. This is done with the analog-to-digital converter (ADC), which quantizes the sensor output into discrete values called gray levels. The maximum number of possible gray levels is given by the number of bits, n , in the ADC:

$$L = 2^n . \quad (4.44)$$

In this application, the internal ADC of the camera is used to minimize noise introduced in the coaxial transmission line. For this digitizer, $n = 8$ and $L = 256$.

Quantization Uncertainty

There is an uncertainty in the digital gray levels due to the quantization process (Sheingold, 1980). The quantization uncertainty can be modeled with a first-order approximation. Consider the signal voltage from the camera e , which is digitized to a discrete value l shown in Figure 4.9. For an input voltage between e_a and e_b , the digital output will be $l = 1$. The uncertainty due to quantization is equal to the minimum increment which is one least significant bit (LSB) of the digitizer. The LSB is the ratio of the input voltage range to the number of bits in the converter,

$$LSB = \frac{(e_{max} - e_{min})}{2^n} . \quad (4.45)$$

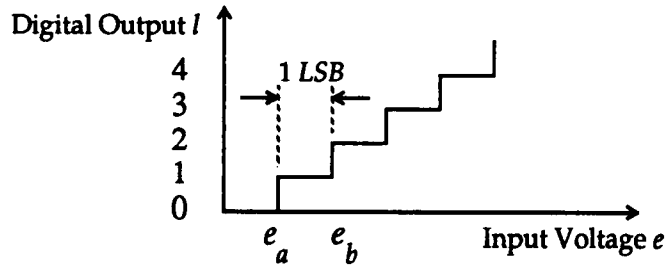


Figure 4.9. Digitizer Transfer Function.

Transfer function of an ideal digitizer, which converts continuous function e to a discrete value.

The quantization uncertainty is a zero-mean, uniform probability distribution within one LSB shown in Figure 4.10. The mean is zero because it is always at the midpoint of one LSB and the analysis applies to any arbitrary voltage segment. The error due to quantization uncertainty is the standard deviation of the probability distribution given by

$$\epsilon_{\sigma} = \frac{LSB}{\sqrt{12}} \quad (4.46)$$

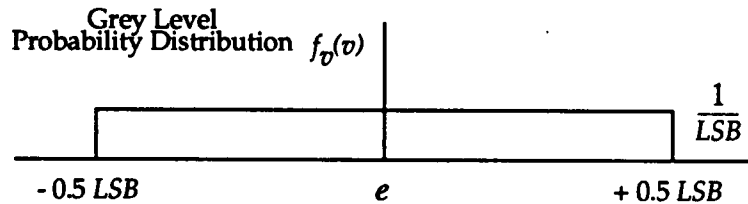


Figure 4.10. Quantization Probability Distribution.

Probability distribution function of the idealized analog-to-digital converter input voltage.

The reflectance can vary from 0 to 1.0, and there are 256 gray levels to represent the reflectance. Using the values in Eq. (4.46), the reflectance uncertainty due to quantization error is 0.001, which is considered negligible compared to the other expected uncertainties.

CHAPTER 5

IMAGE NORMALIZATION

The first step in evaluating the severity of currency flaws is to isolate the flaw components from their background. The approach taken here is to employ a change detection algorithm, which is fundamental to many machine vision applications. Change detection algorithms identify points in the field of view with significant differences between two input images. The differences can be caused by (1) object motion, (2) addition or removal of an object, (3) illumination changes, or (4) noise due to the quantization process (Skifstad and Jain, 1989). Since the note structure is stationary during inspection, object motion is not of concern. Printing flaws occur as the result of excess-of-ink and dearth-of-ink events and should be detected by the inspection system. Illumination changes and quantization noise must be mitigated so that the system responds only to printing flaws.

Change detection can take place at the pixel level or at a higher, feature level. High-level change detection algorithms operate by comparing features such as lines and corners in two digitized images. Change detection at the pixel level has the advantage of being particularly fast because hardware is available for real-time implementation. The simplest approach to pixel-level change detection is to subtract one image from a reference, retaining the resultant difference image. The change detection process can be expressed as

$$d(x, y) = f(x, y) - f_r(x, y) , \quad (5.1)$$

where $d(x, y)$ is the difference image over all locations x and y , $f(x, y)$ is the acquired image of the note under test, and $f_r(x, y)$ is the stored image of a known-good reference note. The reference note represents the ink structure to be subtracted from the test note, leaving only the printing flaws in the difference image.

While image subtraction is the most direct change detection method, it is highly susceptible to illumination changes and spatial differences. Illumination changes occur when the radiant intensity striking the subject varies from one acquisition to the next due to bulb aging, line voltage variations, or simply an accumulation of dust on the optical surfaces. Intensity normalization is

used to compensate for illumination changes so that the images are acquired and measured under similar conditions. Spatial differences, which accentuate the ink edges, occur from a displacement of the test image. Displacements can result from imprecise positioning of the test note, dimensional changes in the note due to temperature and humidity, and normal variations in ink topology. The sensitivity to spatial differences is illustrated in Figure 5.1, where an arbitrary image was translated four pixels in the horizontal and vertical direction and then subtracted from the original image. The difference image was thresholded at gray level 16 for clarity. Note the pronounced edges caused by the spatial difference in identical images. If uncorrected, the inspection system would interpret the edges as a flaw condition even though the human eye would not. A method of registering the two images to subpixel accuracy is used to normalize the two images spatially. An algorithm to further reduce edge artifacts in the difference image is given in the next chapter.



Figure 5.1. Misregistration Error in an Uncorrected Difference Image.

The difference image was obtained by translating a test image by four pixels in both horizontal and vertical directions and subtracting with the original image.

Intensity Normalization

As mentioned earlier, the image differencing technique is most effective when illumination variations are eliminated. A change in the illumination level can cause an amplitude shift in the difference image, which would be interpreted incorrectly as a global structural change. Therefore, the image differencing method must be used in conjunction with a normalization procedure to remove temporal variations in illumination.

It is important that the response of each pixel in the image be independent of the response of its neighbors. Some cameras have an automatic gain control, which manipulates the gray scale in response to changes in illumination, thus losing gray scale calibration. The response of any given pixel thus becomes a function of every other pixel in the sensor. A key assumption for accurate photometric measurements is that the output of each pixel is dependent upon only the illumination incident on that pixel (Batuscheck, 1987).

Gray Scale References

Reflectance can be defined as the ratio of the reflected flux from a test surface to the reflected flux of a Lambertian surface under identical illumination and viewing conditions. A Lambertian surface reflects equally well in all directions (i.e., it obeys Lambert's cosine law of emission). A surface that obeys this law for all directions of incident light is called a uniformly diffusing reflector. A surface that reflects all incident light, such as magnesium or barium oxide, is a perfectly diffusing reflector (Longhurst, 1967) in which the surface brightness depends only on the direction of illumination (Horn, 1977). It was shown in Eq. (4.43) that the measured reflectance at x, y in the image can be made invariant to illumination changes by normalization:

$$r(x, y) = \frac{ke_i(x, y)}{e_s}, \quad (5.2)$$

where k is a constant related to the lighting geometry; e_i is the camera signal amplitude at x, y in the test image, and e_s is the brightness of a Lambertian surface. This is known as the absolute method of reflectometry in which the reflectance is determined comparatively (Hardy and Perrin, 1932). This method assumes a diffuse illumination source and viewing angle normal to the scene surface. Both of these conditions are met, as described in Chapter 4.

The gray scale of $f(x, y)$ is maintained by normalizing to a rectangular strip of diffuse photographic paper with $r = 0.9$ at a fixed location in the field of view. The reflectance of the white paper is factored into constant k in Eq. (5.2). The paper may not be perfectly diffuse; it has been reported that ordinary typing paper can have a 25% specular reflectance component (Westphal and Nagel, 1987). While specular reflections would violate the assumptions used to derive the reflectance equations, they can be eliminated by positioning the illumination sources at 45° to the surface normal, causing any specular reflections to be directed away from the lens at the same angle (Ray *et al.*, 1983). Even though the surface may not be a perfectly diffusing reflector, this approximation has given useful results for relative measurements (Smith, 1983). The geometry of the Lambertian surface within the field of view is shown in Figure 5.2.

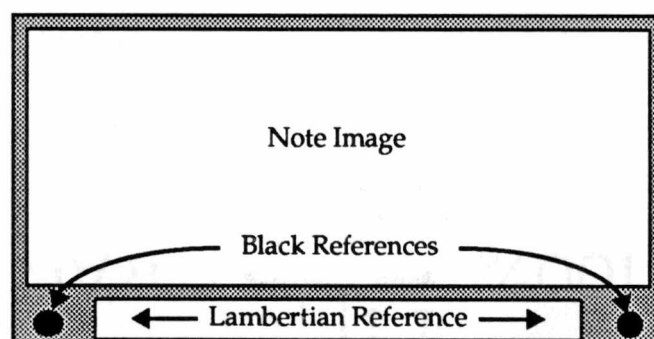


Figure 5.2. Geometry of Gray Scale References.

Illustration of the position of the fixed Lambertian surface used for the white reference and the opaque black references in relation to the test image.

Photometric Transformation

The method chosen for intensity normalization is to adjust the gray scale until certain features in the test image match a predetermined, external reference. The gray scale is defined here as the relationship between the sensor output level e_i and the discrete pixel intensity s , given by

$$s = Q(e) , \quad (5.3)$$

for $s = 0, 1, 2, \dots, 255$, where Q is the quantization function.

The gray scale of $f(x, y)$ is aligned to an external reference rather than to the ink and substrate of $f_r(x, y)$ because it is desired to measure the reflectance difference between $f(x, y)$ and $f_r(x, y)$ as defined by the global flaw model in Eq. (3.10). This would not be possible if the ink and substrate of $f(x, y)$ were shifted to exactly match $f_r(x, y)$.

Changes in the illumination level are corrected by *contrast stretching*, to match the intensity of the Lambertian surface in the test image with the predetermined reference level. Consider test image $f(x, y)$ and its corresponding intensity-normalized image $f_n(x, y)$ created from f . Further, let s and z be any discrete gray levels in f and f_n respectively. Now, for every pixel in f with value s , the corresponding pixel in f_n is assigned a value z according to

$$z = T(s) , \quad (5.4)$$

where T represents an arbitrary gray level transformation function. To compensate for global shifts in gray levels due to illumination, $T(s)$ is a linear function:

$$T(s) = ms + d , \quad (5.5)$$

where m is the slope and d is the offset. Illumination differences present at the time of each acquisition are compensated through proper choice of m and d . The intensity of the Lambertian surface is given by e_s , the sensor output level of pixels constituting the diffuse white paper in the test image. A corresponding intensity e_b is also found for a diffuse, optically black surface. The black surface absorbs nearly all of the incident light (i.e., its reflectance is ~ 0). If the white and black reference values we would like to match are r_s and r_b , respectively, then the coefficients of Eq. (5.5) are determined by

$$m = \frac{r_s - r_b}{s_s - s_b} \quad (5.6)$$

and

$$d = r_s - ms_s. \quad (5.7)$$

The gray levels of $f_n(x, y)$ are mapped from $f(x, y)$ according to

$$f_n(z) = T \{ Q[f(e)] \}, \quad (5.8)$$

where T is inversely proportional to Q such that $T(Q)$ is constant. Thus any variation of Q as the result of changes in the illumination are cancelled by $T = Q^{-1}$. After the intensity transformation, the pixel values of $f_n(x, y)$ represent the surface reflectance of $f(x, y)$, with z_b corresponding to the reflectance of the black reference $r_b = 0$ and z_s to the white reference $r_s = 0.9$. The numerical value of any pixel in $f_n(x, y)$ is equivalent to the product of the surface reflectance at location x, y and the Lambertian value:

$$f_n(x, y) = r(x, y) z_s. \quad (5.9)$$

The correspondence between the surface reflectance and the pixel values of any f_n is established by normalizing to the Lambertian surface in Eq. (5.2). This correspondence is held constant for all subsequent f_n by normalizing the gray scale to the fixed reference.

As an illustration, consider the case where r_s and r_b are assigned values of 235 and 10 respectively. Assume that s_s and s_b in the test image are found to be 225 and 40 respectively. Transfer function $T(s)$ is determined from Eq. (5.6) and (5.7)

$$T(s) = 1.07s - 5.75, \quad (5.10)$$

as illustrated in Figure 5.3, which shows that all pixels with gray level 50 in $f(x, y)$ are mapped to 48 in normalized image $f_n(x, y)$.

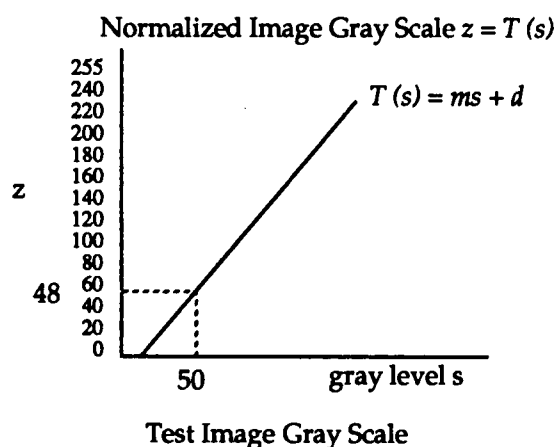


Figure 5.3. Intensity Mapping Function.

Spatial Normalization

Before the test image can be subtracted from the reference, it must also be aligned spatially to compensate for any differences in position or magnification. This is done by measuring the position of $f(x, y)$ relative to $f_r(x, y)$ and conforming $f(x, y)$ to minimize the separation between them. The displacement is measured by determining the coordinates of fixed topological sites called tie-points in $f(x, y)$ and $f_r(x, y)$, that are related to each other by the coordinates of the camera. The

displacement at each tie-point describes the horizontal and vertical separation of the two images. The coordinates of the test image are found through application of a multistage correlation analysis to each tie-point. The point of maximum cross correlation is located to an integer value with a coarse-correlation procedure and estimated to a fractional value with a fine-grained correlation.

Coarse Correlation

The coarse correlation uses the sequential similarity detection algorithm (SSDA) to locate the point of maximum cross correlation between two images to an integer pixel (Barnea and Silverman, 1972). The SSDA accumulates the absolute difference of randomly selected points in the two images. If the accumulated difference grows rapidly, the two images are not well-correlated. Let S be an array of $L \times L$ within $f(x, y)$, and W be an $M \times M$ array within $f_r(x, y)$ with $M < L$. The coarse correlation is performed by moving $W(l, m)$ within $S(i, j, l, m)$. The pair i, j is the index over the range of S , while the pair l, m corresponds to the coordinates of window W as indicated in Figure 5.4. As region W is sequentially scanned over S , points l, m from W and S are selected from a random, nonrecurring sequence k at each position of W . The absolute difference of the selected points in W and corresponding points in S is accumulated and compared to a threshold function.

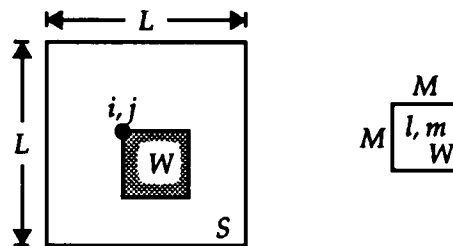


Figure 5.4. SSDA Correlation Windows.

Template window W moves over search window S in a sequential scan. At any point i, j in S , the absolute difference between W and S is accumulated at points l, m from both windows.

For W of size M , the accumulated difference $E(i, j, k)$ is given by

$$E(i, j, k) = E(i, j, k-1) + |S[i, j, l(k), m(k)] - W[l(k), m(k)]|, \quad (5.11)$$

where $E(i, j, 0) = 0$ and the number of points considered in the sequence k is constrained by $1 \leq k \leq M^2$. If E exceeds threshold $T(k)$, then $W(l, m)$ is moved to the next position and the process is repeated.

When the W is registered in S , $E(k)$ is the accumulated sum of the image noise. When W is misregistered, the accumulated difference $E(k)$ is the sum of the image noise and registration differences. At each point in sequence k , if the difference between W and S is due to image noise only, then $E(k)$ will increase slowly and will not exceed the threshold. If the difference is due to dissimilarities in the image topology, then $E(k)$ will rise sharply and quickly exceed the threshold as shown in Figure 5.5. When the threshold is exceeded, k is stored along with the position i, j of window W . When W completes the scan of S , the position with highest k is the correlation maxima i_p, j_p to the nearest whole pixel. The advantage of this algorithm is its ability to quickly ascertain that W is not well-registered in S , usually after only a few points have been accumulated. Conventional cross-correlation methods require that all $M^2 - 1$ points be considered for a given position of W .

The threshold is generated from the statistics of uncorrelated, random variations between pixels in $f(x, y)$, and $f_r(x, y)$ and is given by

$$T(k) = \frac{1}{\lambda} e^{-k\lambda}, \quad (5.12)$$

where λ is the mean of the image noise in W and $k > 0$.

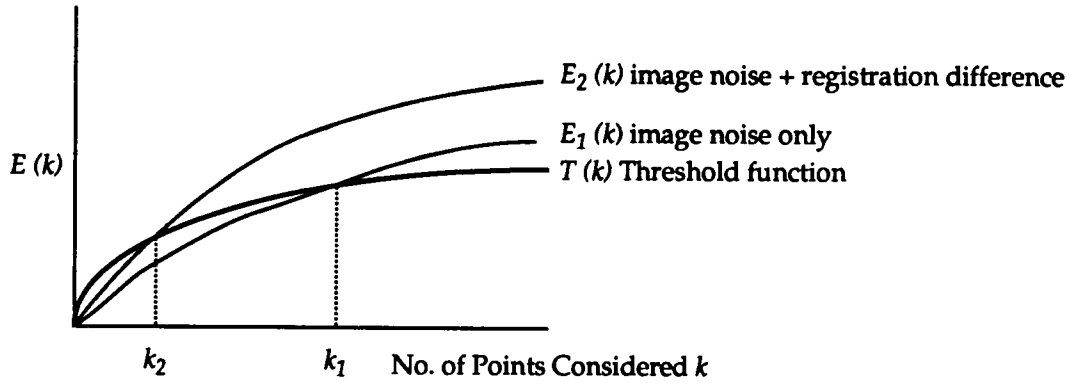


Figure 5.5. SSDA Threshold.

The relationship of the accumulated difference $E(k)$ and the threshold function $T(k)$. $E_1(k)$ has a higher cross-correlation than E_2 because it grows more slowly.

Fine Correlation

After the integer coordinates of correlation maxima ζ_p have been determined, a classical normalized correlation is applied to 3×3 subwindow D , centered on the peak at i_p, j_p . The normalized coefficients ζ_{ij} for the nine points in D are determined from

$$\zeta^2(i, j) = \frac{\left[\sum_{l=1}^M \sum_{m=1}^M D(l, m) S(i_p, j_p, l, m) \right]}{\left[\sum_{l=1}^M \sum_{m=1}^M D^2(l, m) \right] \left[\sum_{l=1}^M \sum_{m=1}^M S^2(i_p, j_p, l, m) \right]} \quad (5.13)$$

for $(i_p - 1) < i < (i_p + 1)$ and $(j_p - 1) < j < (j_p + 1)$.

The technique to register the test and reference images to subpixel accuracy is based upon fitting the correlation points found in Eq. (5.13) to an elliptic-paraboloid surface described by

$$\zeta(x, y) = ax^2 + by^2 + cx + dy + e, \quad (5.14)$$

where $\zeta(x, y)$ is the correlation value at location x, y , and a, b, c, d and e are coefficients of the polynomial used to fit the surface to ζ . The polynomial coefficients in Eq. (5.14) are evaluated from the nine ζ values with a least-squares regression.

The surface represents the correlation topology surrounding ζ_p . There is a $\pm 1/2$ pixel uncertainty in the location of ζ_p because window $W(l, m)$ moves across S in integer steps. This limitation in accuracy is improved with a subpixel correlation algorithm, which has an accuracy of $\pm 1/16$ pixel (Tobin *et al.*, 1989). The exact location of ζ_p is estimated by determining the coordinates of the surface peak in Eq. (5.14) from

$$\nabla \zeta(x, y) = 0. \quad (5.15)$$

This yields two expressions for the coordinates of ζ_p in terms of the coefficients in Eq. (5.14),

$$x_p = -\frac{c}{2a} \quad (5.16)$$

and

$$y_p = -\frac{d}{2b}, \quad (5.17)$$

where x_p, y_p are the coordinates of the correlation surface maxima to a fractional pixel value.

Geometric Transformation

The fine correlation process culminates in an array $V(n)$ of fractional displacement values for each tie-point $n = 1, 2, \dots, N$. The displacements are used to generate a transformation function, which maps the tie-points in the test image to those in the reference. There are six tie-points to spatially align $f(x, y)$ with $f_r(x, y)$, distributed in two rows of three columns each. The image $f(x, y)$ is repositioned in space through geometric transformation. The transformation is linear in the y axis and quadratic in x according to the distribution of tie-points. The linear-quadratic geometric transformation of a two-dimensional image $f(x, y)$ is given by

$$X(u, v) = U^T A V \quad (5.18)$$

and

$$Y(u, v) = U^T B V, \quad (5.19)$$

where x, y are coordinates of source pixels to be mapped to u, v in destination image $f_s(u, v)$. The vectors in Eqs. (5.18) and (5.19) are defined as

$$U^T = \begin{bmatrix} 1 & u & u^2 \end{bmatrix} \quad (5.20)$$

and

$$V^T = \begin{bmatrix} 1 & v \end{bmatrix}, \quad (5.21)$$

with the transformation matrices A and B defined by

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \quad (5.22)$$

and

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ b_{31} & b_{32} \end{bmatrix}. \quad (5.23)$$

The elements of A and B are determined from x and y , the known locations of tie-points in the test image, by expanding Eqs. (5.18) and (5.19) and solving for A and B . This gives an expression for the location of an arbitrary pixel in terms of the destination pixels (i.e., backward mapping),

$$x = a_{11} + a_{12}v + a_{21}u + a_{22}uv + a_{31}u^2 + a_{32}u^2v \quad (5.24)$$

and

$$y = b_{11} + b_{12}v + b_{21}u + b_{22}uv + b_{31}u^2 + b_{32}u^2v \quad (5.25)$$

for each tie-point. Since there are six tie-points, this yields six equations to solve the six unknowns in A and B . Let x_n be the horizontal coordinate of tie-point $n = 1, 2, 3 \dots 6$ with similar notation for y . The equation for x_n is written

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} = \begin{bmatrix} 1 & v_1 & u_1 & u_1v_1 & u_1^2 & u_1^2v_1 \\ 1 & v_2 & u_2 & u_2v_2 & u_2^2 & u_2^2v_2 \\ 1 & v_3 & u_3 & u_3v_3 & u_3^2 & u_3^2v_3 \\ 1 & v_4 & u_4 & u_4v_4 & u_4^2 & u_4^2v_4 \\ 1 & v_5 & u_5 & u_5v_5 & u_5^2 & u_5^2v_5 \\ 1 & v_6 & u_6 & u_6v_6 & u_6^2 & u_6^2v_6 \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{12} \\ a_{21} \\ a_{22} \\ a_{31} \\ a_{32} \end{bmatrix}, \quad (5.26)$$

or, in compact form,

$$x = C(u, v) a \quad (5.27)$$

and

$$y = C(u, v) b. \quad (5.28)$$

The a and b vectors in Eqs. (5.27) and (5.28) correspond to the elements of A and B matrices, which perform the geometric transformations described in Eqs. (5.18) and (5.19). The elements of a and b can be found by matrix inversion:

$$a = C^{-1}x \quad (5.29)$$

and

$$b = C^{-1}b . \quad (5.30)$$

After spatial normalization, test image $f(x, y)$ is registered to $f_r(x, y)$ at the six tie-point locations. Because of the normal variations in printing, there can still be substantial energy in the difference image of an unflawed note. Consequently, a filtering algorithm is applied to the difference image to reduce the residual artifact energy while leaving true flaws intact. This algorithm is the topic of the following chapter.

CHAPTER 6

NOISE SUPPRESSION

There are significant spatial variations between any two given currency samples. Position-dependent displacements between the test and reference images can cause large errors in the difference image. The errors are referred to as edge noise because they are highly correlated with topological features of high-contrast transitions (ink edges) in the note. The errors are the result of naturally occurring variations in the position of the note edges. Edge noise is seen in the difference image after subpixel alignment of two distinct notes in Figure 6.1. The ghost image of the note structure is the residual misregistration due to minute spatial variations of the notes. Because edge noise obscures the true flaws by reducing the signal-to-noise ratio, the error magnitude must be reduced in order to detect the desired flaws.

The approach to increasing the flaw signal-to-noise ratio is twofold: (1) to reduce the error by aligning the spatial coordinates of the two images, and (2) to further reduce the error by desensitizing the detection algorithm to features near edges in the reference. The alignment problem is complex because the samples can be shifted, rotated, and stretched in a nonlinear fashion due to mechanical stresses present in the printing process. The method of registering the images to subpixel accuracy in two dimensions is based on specifying an elliptic-paraboloid to local correlational data as described in Chapter 5. The sample is aligned with the reference by geometric transformation applied to the test image.

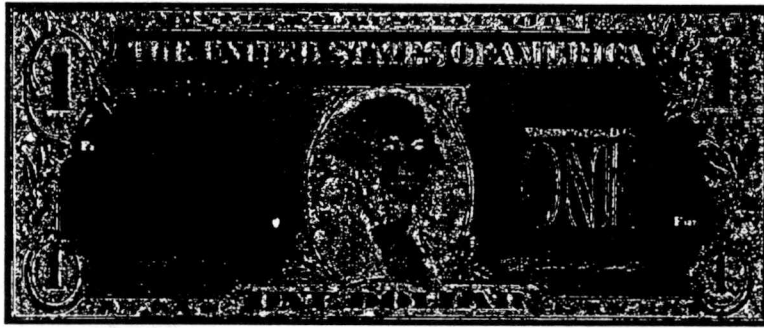


Figure 6.1. Edge Noise after Subpixel Registration.

The flaws found on the note are isolated from their background with a three-part noise-suppression algorithm. The algorithm consists of (1) attenuating residual artifacts remaining after the registration process with a structural filter, (2) performing a series of morphological operations to further attenuate the artifacts and merge closely spaced features, and (3) applying a linear decision threshold to segment the flawed features. After the image artifacts have been reduced, each candidate flaw is analyzed to determine the location, area, and contrast parameters required for the local flaw model in Eq. (3.6).

Structural Filter

Residual misregistration is present in apparently similar documents even after spatial alignment due to differences in engraving plates, interpolation errors in the geometric transformation process, and statistical variations in position arising from uncertainties in the printing process such as nip pressure, ink viscosity, or ink surface tension. In order to reduce the edge noise present after registration and subtraction, a structural filter was designed to suppress registration errors correlated to the print structure without eliminating valid flaws (Jatko *et al.*, 1990).

In a perfectly registered image, the edges of the test image are located at the same position as the reference. The position of an arbitrary ink edge in the test image is modeled in one dimension by a normal probability distribution with mean at ζ and variance σ^2 :

$$P_e(x) = \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) e^{-\left(\frac{x-\zeta}{2\sigma} \right)^2}, \quad (6.1)$$

where ζ is the edge position in the reference. While one-dimensional functions are used for convenience in understanding the algorithm, the method is applicable to two-dimensional images. The model is based on the expectation that edges in the test image are highly correlated to the reference, with random variations around the expected edge position.

Mean edge position ζ is the expected position of the reference ink edges, which can be represented by

$$\zeta(x) = \frac{d}{dx}(f_r(x)). \quad (6.2)$$

The standard deviation σ in Eq. (6.1) is a constant selected for the particular document being inspected. Its value indicates the degree of variability of the printing press, which may vary with time. σ is obtained from either *a priori* estimates for the press based on historical data, or from *a posteriori* knowledge of the edge distributions measured in samples of the test population.

Figure 6.2 shows the expected position ζ of a horizontal edge in $f_r(x, y)$. Beneath $f_r(x, y)$ is the same edge in test function $f(x)$. Because of the normal variation in edge position described earlier, $f(x)$ is assigned a tolerance region in edge position corresponding to the distribution in Eq. (6.2). The width of this region is selected as 3σ to enclose 99% of the random edge variations in $f(x)$. If the edge of $f(x)$ is within $\pm 3\sigma$ of ζ , it is inside the tolerance region and is defined to be the result of an acceptable printing variation. If the edge position is outside the region, it is considered to be caused by a printing defect. Features inside the tolerance region are ignored by the inspection system, while those outside the region are detected as printing flaws.

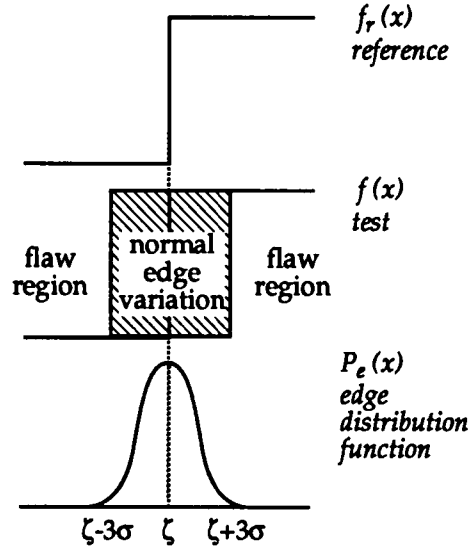


Figure 6.2. Probability Distribution Function of Edge Position.

The structural filter is a two-dimensional, spatially dependent weighting function $w(x, y)$. The pixels in $w(x, y)$ represent unique coefficient values ranging from 0 to 1.0 at each x, y . Weighting function $w(x, y)$ is multiplied with $f_d(x, y)$ to form an attenuated difference image $f_a(x, y)$, given by

$$f_a(x, y) = w(x, y) f_d(x, y) . \quad (6.3)$$

Ideally, the purpose of $w(x, y)$ in Eq. (6.3) is to reduce the amplitude of any feature in $f_d(x, y)$ lying within the tolerance region. This can be accomplished by making the coefficients of $w(x, y)$ small near areas of high structural uncertainty in $f(x, y)$ such as near edges of $f_r(x, y)$. Conversely, the coefficients are high in areas of low uncertainty (several pixels away from the edges). Because the topology of the reference is fixed for all acquisitions, the spatial relationship of $w(x)$ to $f_r(x)$ is established by setting the magnitude of each element in w proportional to its distance from the expected edge position. An ideal weighting function will negate the edge variation of Eq. (6.1) by reducing the edge amplitude near ζ according to

$$w(x) = 1 - e^{-\left(\frac{x-\zeta}{2\sigma}\right)^2} , \quad (6.4)$$

where $0 \leq w \leq 1.0$. This is an inverted Gaussian function, which is zero at ζ and unity for points exceeding 3σ from ζ . Features in $f_d(x)$ that are within 3σ of ζ are attenuated by Eq. (6.3), while features farther away from ζ are unchanged.

The effect of spatial attenuation by the weighting function is illustrated in Figure 6.3, in which reference $f_r(x)$ is shown with a misregistered test function $f(x)$ containing a print defect. Note that the edge artifact arising from misregistration is indistinguishable from the flaw in $f_d(x, y)$. In attenuated function $f_d(x)$, the amplitude of the artifact has been reduced significantly relative to the flaw. The flaw is further segmented from the artifact by intensity threshold T , chosen to eliminate features with amplitude less than the background noise. This allows the flaw to be fully isolated in the thresholded image $f_i(x)$.

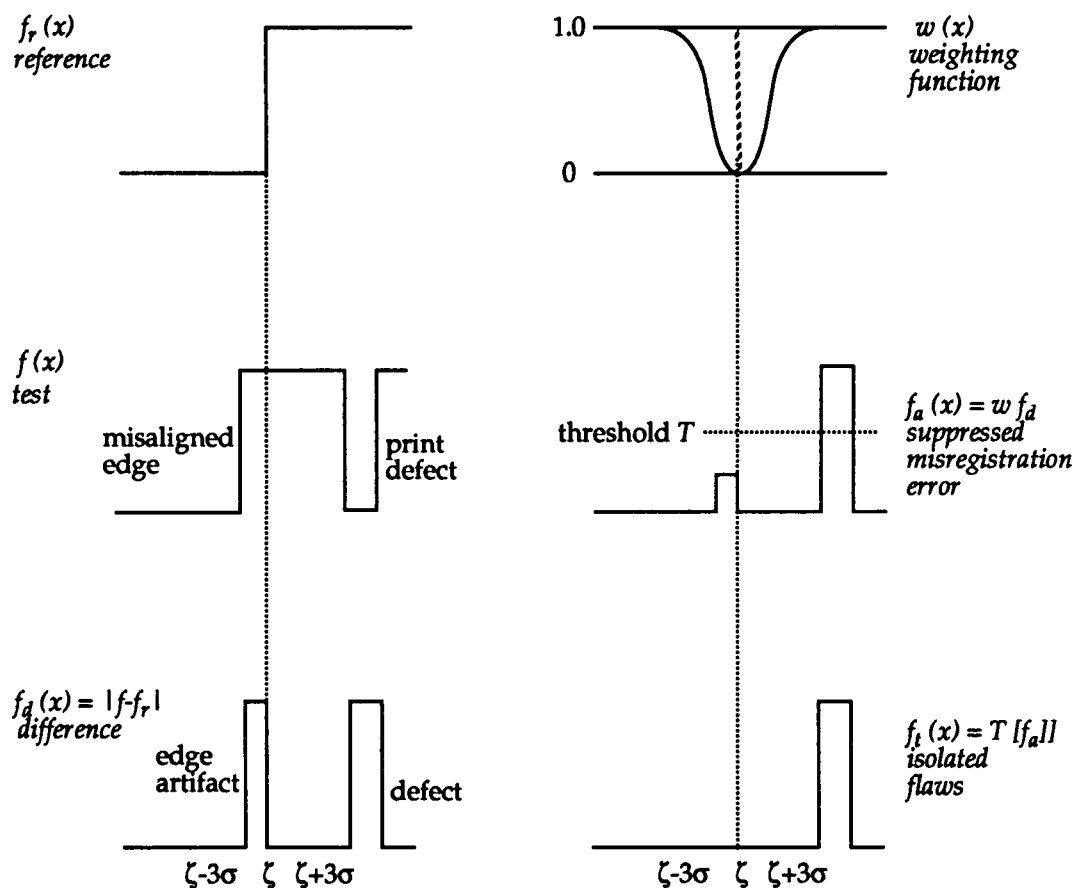


Figure 6.3. One-Dimensional Edge Noise Suppression.

The absolute difference of test image $f(x)$ and reference $f_r(x)$ results in a registration error in addition to the actual flaw magnitude in $f_d(x)$. A weighting function $w(x)$ is derived from $f_r(x)$ and multiplied with $f_d(x)$ to suppress the registration error without affecting the flaw. The resultant image is $f_a(x)$, which is thresholded to isolate the flaw in $f_t(x)$.

Weighting Function

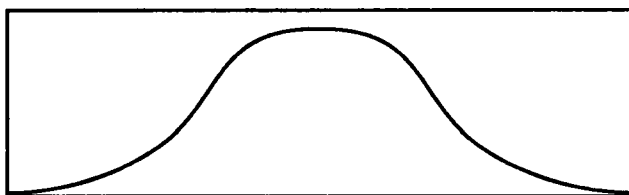
The weighting function in Eq. (6.4) is a continuous function that cannot be implemented directly for a quantized image. Therefore, a discrete first-order approximation to $w(x, y)$ must be substituted. The approximation $\tilde{W}(x, y)$ consists of two parts, (1) the *a priori* estimate of the edge variation, and (2) the *a posteriori* estimate. The *a priori* estimate is a spatial approximation of Eq. (6.4) based on the expected behavior of the press. The *a posteriori* estimate is a correction term based on measured edge variations from the test population. The first term represents the baseline edge variation, and the second term corrects for systematic deviations from the first term. The approximation to the weighting function is given by

$$\tilde{W}(x, y) = a [f_r(x, y) \otimes k(x, y)] + \frac{b}{N} \sum_{i=1}^N |f_i(x, y) - f_r(x, y)|, \quad (6.5)$$

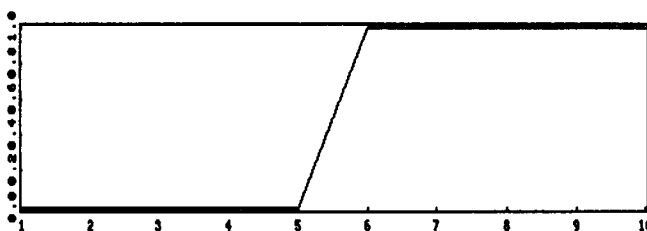
where $\otimes$ denotes the spatial convolution operator. The first term in Eq. (6.5) is generated by convolving the reference image with a two-dimensional kernel (Ballard and Brown, 1982). This combines both the mean edge position from $f_r(x, y)$, and the expected variation σ in one operation. By choosing an appropriate size and coefficients for k , the approximation can be made as near to Eq. (6.4) as desired. The image is scaled so that the edge intensities lie within the required range $0 \leq w \leq 1.0$. A set of representative one-dimensional kernels in Figure 6.4 shows how the approximation improves by increasing the kernel size.

The second term in Eq. (6.5) represents the variations in edge position, experimentally measured from a sample of the test population. The accumulated, absolute difference of N test images $f_i(x, y)$ with defined reference $f_r(x, y)$ compensates for any systematic variations inherent in the printing process. The coefficient values of a, b are empirically determined from historical data or observation such that $a + b = 1$. Approximation $\tilde{W}(x, y)$ is predetermined and stored in memory along with the reference image.

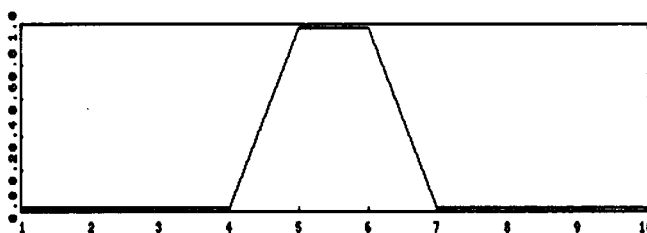
$w(x)$ desired function



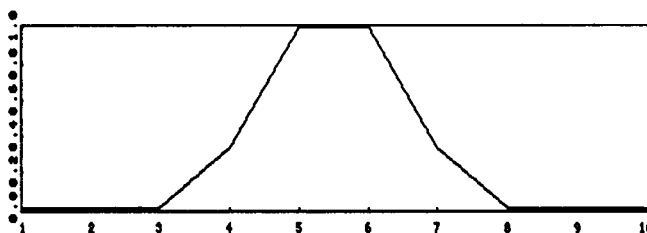
(a) $f_r(x)$ reference edge



(b) $f_r(x) \otimes \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$



(c) $f_r(x) \otimes \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \end{bmatrix}$



(d) $f_r(x) \otimes \begin{bmatrix} -1 & -2 & -4 & 0 & 4 & 2 & 1 \end{bmatrix}$

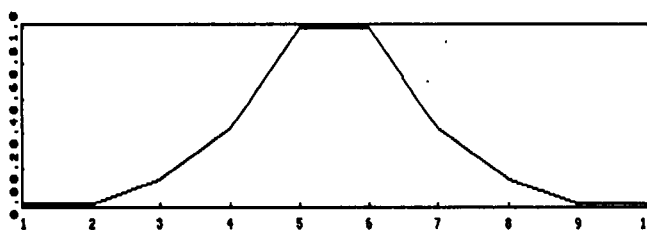


Figure 6.4. Edge Extraction Kernels.

Sample convolution kernels to extract reference edges in approximation to weighting function $w(x, y)$. (a) shows a horizontal edge in the reference; (b) shows the result of spatial convolution with the 1×3 kernel; (c) and (d) show similar results for larger kernel sizes. Note that the approximation to $w(x, y)$ improves with kernel size.

Morphological Filter

The spatial attenuation operation can leave many small artifacts in the attenuated difference image. These artifacts are removed with a sequence of morphological operations on $f_a(x, y)$. The morphological operations are grey-scale erosion and dilation, which are nonlinear operations performed at each pixel location (Maragos, 1987). In erosion, the output pixel is the minimum value of a 3×3 kernel centered at the pixel of interest in $f_a(x, y)$. In dilation, the maximum value of the kernel is chosen. An erosion removes one perimeter pixel from the larger features and eliminates features that are one or two pixels on a side. A dilation operation adds one perimeter pixel to all features. The morphological operations are defined by the following equations for erosion and dilation respectively:

$$f_m(p, q) = \text{Min} [f_a(k, l)] , \quad (6.6)$$

and

$$f_m(p, q) = \text{Max} [f_a(k, l)] , \quad (6.7)$$

for all k, l in the kernel centered at p, q in input image $f_a(x, y)$. The result of the morphological filter is $f_m(x, y)$.

The particular sequence used is an erosion followed by two dilations and, finally, another erosion. Features smaller than 2×2 are eliminated by the first erosion, and larger features are shrunk by one perimeter pixel. The image is then dilated once to enlarge the features to the original size, then dilated again to merge closely spaced features. The size of all image features is increased as a result of the second dilation. The image is eroded for a second time to restore the remaining features to their original size. This sequence ensures that a large flaw (which was bisected as a result of the attenuation procedure) will be merged to its original size. Additionally, closely spaced features tend to be visually integrated by the observer into a single component. Figure 6.5 shows the results of the morphological filter on a binary example. The input image contains two larger flaws and a small artifact. As a result of the morphological operations, the larger flaws are merged into a single, well-defined flaw while the artifact is eliminated.

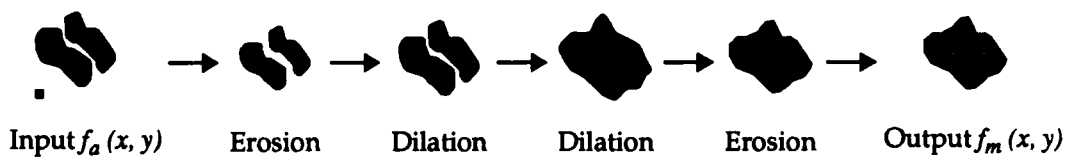


Figure 6.5. Morphological Filtering Operation on a Binary Image.

Input $f_a(x, y)$ is eroded to remove point-flaws, then the resulting image is dilated twice to merge closely spaced flaws, and finally eroded again to form output image $f_m(x, y)$.

Threshold Function

The lower limit of flaw detectability is determined by the value of threshold function T . It is necessary to set T high enough to exclude edge artifacts and noise but not so high that an excessive number of low-contrast flaws are overlooked. The threshold level is chosen by considering the limits of discrimination of the eye. The contrast sensitivity of the eye has been measured by exposing an observer to a uniform field of brightness, B , surrounding a well-defined region of brightness, $B + \Delta B$. The level of ΔB is increased from zero until a just-noticeable difference is perceived by the observer. The ratio of $\Delta B/B$ is called the Weber ratio, and is a nearly constant value of 2% for a wide range of brightness background levels (Gonzalez and Wintz, 1977). In humans, contrast sensitivity is a function of background intensity, known as brightness adaptation, but for fixed backgrounds with constant illumination, Weber's ratio is a reasonable estimate of perception limits (Pratt, 1978). This is in general agreement with the least perceptible brightness change of 1.5% for modulated light reported by Dow (Hardy and Perrin, 1932).

Under constant illumination, the Weber ratio corresponds to a least perceptible *reflectance* difference in the substrate of ~ 0.02 . This reflectance difference is then used to determine the corresponding *density* difference in the substrate and ink regions. Using Eq. (3.6), the least perceptible *density* difference is 0.02 for the substrate and 0.125 for the ink. The inequality of the

least perceptible density difference for ink and substrate suggests that an observer has a higher sensitivity to blemishes occurring in the open substrate region of the note. The operational threshold is selected to be the mean of the ink and substrate least perceptible density difference. The threshold is applied after the morphological filter according to

$$f_t(x) = \begin{cases} 0, & f_m(x) < T \\ f_m(x), & \text{otherwise} \end{cases} \quad (6.8)$$

where $f_t(x)$ is the thresholded image containing all features of amplitude greater than the threshold $T = 0.07$.

The standard deviation in substrate reflectance for a \$1 note was measured with the camera to be $\sigma_s = 0.023$. This value is used as an estimate of the random variation in reflectance in the note substrate. The maximum expected variation in substrate reflectance is $3\sigma = 0.07$ with a 99% confidence level. Again using Eqn. (3.6), the maximum expected surface variation in terms of halftone density is $h = 0.055$. The relationship of the flaw detection threshold to the limits of perception for ink and substrate, and to the expected random brightness variations in the paper, is shown in Figure 6.6.

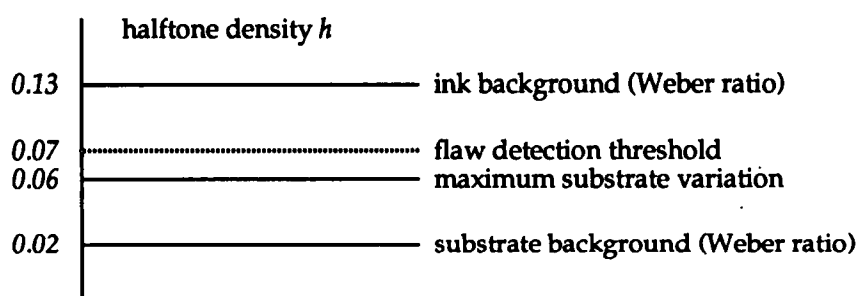


Figure 6.6. Perception Thresholds Based on Weber Ratio.
(not to scale).

CHAPTER 7

PHYSICAL IMPLEMENTATION MODEL

Hardware Architecture

A physical realization was designed to implement the previously described flaw detection algorithms with commercially available image-processing equipment. The physical model consists of four subsystems: (1) the host CPU subsystem, (2) the data storage subsystem, (3) the image-processing subsystem, and (4) the image acquisition system. A block diagram of the physical model is shown in Figure 7.1.

The host CPU controls the imaging operations by issuing commands to the image-processing boards over the VME bus. The image-processing subsystem acquires the images from the camera and isolates the desired features in the image. The data storage system stores the CPU operating system and the data obtained as a result of the flaw evaluation process. The host and image boards operate in a VME chassis, which mounts within a standard equipment rack along with the data storage subsystem. The image acquisition subsystem consists of the high-resolution video camera, optics, and illumination.

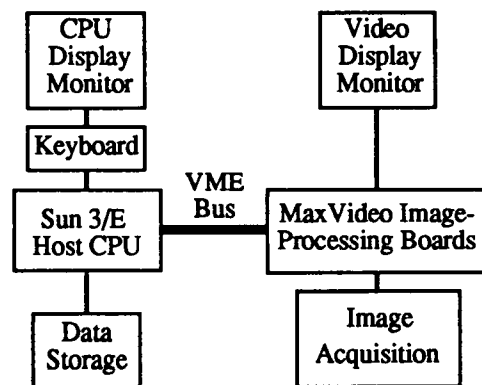


Figure 7.1. Block Diagram of the Physical Model.

Host CPU Modules

Three VME modules make up the host CPU, which controls the operation of the other subsystems. One module is dedicated to each of the following functions: (1) the central processing unit containing the 68020 microprocessor, (2) the display buffer, and (3) the disk-network interface. The host runs the flaw severity software routines. The display buffer contains the bit-mapped graphics plane for viewing on the CPU monitor. An Ethernet communications module provides a fast data link to other devices on the network and to the data storage unit. The configuration of the VME modules and their physical placement in the chassis are shown in Figure 7.2. The first slot in the VME chassis is occupied by the host CPU, which is also the bus arbitrator.

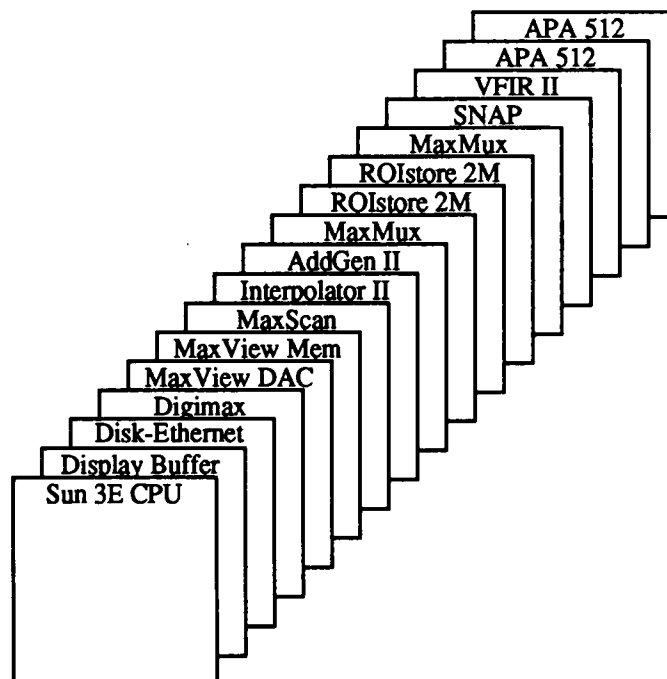


Figure 7.2. Configuration of VME Chassis Modules.

Image-Processing Modules

The image-processing system consists of 14 modules, each with a specific function in flaw severity evaluation. The host CPU communicates with the image-processing modules over the VME bus. Images are distributed over a high-speed, proprietary digital data bus so that the host is not burdened with the mechanics of propagating images along the 10-Mpixel/s image pipeline. A brief description of each MaxVideo™ module and its function in flaw evaluation follows. The schematic diagrams of the image-processing system are found in Appendix A.

Digimax • The Digimax module is an RS-170 analog-to-digital converter. In this application, the Digimax is used solely to generate the timing signals required by the other MaxVideo modules as digitization is performed by the camera.

MaxView • The MaxView consists of two modules to convert the digital video stream to a 1280 x 1024 resolution analog signal for the CRT display. The MaxView memory has 2 Mbytes of image memory connected to the MaxView digital-to-analog converter (DAC) board via a front panel jumper. Images are transferred from the other modules over the digital video bus. The scanning format of the DAC is software programmable.

MaxScan • The MaxScan is an asynchronous analog-to-digital converter used to convert analog video from the camera to digital stream format. Its function is similar to the Digimax except that the scanning parameters are software programmable. The digital output from the camera is applied to the P11 connector of the MaxScan. The camera signal is buffered and reformatted to fit into the image buffers.

AddGen • The Interpolator and Address Generator board set, referred to as the Warper, manipulates the image geometry at pipeline rates. The Address Generator calculates a location in the source image according to a 4 x 4 transformation matrix for each pixel in the destination image.

Interpolator • The Interpolator reads the source pixel and its neighbors and uses a $\frac{\sin(x)}{x}$ interpolation function to determine the value of the destination pixel.

MaxMux • The MaxMux is a central video switching multiplexor. Each MaxMux can be configured as a combination of inputs or outputs with a programmable interconnection matrix. This allows the flow along the video pipeline to be changed dynamically to achieve the desired video path. The MaxMux contains one 16-bit video look-up table and 16-eight bit tables for intensity mapping functions.

ROIstore • The images are stored in region-of-interest buffers called ROIstore modules. Each ROIstore has a 2-Mbyte capacity partitioned into four 1024 x 512 frames. Image size is dynamically programmable from 1 x 1 to 4096 x 4096 via the ROI timing bus.

SNAP • The systolic neighborhood array processor finds the minimum, maximum, or median pixel within a 3 x 3 pixel neighborhood. The minimum and maximum functions are used in the morphological filter.

VFIR • The video finite impulse response Filter (VFIR) performs convolutions on the digital pipeline with up to 8 x 8 kernels. The size of the kernel and its coefficients are programmable. The VFIR is used to extract edge data used in the weighting function image.

APA • The APA boards perform a connectivity analysis on the image to determine the size and location of the flaws.

Data Storage System

The data storage system consists of two 300-Mbyte disk drives, one 1/4 in. tape cartridge drive, and one 8-mm tape drive as shown in Figure 7.3. The CPU operating system is retained on one disk, and the collected flaw severity data are retained on the other disk.

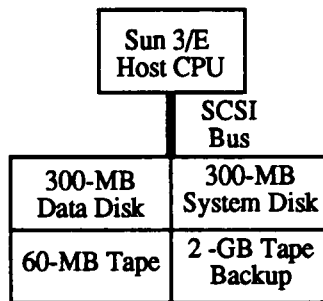


Figure 7.3. Block Diagram of Data Storage System.

Frame Buffer Format

The video memory on the two ROIstore boards and the MaxView board has been partitioned into 12 frame buffers, 1024 pixels wide and 512 pixels tall. The dimensions were chosen to maximize the number of buffers from the available memory. If the buffers had been made larger, say 1500 x 1000, only one buffer could be implemented per ROIstore and nearly 60-kbytes would be left unusable per board. The memory on each board is physically separated into most and least significant planes, which can operate independently of the other through the front-panel video connectors. Therefore, it is possible to read one image from the least significant plane while simultaneously writing another image into the other plane.

A buffer was created to store the intermediate results of each image operation to permit later analysis of algorithm effectiveness. The notation, purpose, and physical board location of each frame buffer are given in Table 7.1. A graphical representation of the ROIstore and MaxView buffer format is given in Appendix B.

Table 7.1. Frame Buffer Description.

Nomenclature	Image Contents	Location
NUT (<i>Note Under Test</i>).	Camera acquired image.	ROIstore 1-1.
MORP (<i>Morphology</i>).	Results of the morphological filter.	ROIstore 1-2.
IWP (<i>Intensity Warped</i>).	Intensity variations removed.	ROIstore 1-3.
DIF (<i>Difference</i>).	Absolute difference image.	ROIstore 1-4.
REF (<i>Reference</i>).	Ideal or "golden" note image.	ROIstore 2-1.
FLW (<i>Flaw</i>).	Isolated flaws.	ROIstore 2-2.
SWP (<i>Spatial Warp</i>).	Spatial variations removed.	ROIstore 2-3.
ADF (<i>Attenuated Difference</i>).	Results of the noise filtering process.	ROIstore 2-4.
VREF (<i>Reference</i>)	Upper half of video monitor display.	View 1-1.
VNUT (<i>Note Under Test</i>)	Lower half of video monitor display.	View 1-2.
EDG (<i>Edge map</i>).	Weighting function to suppress spatial errors.	View 1-3.
REG (<i>Region map</i>).	Flaw severity regions.	View 1-4.

Image Pipeline

The note images are processed in a linear sequence or pipeline (shown in Figure 7.4). Upon completion of each operation, the image is propagated to the next stage. The pipeline begins with the image acquisition function. The high-resolution camera converts the image intensity to a digital bit stream, which is stored in the NUT buffer and the VNUT buffer. Next the image intensity is normalized to correct for illumination or exposure drift and stored in the IWP buffer. The image is then normalized for spatial position to achieve alignment with the reference note. After the image has been corrected for intensity and spatial variations, it is stored in the SWP buffer. The SWP image is used to compare the test note with the reference during all subsequent measurements. After the normalizations, the absolute difference of the reference image REF and the SWP image is computed and stored in the DIF buffer. The structural filter is then applied to suppress the residual misregistration in the DIF image. This procedure also encodes the noticeability region factor and the flaw contrast for each pixel. The resultant image is the attenuated difference image and is stored in the ADF buffer. The morphological filter is applied to the ADF buffer to remove insignificant features and the results are stored in the MORP buffer. The MORP buffer is intensity-thresholded to exclude any intensity bias and is written to the thresholded flaw buffer, FLW. The connectivity

analysis boards read this buffer to label the flaws and store their size and location in a data structure. The local flaw grade is found by reading each flaw in the data structure and determining the average density of the flaw. The global flaw grade is determined from the average reflectance of the SWP image.

Software Architecture

The software was written in distinct segments called modules or functions in the C programming language. The functions are compiled and collected into condensed files called libraries. One function can execute or call other functions to create a hierarchy of operations. By combining functions in this manner, a complex algorithm can be realized.

In the description of software operations, the following conventions will be used. The names of software functions as they are seen in the code are written in **bold** typeface. Variables used for temporary data storage are written in *italic* typeface. Numerical constants, message flags, and macro definitions are written in CAPITAL letters.

The top-level software function is called **main**. The currency evaluation algorithm follows the functional flow chart shown in Figure 7.5. A description of each function is given in the following sections along with its flow chart in Appendix B.

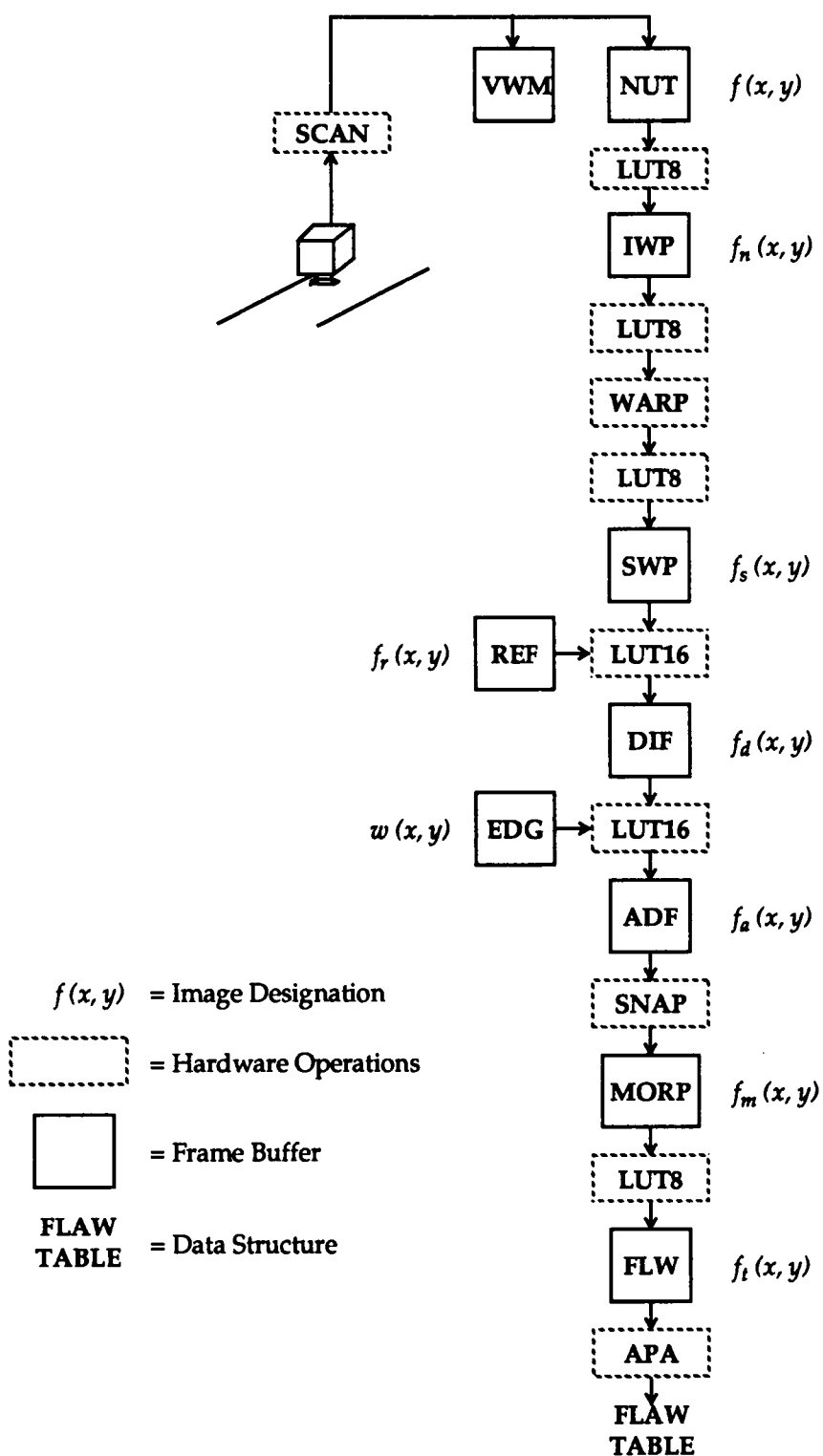


Figure 7.4. Image Pipeline.

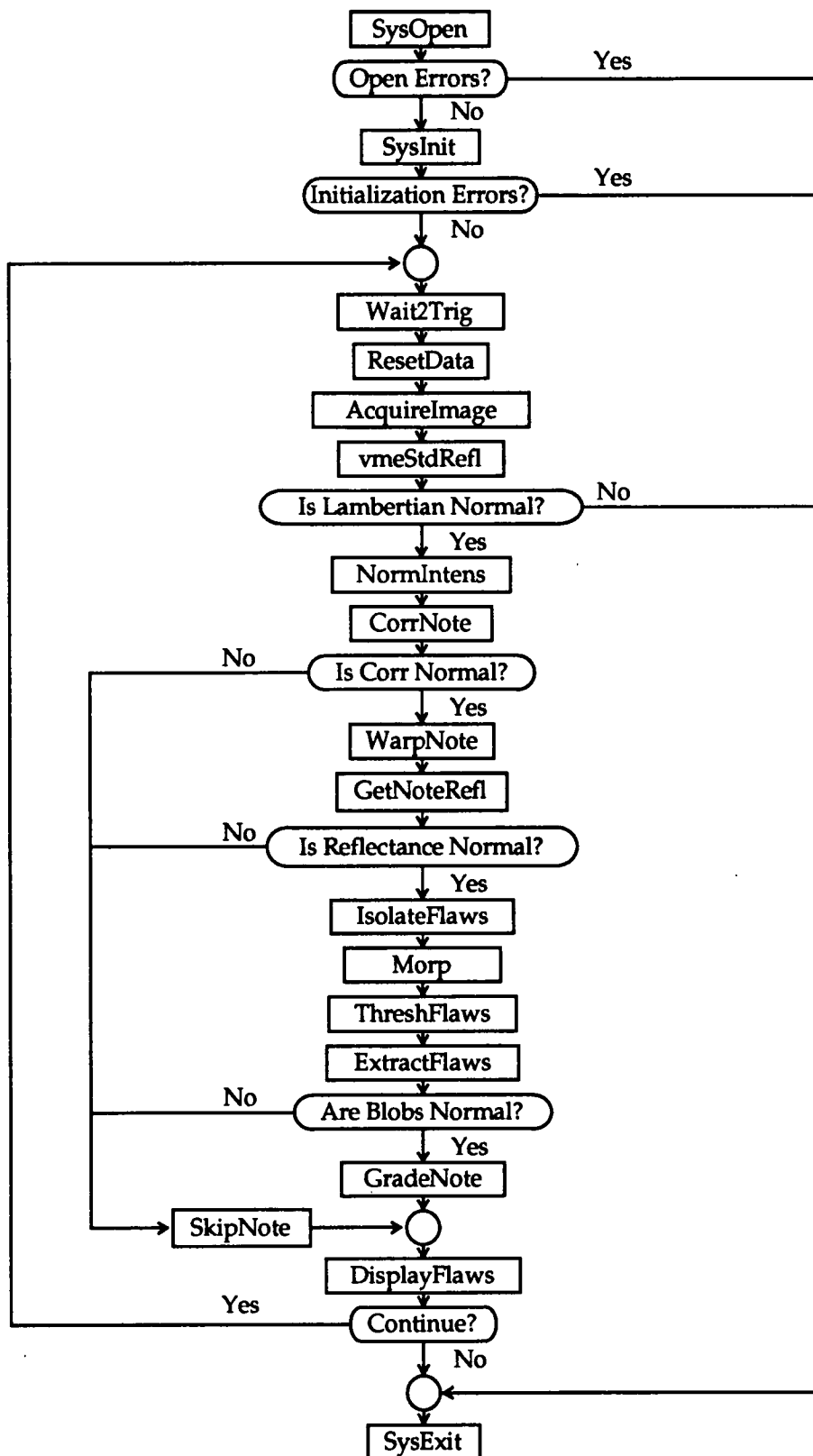


Figure 7.5. Currency Evaluation Flowchart.

Data Structures

In order to organize the data acquired during note processing, a set of software data structures was devised. Each data structure consists of related variables grouped together under a common heading. The data structures are referred to as: (1) *Board*, (2) *Calibration*, (3) *Note*, and (4) *FlawTable*. The individual elements of each data structure are described in Appendix B.

Initialization

The host CPU controls the image-processing hardware through the use of two classes of software, the hardware primitives and the system control functions. The primitives are functions that set the hardware registers with the binary patterns to activate the desired operation. They are temporarily held in a command instruction buffer called a queue. The queue accumulates commands until the next vertical interval occurs; then all instructions in the queue are written to the hardware registers during the interval. The system control functions create the data structures and initialize the system to a known state.

The currency evaluation program begins with the **SysOpen** call, which opens each of the hardware boards. **SysOpen** returns a status flag to indicate whether the open procedure was successful. If an error is returned, indicating that one or more of the boards was not opened properly, the program calls **SysExit**, which closes all boards, restores the system interrupt vectors, and returns control to the operating system. If **SysOpen** was successful, **SysInit** is called to set all boards, data structures, buffers, arrays, and variables to their initial state. **SysInit** also returns a status flag to successful completion. If **SysInit** was unable to initialize the system, **SysExit** is called. If there were no initialization errors, the program enters the main loop to evaluate currency. The data structures are set to their initial values with **ResetData** in preparation for acquiring note data.

Image Acquisition

Image acquisition functions are initiated by the image capture sequence in the camera and the subsequent transfer of data to the frame buffer. The camera can be operated in one of eight modes of operation. The modes are set by the shutter, image capture, and exposure controls, which are activated externally. For acquisition of static notes, a tabletop stand with fluorescent lighting is used to illuminate the test objects. Because the illumination is continuous, the camera shutter must be enabled to prevent ambient light from saturating the sensor between exposures.

Image acquisition is initiated by strobing the image capture control LOW. After the sensor has been exposed, the digitized image is transferred from the camera to the MaxScan module. The internal digitizer of the camera is used instead of the MaxScan digitizer to minimize the induced noise from the coax transmission cable. The MaxScan formats the full-frame serial data from the camera into the correct image dimensions and writes it into the frame buffer. The digitized image is also written into the View memory for display on the CRT monitor. The frame buffer containing the acquired test image is referred to as the note-under-test (NUT) buffer. The image acquisition function is called **AcquireImage**, which fires the camera, records the time when the acquisition began, and determines the black and white standard reflectance in the acquired image.

Determining the Standard Reflectance

The intensity of the standard reflectors, described in Chapter 5, is determined by **vmeStdRefl**. The standard white reflector consists of a diffuse, uniform, white paper strip. The standard black reflector is a darkened circular slot in the mechanical fixture beneath the camera. The slot is painted flat black and is shadowed from the illumination by the slot depth, forming a low-reflectance area. The standard reflectors are digitized along with the note and indicate the illumination level at the time of acquisition. This measurement is used to normalize the intensity scale of the acquired image to match conditions when the reference image was acquired.

The intensity of standard white reflector is sampled at nine locations (called patches) in the image. The average intensity of any patch i with width w and height h is calculated by the host CPU according to

$$\bar{P}_i = \frac{1}{wh} \sum_{n=1}^w \sum_{m=1}^h f_i(n, m) \quad (7.1)$$

for $i = 1, 2, 3, \dots, 9$, where $f_i(n, m)$ is the patch centered at n, m in image $f(x, y)$. The intensity of the Lambertian reflectance r_i is determined from P_i by

$$r_i = \frac{1}{N} \sum_{i=1}^N \bar{P}_i, \quad \forall [(\zeta - 3\sigma_p) \leq \bar{P}_i \leq (\zeta + 3\sigma_p)] \quad (7.2)$$

where σ_p is the expected standard deviation of P_i and ζ is the expected mean value. All values of P_i that are within $3\sigma_p$ of ζ are averaged. The standard white reflectance r_l is stored in the *Lamb* element of the *Note* data structure. The black reflectance value r_b is determined by averaging the pixels within the standard black reflector according to Eq. (7.1) and is storing the mean in the *Black* element of the *Note* data structure.

Image Normalization

The images may be acquired under illumination conditions quite different from the reference image due to bulb aging, line voltage variations, and environmental dust. In order to maintain photometric accuracy, the test image is intensity normalized or warped to the reference image.

The grey level of a pixel at x, y in the intensity normalized image $f_n(x, y)$ is given by Eq. (5.8):

$$f_n(x, y) = T_z[f(x, y)] , \quad (7.3)$$

where $f(x, y)$ is the note-under-test and $T_z[n]$ is the n th element of the discrete intensity mapping function T_z .

After the test image has been acquired and the standard reflectance has been measured with *vmeStdRefl*, the intensity normalization is performed by *NormIntens*. Mapping function T_z is created so that the standard reflectance of the test image matches the corresponding values for the reference image found in the *Calibration* data structure.

If m is the gain factor and d is the offset, then for any grey level z , the elements of the array are given by

$$T_z[z] = \begin{cases} r_b, & \text{if } (z < r_b) \\ mz + d, & \text{if } (r_b \leq z \leq r_l) , \\ r_l, & \text{otherwise} \end{cases} \quad (7.4)$$

for $z = 1, 2, 3, \dots, 255$ subject to the constraint that T_z is restricted to integers by rounding to the nearest whole value.

The factors m and b were previously determined in Eqs. (5.6) and (5.7) as,

$$m = \frac{r_s - r_b}{s_s - s_b} \quad (7.5)$$

and

$$d = r_l - ms_l, \quad (7.6)$$

where r_l and r_b are the values of the standard white and black reflector from the reference image, and s_l, s_b are the corresponding values in the test image.

Array T_z is loaded into a look-up table, and the grey levels of image $f(x, y)$ are mapped through the table to new values in $f_n(x, y)$. The intensity-normalized image $f_n(x, y)$ is stored in the intensity-warped or IWP buffer.

Spatial Normalization

Before the intensity normalized image $f_n(x, y)$ can be subtracted from the reference, it must be aligned spatially with the reference to compensate for any differences in position or magnification. This is done by measuring the spatial displacement of the test image relative to the reference. Then $f_n(x, y)$ is aligned to $f_r(x, y)$ by manipulating the geometry of $f_n(x, y)$ described in Chapter 5. The spatial displacement is the distance between fixed topological sites called tie-points in the test image with respect to the same point in the reference image. The tie-point locations in the test image are determined by application of a multistage correlation analysis to each tie-point region. A coarse correlation locates the cross-correlation peak to an integer value; then a fine-grained correlation estimates the peak location to a fractional value.

The software function **CorrNote** performs the coarse correlation algorithm on each tie-point. When the integer peak of a tie-point has been found, **CorrNote** calls **norcorr**, which performs the normalized correlation on the 3×3 neighborhood surrounding the integer peak. **CorrNote** also checks to ensure that the maximum correlation value is found in the center element of the 3×3 window. If not, the window is moved in the direction of the highest derivative and the process is repeated until the center element contains the correlation maxima. When the correlation peak is

located in the center element, *ellipse* determines the subpixel location of the peak by fitting a paraboloid surface to the correlation points in the 3×3 window and calculating the surface gradient. The subpixel peak location is the coordinate pair, which satisfies the surface gradient equation. The spatial displacement values are stored in the *shift* array.

Each tie-point is processed in the manner described. When all tie-points are completed, *solve* calculates the transformation matrices from the spatial displacement values of the test image. The matrices specify the geometric transformation required to warp the test image to match the reference. The geometric transformation is performed by *WarpNote*, which controls the Warper boards to warp image $f_n(x, y)$. The Warper board image buffer is too small to warp the entire image at once, so the 1024×512 source image is divided into 8 pieces called tiles. Each tile is 256×256 and has a different transformation matrix due to the displacement of the tiles. The matrices for all 8 tiles are calculated prior to beginning the warp. *WarpNote* transfers the pixels from $f_n(x, y)$ through the Warper to the spatially normalized image $f_s(x, y)$, beginning with the upper left tile. The Warper interpolates each pixel in the destination tile based on the transformation matrix and the surrounding pixels in the source tile.

Flaw Isolation

At this point in the image pipeline, the test note has been acquired and normalized to a known position and reflectance scale. The flaws on the test note now must be isolated from the normal image features. This is done by subtracting the reference image from the normalized test image, leaving only those features not common to both images. Two operations are used to isolate the flaws from their background: (1) the image subtraction, and (2) the structural filter to suppress artifacts remaining after image subtraction. There are three operations in the image subtraction, (1) calculating the absolute reflectance difference of $f_s(x, y)$ and $f_r(x, y)$, (2) applying a linear decision threshold, and (3) converting from reflectance to halftone density equivalents. These operations are combined into a single equation, which is precomputed and stored in a video look-up table.

In the local flaw model, the contrast between a flaw and its background is measured in units of halftone density, defined as the percentage dot coverage in an acetate overlay, as given in Eq. (3.6). The overlay was created by printing small uniformly spaced dots in a regular pattern over a rectangular patch. The transmittance or amount of light that passes through the patch is determined by the concentration or density of dots. The transmittance is increased by spacing the dots farther apart or conversely decreased by reducing the dot spacing by

$$H = 1 - T , \quad (7.7)$$

where T is the transmittance and H is the halftone dot density over an arbitrary region. The conversion from image intensity to halftone dot coverage is based on the theory of multilayer reflectance and transmittance and is described in Chapter 3. H is a continuous function but, because of quantization, it is constrained to finite values. Perceptual studies have shown that the human eye can perceive only 30 to 40 discrete levels of absolute intensity (Gonzalez and Wintz, 1982). In order to more closely match the performance of human observers, H is quantized into 32 levels, giving a resolution of 0.03 per step by a straight-line transformation:

$$f(H) = aH(r) + b , \quad (7.8)$$

where $H(r)$ is evaluated according to Eq. (3.6) at x, y and a, b are determined from the dynamic range of $0.0 \leq H \leq 1.0$. If $f(H)$ is represented by n binary digits, the linear coefficients are given by

$$a = \frac{2^n - 1}{H(1) - H(0)} \quad (7.9)$$

and

$$b = (2^n - 1) - aH(1) . \quad (7.10)$$

In this application $n = 5$, thus $a = 31$ and $b = 0$.

Evaluating H at each pixel would require solving 524,288 quadratic equations per image. The CPU time required to solve explicitly for each pixel would be unacceptable. Therefore, H is precalculated with the function `halftone` for all possible values and stored in a look-up table. This allows the entire image to be solved in one 60-ms frame. The fundamental equation to obtain the difference image and convert from reflectance to halftone density is

$$f_d(x, y) = \begin{cases} 0; & \text{if } [|f_s(x, y) - f_r(x, y)| < k] \\ H(r); & \text{otherwise} \end{cases} \quad (7.11)$$

where k is a predefined threshold function to eliminate low-contrast artifacts and H is the halftone density function of the spatially normalized image and reference.

The look-up table is a single-dimensional array A with 65,535 elements. Two 8-bit pixels a, b are combined into a single 16-bit number ab representing the array element to be indexed. The value stored at $A[ab]$ is the solution to an arbitrary function $f(a, b)$. The look-up tables allow the solution to any complex function such as $H(r)$ to be computed beforehand and stored in the table. Images $f_r(x, y)$ and $f_s(x, y)$ are the inputs to the look-up table. The output of the table is the difference image $f_d(x, y)$. The function `IsolateFlaws` sets the path through look-up table A and stores the results in the difference (DIF) buffer.

Structural Filter

The structural filter operation is also performed by `IsolateFlaws` at the same time as the image subtraction. The mathematical operation $f_a(x, y) = w(x, y)f_d(x, y)$ where $w(x, y)$ is the weighting function described in Chapter 6, is similarly done with a 16-bit look-up table. The resultant image $f_a(x, y)$ is called the attenuated difference image and is stored in attenuated difference (ADF) buffer.

Morphological Filter

The morphological filter is a sequence of erosion and dilation operations on $f_a(x, y)$. It removes insignificant flaws from the image and merges closely separated flaws. Erosion shrinks the features by one perimeter pixel and dilation expands them by a similar amount. The sequence consists of an erosion, followed by two dilations, and finally another erosion. The morphological operations are performed with a hardware minimum and maximum filter. The results of the filter are stored in the morphological image $f_m(x, y)$.

Flaw Threshold Calculation

After the common-mode pixels have been removed and the printing variations have been suppressed, the image is thresholded by **ThreshFlaws** to complete the flaw isolation procedure. The purpose of **ThreshFlaws** is to determine a threshold level that will remove any artifact noise and global flaw components from $f_m(x, y)$, and to store the function in a look-up table. The image is read from the MORP buffer, through the look-up table and written into the FLW buffer. The resultant image $f_t(x, y)$ is used in the connectivity analysis to measure the area and location of each flaw.

The pixel value at $f_t(x, y)$ is given by the following relationship:

$$f_t(x, y) = \begin{cases} 0, & \text{if } [f_m(x, y) < T] \\ f_m(x, y), & \text{if } [T \leq f_m(x, y) \leq M] , \\ M, & \text{otherwise} \end{cases} \quad (7.12)$$

where T is the thresholding constant and M is the maximum value permitted.

ThreshFlaws reads the substrate and ink reflectance of the reference and test images from the *Calibration* and *Note* data structures respectively. Each reflectance is converted to normalized halftone densities by the subroutine **NormDensity**. The conversion algorithm is identical to **halftone** except that the densities are normalized to a five-bit short integer with values from 0 to 31 to match the pixel intensity scale in $f_m(x, y)$. The values returned by **NormDensity** represent the magnitude of the difference between the reference substrate reflectance and the test substrate

reflectance in halftone density units. The larger value of the two is summed with a constant integer to form threshold T . The constant integer provides headroom from pixel noise on top of the signal. The sensitivity to artifacts becomes excessive if the headroom is not included in the threshold computation. The threshold is determined by the following relationship:

$$T = \max \left(\frac{H(R_s)}{H(R_i)} \right) + N, \quad (7.13)$$

where $H(R_s)$ is the difference between the reference and test substrate density and $H(R_i)$ is the ink difference. N is the constant representing the noise margin.

It is necessary to determine the threshold in this manner in order to maximize the orthogonality between local and global flaws. Consider a note with an excess ink flaw on the substrate region as shown in Figure 7.6a. The pixel values in this example are given in reflectance grey levels rather than density for convenience. The intensity of the reference substrate is 180 and the reference ink is 60. The test substrate and ink are identical to the reference except for the localized excess ink spot at 100. In the difference image shown in Figure 7.6b, the pixels are zero everywhere except in the area of the local flaw, which is $dF = 180 - 100 = 80$. The difference image is thresholded to eliminate any pixel noise leaving only the local flaw component.

Now consider Figure 7.6c, where the test note also contains a global flaw component such as light print and the substrate is darker than normal. In this case the reference pixels are unchanged, but the test substrate is 160 and the ink is 100. The difference image is shown in Figure 7.6d which illustrates the additional component due to the global flaw. The difference image is shifted by dS , the difference between the reference and test substrate reflectance. The global flaw amplitude is dI , the difference between the reference and test ink reflectance. The local flaw amplitude is dF , the difference between the reference substrate reflectance and the reflectance of the local flaw. Under these conditions, $dF = 80$, $dI = 40$ and $dS = 20$. In order to isolate the local flaw component from the global flaws, the threshold must be set above the highest global component. In this case, the threshold is set to 50 to define all $f_m(x, y) \leq 50$ as global flaws and all $f_m(x, y) > 50$ as local flaws. The amplitude of the flaw is not important at this stage since the flaw amplitude or contrast is measured elsewhere. The threshold is computed according to Eq. (7.13) and is implemented by mapping the contents of $f_m(x, y)$ through the look-up table. The results of the threshold operation are stored in the FLW buffer.

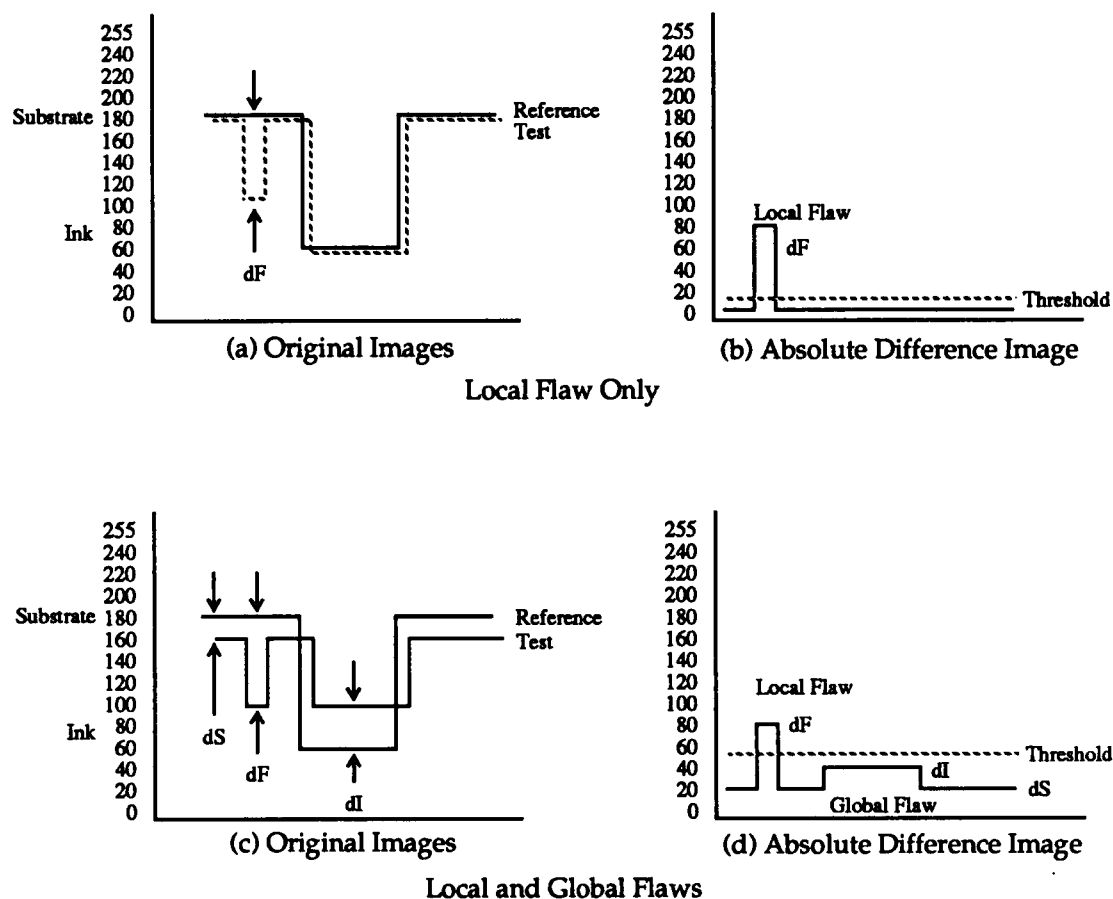


Figure 7.6. Isolating Local Flaws from Global Flaws.

(a) The reference and a test image with a local excess ink flaw but no global defects. (b) After the absolute difference of (a). (c) A global flaw added. (d) The difference image showing the magnitudes of the global defects. The threshold must be set to $dS < T < dF$.

Flaw Measurement

Once the local flaws are isolated from the background, their location, area, and contrast can be determined. Pixels joined together by eight-way connectivity in $f_i(x, y)$ are defined to be a flaw component or macroflaw. Eight-way connectivity occurs when a pixel is directly adjacent to another pixel along a vertical, horizontal, or diagonal axis. Flaw measurement is done in two stages, (1) connectivity analysis in which the location of each macroflaw is determined, and (2) flaw evaluation where the region, area, and equivalent halftone density are calculated.

Connectivity Analysis

The APA connectivity analysis boards locate all significant macroflaws in $f_i(x, y)$ and store their coordinates in the *FlawTable* data structure. A macroflaw is considered significant if its size exceeds a preestablished limit.

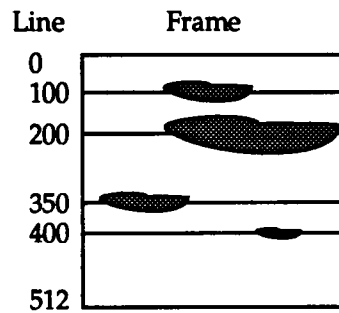
The APA image buffer capacity is 512×512 which is half the size of the image $f_i(x, y)$. Therefore, image $f_i(x, y)$ is divided into two parts, with the left half processed first and the right half following. Pixels related by eight-way connectivity are given a numerical label to identify them as a connected group or blob.

A limitation of the hardware is that no more than 255 blobs can be labelled in one frame. Because a note may have more than 255 macroflaws, a floating window is used to process up to 32,640 macroflaws per note. The software-programmable window or scanning frame sets the dimension of the connectivity analysis scan. The width is set to the maximum of 512 pixels, and the height is allowed to vary from 8 to 512 lines. If more than 255 macroflaws are detected within an eight-line window on a note, it is declared ungradeable.

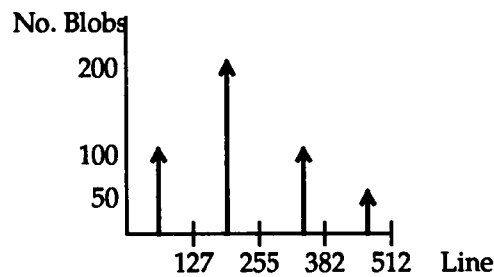
The connectivity analysis algorithm is activated with the software function **ExtractFlaws**. **ExtractFlaws** transfers the left half of the FLW buffer to the APA buffer and calls **canal**, which performs the connectivity analysis. After the left half of the image is completed, the process is repeated for the right half.

The connectivity analysis in canal comprises an inner and outer loop, which continue until predefined conditions are satisfied. The outer loop sets the height of the scanning frame, checks the number of times the outer loop has been executed, and calls **FindBlobs**, the inner loop. A hardware register on the APA board indicates the status of the blob parameter queue. If the queue contains more than 255 blobs and a queue memory access is attempted, the board will crash. **FindBlobs** checks the register to determine the status of the queue. If there are fewer than 256 blobs in the frame, the location and area of the blobs within the scanning frame are determined and the inner loop returns the **DONE** flag to the outer loop, indicating that the connectivity analysis is completed. If there are more than 255 blobs in the frame, the inner loop is halted and the **RESIZE** flag is returned. The frame is repeatedly divided until fewer than 256 blobs are contained within. If the frame is reduced to the minimum size of 8 lines and still contains more than 256 blobs, an **ERROR** flag is returned, indicating the note cannot be graded accurately. If the blob area obtained from the parameter queue exceeds the minimum limit stored in the *MinFlawSize* element of the *Calibration* data structure, the coordinates of the blob's bounding rectangle are appended to the *FlawTable* data structure.

In order to illustrate the operation of the windowing algorithm, consider a frame that contains a total of 450 blobs concentrated in four clusters. The first cluster has 100 blobs centered on line 100, the second cluster of 200 blobs is centered on line 200, the third cluster of 100 is centered on line 350, and the fourth cluster of 50 blobs is on line 400 as shown in Figure 7.7.



(a) Blob Distribution



(b) Blob Distribution Profile

Step	Iteration		Window		#Blobs	Scan Frame
	Outer	Inner	Start	Stop		
1	1	1	0	511	450	
2	1	2	0	255	300	
3	1	3	0	127	100	
4	2	1	127	511	350	
5	2	2	127	319	200	
6	3	1	319	511	150	
						

(c) Window Sequence

-  Region being scanned
-  Valid frame < 256 blobs
-  Completed frame
-  Unscanned region

Figure 7.7. Connectivity Analysis Windowing Algorithm.

Initially, the outer and inner loop counters are cleared and the scanning frame is set to begin on line 0 and end on line 511. Because there are 450 blobs in the frame, the RESIZE flag is returned by the inner loop. The inner loop counter is incremented and the frame is reduced to line 255. There are now 300 blobs in the frame, and the inner loop again returns RESIZE. The inner loop counter is incremented and the frame is reduced to line 127. The frame now contains 100 blobs. The blob coordinates in this frame are extracted from the parameter queue and written into the first 100 elements of the *FlawTable*.

On the second iteration of the outer loop, the frame begins at line 127 and extends to line 511. There are 350 blobs, so the frame is divided in half. The new ending line is found from the old frame dimensions, $(511 - 127) 2 + 127 = 319$. The starting line is 127 and the ending line is 319. There are 200 blobs in this frame, so the connectivity analysis can proceed normally. The new blobs are added to the *FlawTable*, which now contains 300 entries.

On the third iteration of the outer loop, the scanning frame begins on line 319 and extends to line 511. There are 150 blobs in this frame, so the final blobs are read from the queue and added to the *FlawTable* for a total of 450 entries.

Flaw Evaluation

The local flaw grade is calculated from Eq. (3.1),

$$F_l = 3.93 \left[\sum_{j=1}^5 R_j \sum_{k=1}^m H_{jk}^{1.76} A_{jk}^{0.75} \right]^{0.2}, \quad (7.14)$$

where the flaw severity grade F_l is the summation of m flaw components on the note. The left summation index j is over the five noticeability regions where the flaw components are located. The right summation index k is over the m flaw components within region j .

The parameters to be determined by the inspection system are the flaw coverage area A and the average density H of each flaw component k within region j . Recall that the pixels in $f_t(x, y)$ represent the halftone density at location x, y . Let a new variable D_{jk} be the sum of all pixels in $f_t(x, y)$ within the boundary of flaw component k in region j defined by:

$$D_{jk} = \sum_x \sum_y f_t(x, y), \quad \forall [f_t(x, y) \in (j \cup k)]. \quad (7.15)$$

If S_{jk} is the number of pixels found in flaw component k of region j , then the average density H_{jk} is:

$$H_{jk} = \frac{D_{jk}}{S_{jk}}. \quad (7.16)$$

The area A_{jk} of flaw component k in region j is the product of S_{jk} and scale factor κ to convert from pixels to square millimeters:

$$A_{jk} = \kappa S_{jk}. \quad (7.17)$$

Let Φ_k be the grade of flaw component k formed from the sum of all partial products in region j according to

$$\Phi_k = \sum_{j=1}^n R_j H_{jk}^u A_{jk}^v. \quad (7.18)$$

The m flaw components are summed into a single element by

$$\Phi = \sum_{k=1}^m \Phi_k. \quad (7.19)$$

Then, Φ is raised to exponent w and multiplied by scale factor B to yield the local flaw grade F_l :

$$F_l = B \left[\sum_{k=1}^m \Phi_k \right]^w. \quad (7.20)$$

Substituting Eqs. (7.16), (7.17), and (7.18) into Eq. (7.20) yields the form of the local flaw grade equation implemented,

$$F_l = B \left[\sum_{k=1}^m \sum_{j=1}^n R_j \left(\frac{D_{jk}}{S_{jk}} \right)^u (\kappa S_{jk})^v \right]^w. \quad (7.21)$$

Since the summation over k is independent of j , it can be moved outside the first summation by the distributive property. The appropriate coefficients for B , n , u , v , and w are added to achieve the desired form in Eq. (7.14),

$$F_l = B \left[\sum_{j=1}^n R_j \sum_{k=1}^m H_{jk}^u A_{jk}^v \right]^w \quad (7.22)$$

The local flaw equations are implemented with functions **GradeNote** and **micrograde**. **GradeNote** is the high-level function to calculate both the local and global grades. It steps through the *FlawTable* data structure computing the partial flaw grade given by Eq. (7.18) for all flaw components. The bounding rectangle coordinates of each flaw component are listed in the *FlawTable*. **GradeNote** uses the bounding rectangle to define a search space in $f_i(x, y)$ which **micrograde** uses to calculate the flaw grade within the boundary.

Five data arrays are created in **micrograde** to accumulate the flaw area and density. The **COUNT** and **PIXEL** arrays are accumulators to sum the flaw area and density. Each of the five elements in the array corresponds to one of the noticeability regions. The **AREA** and **DENSITY** arrays store the correctly scaled totals for each region. The static array **REGION** contains the regional weighting factors. The values for R_j were previously determined as follows:

$$R_1 = 2.24$$

$$R_2 = 0.48$$

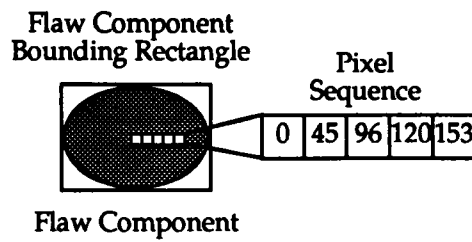
$$R_3 = 1.0$$

$$R_4 = 0.11$$

$$R_5 = 0.17$$

Function **micrograde** sequentially scans image $f_i(x, y)$, which is zero everywhere except at flaw sites. If a pixel is nonzero, the **PIXEL** array bin specified by the pixel region data field is incremented by the value in the density data field. For example, assume the sequence of pixels in the scan to be 0, 45, 96, 120, 153 as shown in Figure 7.8. The binary representation of this sequence is shown along with the contents of the region and density data fields. The noticeability region is encoded in the upper three bits of each pixel, and the halftone density is the lower five bits.

Since the first pixel in the sequence is zero, it is skipped without further action. The next pixel is 45, which represents region 1 with a density of 13. The first bin in the **COUNT** array is incremented by 1, and 13 is added to the first bin in the **PIXEL** array.



Data Field			
Region Density			
MSB			LSB
Pixel	Binary	Region	Density
0	0	0	0
45	001 01101	1	13
96	011 00000	3	0
120	011 11000	3	24
153	100 11001	4	25

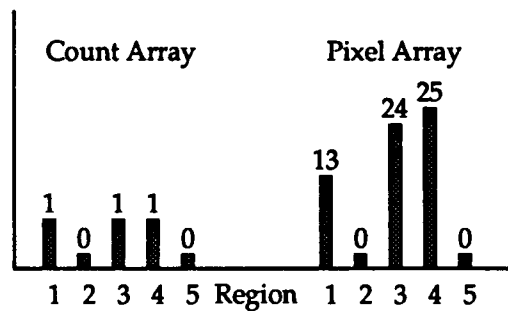


Figure 7.8. Flaw Grading Sequence.

Upper figure shows a local flaw and its bounding rectangle. The pixels within the rectangle are scanned sequentially to locate nonzero pixels. Five pixels are shown with their associated data fields. The data arrays in the lower figure accumulate the data fields from the nonzero pixels.

The next pixel is skipped because the density data field is zero, even though the region field causes the total pixel value to be nonzero. The fourth pixel is 120 which is region 3, with a density equal to 24. The third bin in COUNT is incremented by 1, and 24 is added to the third bin of the PIXEL array. The process is repeated until all nonzero pixels within the bounding rectangle have been accumulated in the appropriate bins.

The following discussion describes the computation of the partial grade for region 1 but is similar for all regions. Bin 1 of the PIXEL array contains the sum of all densities, which is D_{jk} in Eq. (7.21). Similarly, bin 1 of the COUNT array contains the total number of flawed pixels or S_{jk} in Eq. (7.21). The average density is calculated by dividing the values in PIXEL by COUNT. This quotient is scaled to convert to engineering units and stored in the DENSITY array. Likewise, the entry in the AREA array is the product of the COUNT array and the pixel scaling factor to convert to square millimeters. This process is repeated for the remaining regions. The sum of the DENSITY bins is the average density of the flaw component and is written to the *Density* element of the *FlawTable*

The partial grade of the flaw component in Eq. (7.18) is next calculated by summing the products of the DENSITY and AREA arrays. This value is written to the *Grade* element of the *FlawTable* and returned to *GradeNote*. *GradeNote* continues through the *FlawTable*, summing the flaw component grades. Upon completion, the sum of the component grades is scaled to give the local flaw grade, which is written to the *Local* element of the *Note* data structure.

Global Flaw Evaluation

The reflectance of the note paper substrate and ink are required to determine the global flaw grade and to determine the threshold value in Eq. (7.13). A global flaw is one that occurs over a large area of the note surface, typically affecting the entire note. A lightly-printed note in which the ink level was insufficient over the entire note is an example of a global flaw. The global flaw must be differentiated from the smaller, localized flaws such as ink spots during evaluation so that the flaw grades can be made independent of each other.

The parameters required for machine evaluation of global flaw severity are the average substrate and print reflectance required by Eq. (3.12). A square aperture or patch is created, which can be located on the note by the upper left corner coordinates and the length of the sides. Average substrate reflectance is found by positioning the patch over the substrate region and averaging all pixels within the patch. Since image $f_s(x, y)$ is normalized to the standard reflector, the equivalent patch reflectance is found by dividing the average patch intensity by the intensity of the standard reflector.

The ink reflectance R_i and substrate reflectance R_s are determined identically, so only the substrate will be described. The ink reflectance is found by substituting the appropriate patch coordinates. If the patch has coordinates x and y , the average reflectance is given by

$$R_s = \left(\frac{1}{R_l wh} \right) \sum_{x=1}^w \sum_{y=1}^h f_s(x, y) , \quad (7.23)$$

where R_l is the intensity of the standard reflectance strip, and w and h are the patch dimensions.

Reflectance is calculated with the function **GetNoteRefl**, which calls **GetSubRefl** and **GetInkRefl** to measure the average substrate and ink reflectance. If an abnormal condition exists such as a totally black note, an error condition is returned to indicate that the note cannot be graded properly. The function **GetSubRefl** measures the average substrate reflectance within a 16×16 patch. There are six possible locations on the note at which to sample the reflectance. The coordinates of the upper left corner of each patch are stored in the two-dimensional array *SubCoords* of the *Calibration* data structure.

The pixels within the patch are read over the VME bus by the function **vmeStats**, which returns the mean and standard deviation of the patch. The mean p and standard deviation σ are converted to equivalent reflectance by normalizing to the standard reflectance. If p is within predefined limits, the reflectance is considered normal. If p is not within the acceptable range, an error condition is indicated. If σ is within its acceptable range, p is stored in the *Note* data structure. A large σ is indicative of an unexpected ink pattern in the substrate region.

If either p or σ is not within acceptable limits, the process is repeated using the next patch coordinates in the *SubCoords* array. This decreases the likelihood that a localized flaw occurring within a patch region will skew the measurement. If none of the patches in the array are acceptable, an error flag is returned to indicate that the note cannot be graded. The reflectance of the substrate and print is used to determine the global flaw severity according to Eq. (3.12). Computation of the grade is performed by the function **GradeNote**, which reads the reflectance from the *Note* data structure.

CHAPTER 8

EXPERIMENTAL VERIFICATION

A model is judged by its ability to represent reality accurately. The physical model was developed to extract the flaw parameters from currency notes and the algorithmic model to evaluate those parameters. Both models must be tested experimentally to confirm that they are an accurate representation of flaw evaluation.

The testing procedure focuses on three aspects of the inspection system: (1) sensor characteristics, (2) flaw metrology, and (3) flaw perception. The sensor characteristics are important because the capabilities of the sensor define the performance limits of the inspection process. The sensor's photometric performance must be good enough to accurately perceive low-contrast reflectance differences in the field of view. It is important to characterize both the photometry and spatial resolution of the camera.

Flaw metrology is the ability to detect and measure well-defined, isolated features. The contrast and area of simulated flaws on a uniform white background were measured. The background noise from artifacts was controlled to determine machine performance in response to idealized input.

Flaw perception is the capability to simulate the currency evaluation performance of human examiners. The key factor in flaw perception is isolating print defects, which may be camouflaged by their surroundings, and arriving at the appropriate flaw severity grade. In normal operation, flaw perception is used to distinguish the flaws from the printed background. Flaw metrology is used to measure the contrast and area of those flaws identified by the flaw perception stage.

Sensor Characteristics

Procedure for Photometry Measurements

The imaging system was tested to verify the accuracy and repeatability of the basic photometry measurements. The test included spatial resolution, response uniformity, photometric accuracy before and after intensity normalization, intensity normalization, and repeatability. Reflectance accuracy was tested with illumination levels of 100, 50 and 25% of normal. The variation in reflectance was measured to characterize the shot-to-shot repeatability.

Scene irradiance was measured with an International Light research radiometer, Model IL1700. The irradiance at the object plane was 215 footcandles within 1% over the entire field. The illumination source was four 20-W fluorescent lamps powered by a Mercron power supply. The fluorescent tubes were pulsed at a 50-KHz rate, and the scene irradiance was regulated by a photodetector to provide constant illumination.

Photometric accuracy was determined by digitizing a known reflectance with the camera and comparing the measured value with the known reflectance. A Kodak R-9 reflectance step tablet was used for the comparative reference. The R-9 tablet consists of a set of calibrated reflectance densities ranging from 0.0 to 1.20 in incremental steps of 0.15. The actual step reflectance was calculated from the calibrated density by

$$R_a = 10^{-\eta} , \quad (8.1)$$

where R_a is the actual reflectance and η is the reflectance density. The measured step reflectance R_m was determined from the ratio of the mean intensity to a reference intensity, given by

$$R_m = \frac{I_s}{I_r} , \quad (8.2)$$

where I_s and I_r are the mean step intensity and reference intensity respectively. I_s is the spatial average of a 16 x 16 pixel square centered in the step. I_r is the mean intensity of the same patch positioned within an independently known reflectance in the field of view.

Spatial Resolution

A test was performed to measure the spatial resolution of the optical path. The contrast transfer function for the lens and sensor combination is shown in Figure 8.1. The contrast transfer function is similar to the modulation transfer function except that the input stimulus is a series of square waves rather than sine waves. The stimulus for the contrast transfer function is a chart with black bars printed at a known separation and width on a white background. An image of this chart is acquired with the camera, and the relative intensity as a function of spatial resolution is measured. A frequently used figure of acceptable contrast is 20%. The spatial resolution is 64 line pairs/mm at 20%, which is near the theoretical limit of 73 line pairs/mm.

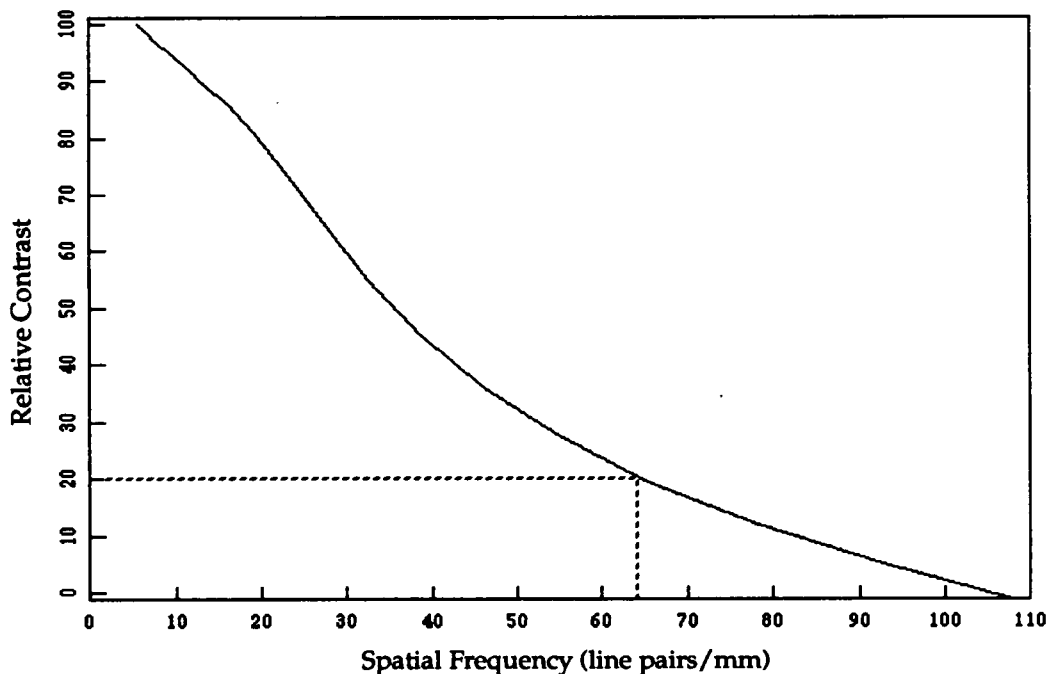


Figure 8.1. Contrast Transfer Function.

Plot of the contrast transfer function for the camera with a 28-mm lens. The contrast transfer function shows the relative amplitude response vs spatial frequency.

Response Uniformity

The response uniformity of the CCD sensor and associated electronics was measured including the mean and standard deviation of individual pixels and small patches of pixels. The mean and standard deviation of single-pixel sampling sites distributed over the entire sensor was evaluated spatially and temporally. Twenty independent frames were acquired under normal and zero illumination to verify the spatial uniformity of the CCD sensitivity. The normal illumination measurements were taken by illuminating a calibrated reflectance tile with 215 footcandles. The zero illumination measurements were made by capping the lens to block all light from the sensor.

The results are shown in Table 8.1. The mean pixel value under zero illumination was 0.004 units out of a possible 256, with a standard deviation of 0.016. The corresponding mean value for normal illumination was 188.793 with a standard deviation of 3.334. The maximum temporal standard deviation of any single pixel was 0.447 units. The spatial standard deviation over the entire sensor for one acquisition was 0.018. The temporal and spatial standard deviation indicates that with over a 99% confidence level, the variation of any given pixel will not exceed 3 units out of 256 from one acquisition to the next. The results show that pixel noise is small compared to the normal process variations encountered in the printed currency and the uniformity of the lighting over time.

Table 8.1. Pixel Response Uniformity.

Illumination	Mean	Standard Deviation
Dark	000.004	0.016
Normal	188.793	3.334

Reflectance Accuracy

Photometric performance was tested to determine whether average image irradiance affects measurement accuracy. The R-9 reflectance step tablet was placed in a dark background field with 0.05 reflectance. The reflectance of the steps was measured in accordance with Eq. (8.2). The dark field background was then replaced with a light background field of 0.89 reflectance and the test was repeated. The results are shown graphically in Figure 8.2 and tabular form in Table C.1 of Appendix C.

The mean reflectance shift from dark field to light field was 0.011 with a maximum reflectance shift of 0.02 for any step. The mean of the dark and light field difference errors was -0.015 and -0.004 respectively. Thus there is little change in reflectance measurement due to background variation. The maximum error observed for either background was less than 0.07. In both cases, the largest error occurred on the unity reflectance step. Since it is unlikely that a unity reflectance will be encountered during operation, this is not significant for the intended application. The reflectance range for currency is from 0.1 to 0.75, where the camera accuracy was best.

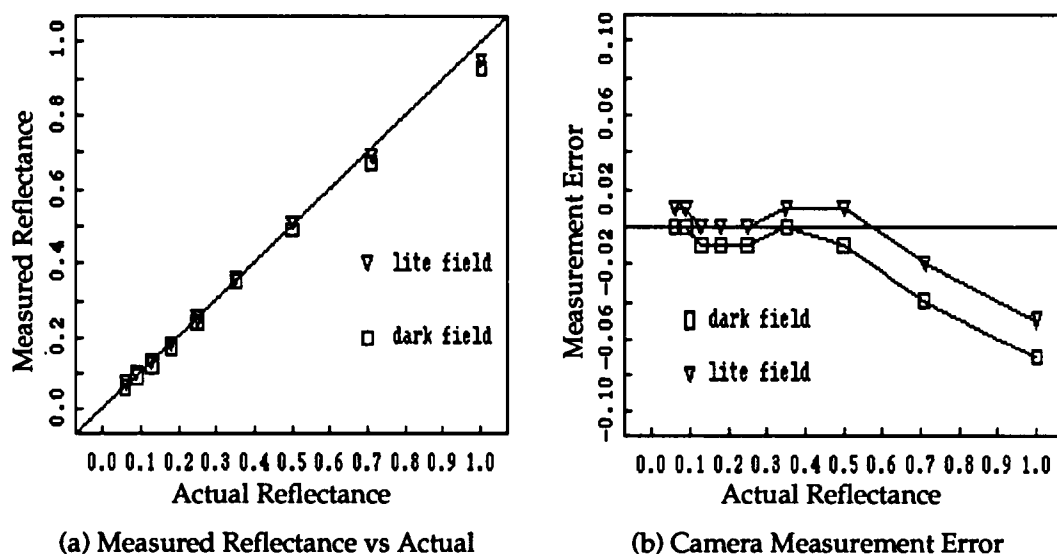


Figure 8.2. Reflectance Accuracy.

(a) Plot of camera-measured reflectance vs actual reflectance for light and dark background fields. (b) Plot of measurement error from (a).

Intensity Normalization

The intensity normalization algorithm maps the intensity scale in one image to match those of a reference. The normalization is intended to ensure that the reflectance scale is constant over time and under changes in illumination. The accuracy of the normalization was measured with the R-9 reflectance step tablet. Dramatic changes in illumination were simulated by reducing the lens aperture. An equivalent 50% reduction in image irradiance was obtained by reducing the lens aperture by one f-stop. The test was performed for equivalent image irradiance levels of 100, 50, and 25% of normal. The test results are shown in Figure 8.3a and in Tables C.2 to C.4. The worst-case reflectance error for all illumination levels was 0.06.

The standard deviation of pixels within the 16 x 16 patch was recorded for each of the irradiance levels above. The standard deviation indicates the amount of reflectance variation caused by intensity mapping. The reflectance variation results are shown in Figure 8.3b and Table C.5. The trend of the standard deviation shows an increase in the intensity variation with reduced illumination.

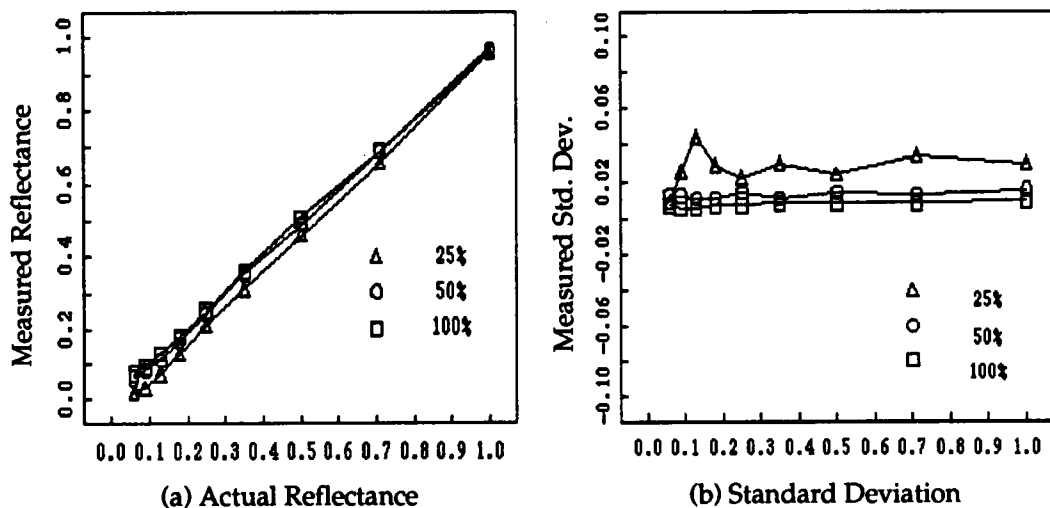


Figure 8.3. Measured Reflectance After Intensity Normalization.

(a) Gray scale of camera-measured reflectance with 100, 50, and 25% illumination. (b) Standard deviation over the 16 x 16 pixel patch.

The effect of the intensity normalization on the gray level distribution is shown in Figure 8.4. A gray level histogram of the normalized reference image is shown in Figure 8.4a, and the histogram of a test note under 50% illumination is shown in Figure 8.4b. The serrated pattern in (a) was caused by an anomaly in the hardware look-up tables used to implement the histogram specification operation to bring the reference intensity scale to a known range. Plate (c) is the result of the normalization operation on image (b). The larger serrations of (c) indicate the gain required to increase the reduced intensities from the lower illumination level. Note that the shape of the histogram is unchanged after the 2:1 normalization.

Temporal Variation

The temporal variation of the camera was checked by recording the measured reflectance of white and black reflectance standards of 0.9 and 0.01 respectively. The white and black reflectance was measured from a fixed location taken during 16 separate acquisitions. Table C.6 shows the results for each shot before and after intensity normalization. The standard deviation of a patch average from shot-to-shot is less than 0.2% under all conditions. The normalization process reduced the standard deviation by 50% for the white reflectance standard, indicating an improvement in the photometric repeatability.

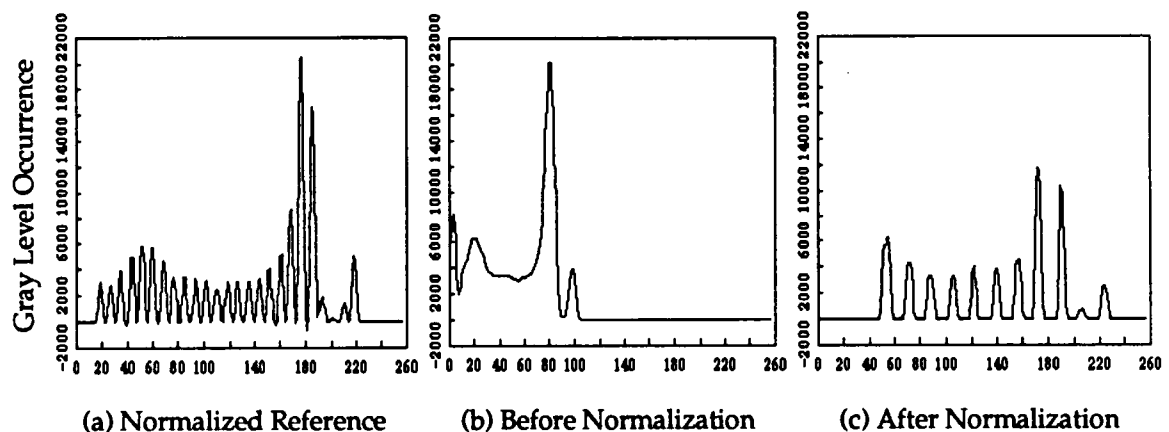


Figure 8.4. Gray Scale Histogram of Intensity Normalization.

(a) Original normalized reference note. (b) Histogram of test note with 50% reduction in illumination. (c) Histogram of test note after intensity normalization.

Flaw Metrology

Spatial Normalization

The accuracy of the subpixel correlation algorithm was tested at each of the six specified points by comparing the calculated note position to the position observed on a graduated translation stage. A note was placed on the translation stage and positioned at an arbitrary starting point. An image representing the starting position of the note was acquired. The note was then translated 0.001 in. and the position of the note was determined with the subpixel correlation function. The note was tested at 0.0, 0.001, 0.002 and 0.003 in. in both the horizontal and vertical directions. The results of this test are shown in Tables C.7 through C.17. In Figure 8.5, a correlation search window on the note is represented by each plot. The circles indicate the note position measured by the correlation algorithm, and the crosses indicate the observed position. The radius of the circles is proportional to the magnitude of the variance over five acquisitions. The worst-case error occurring in tie-point #3 is less than 1/8 pixel.

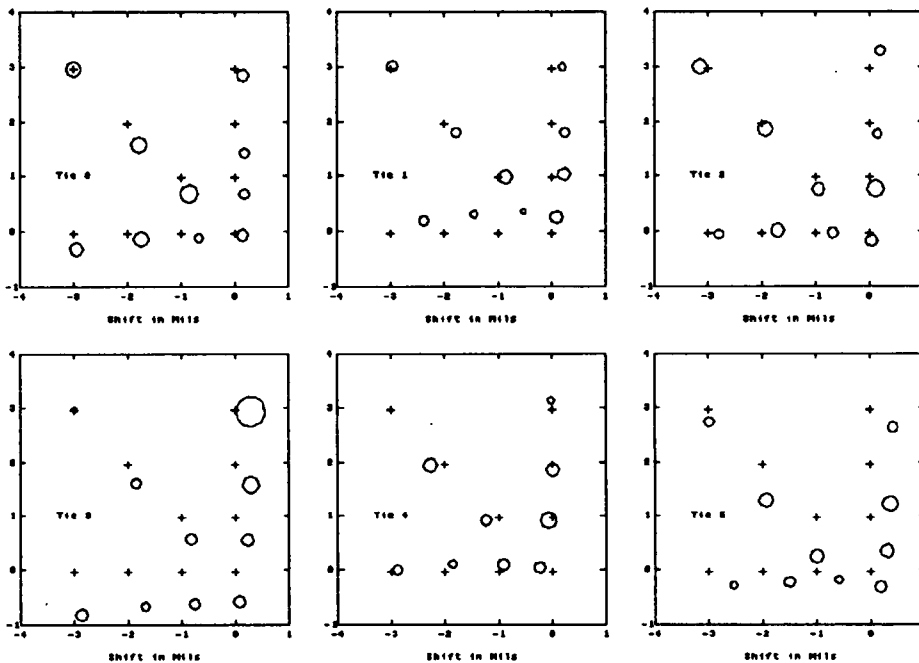


Figure 8.5. Subpixel Correlation Accuracy.

The crosses show the actual observed position and the circles represent the position calculated by correlation. One mil is equivalent to 1/6 pixel.

Noise Suppression

The benefit of the spatial normalization and noise suppression techniques can be quantified by calculating the error in the difference image after each operation and comparing this to the uncorrected image. A metric for the error is defined as the normalized sum of the absolute difference between the reference image and the test image, expressed by

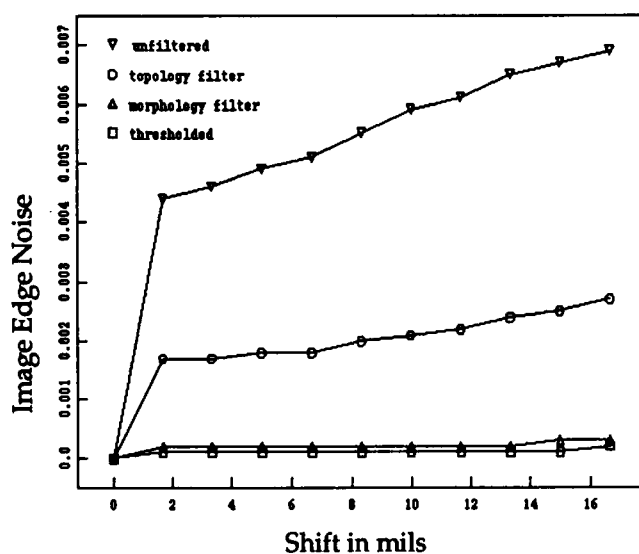
$$\epsilon_i = \frac{\sum_x \sum_y |f_i(x, y) - f_r(x, y)|}{\sum_x \sum_y [f_{max} - f_{min}]}, \quad (8.3)$$

where $f_i(x, y)$ represents the particular difference image being measured.

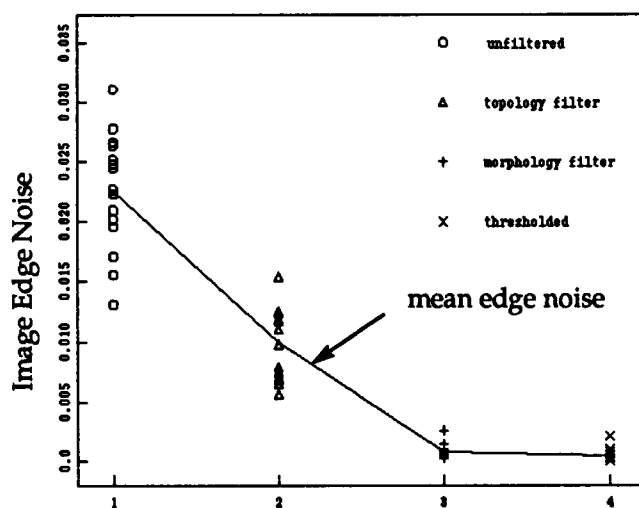
The error metric in Eq. (8.3) was used to evaluate the performance of the noise suppression algorithm. A uniform white card with a series of dark squares was acquired at a starting position and defined to be a reference image. A first-order edge weighting function described in Chapter 6 was generated with a 3×3 Sobel kernel to form an attenuation mask one pixel on either side of each edge in the reference. The card was translated 1.7 mils along the horizontal axis and then a new image was acquired. The reference image was subtracted from the newly acquired image and the error was computed for each stage of the noise suppression algorithm. Table C.18 and Figure 8.6a show the results of the noise suppression filter for an unfiltered, unregistered image. The four traces in Figure 8.6a represent the edge noise (1) prior to filtering, (2) after application of the structural filter, (3) after the morphological filter, and (4) after the intensity thresholding operation. The image error for each case is listed for all incremental shifts in position. Table C.18 shows that the image noise is reduced to 2.8% of its original value as a result of the structural filter.

Table C.19 and Figure 8.6b show the edge noise in 17 difference images of currency notes that were acquired and registered to subpixel resolution in the manner given in Chapter 5. The reference image was subtracted from the registered test image and then the noise suppression filter was then applied to the difference image. The error metric was computed for each intermediate step of the filtering algorithm.

Edge noise can best be visualized by showing the absolute difference between the reference note and a test note in Figure 8.7. Figure 8.7a shows the edge noise from an unregistered test note, while Figure 8.7b shows the same note after registered at six locations to the nearest whole pixel. Figure 8.7c shows the note after the precision is increased to subpixel registration in the six locations. The results of the structural filter using the weighting function and the morphological filter are shown in Figure 8.7d and in Figure 8.7e respectively.



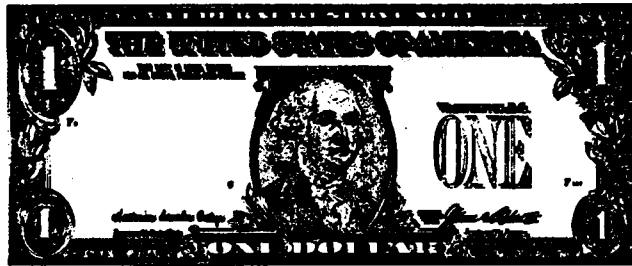
(a) Edge Noise without Registration



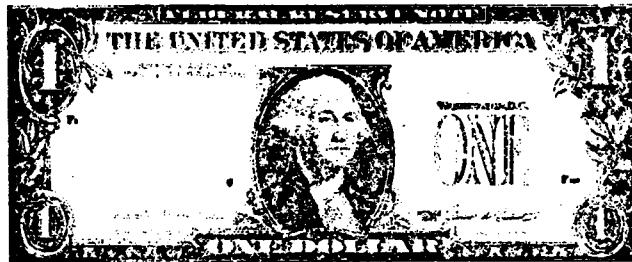
(b) Edge Noise with Registration

Figure 8.6. Effect of Noise Suppression Filter.

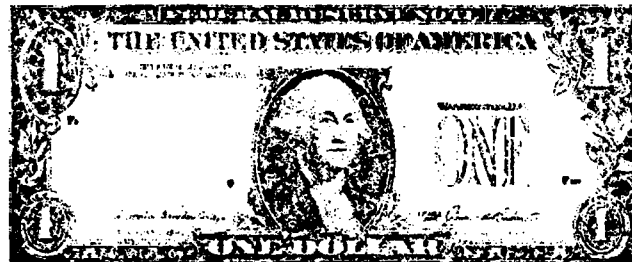
Performance of noise suppression filter using Eq. (8.3) to measure edge energy. (a) Edge noise in images without registration. (b) Edge noise in images with registration. The filter reduced the noise by ~ 97% over the unfiltered case in both (a) and (b).



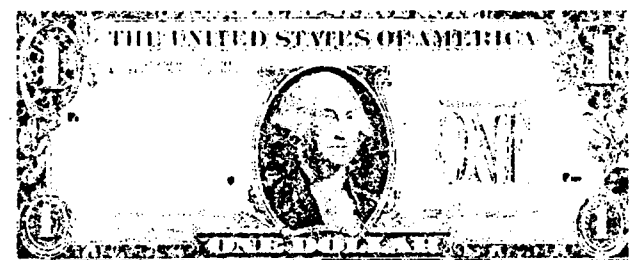
(a) Difference prior to registration or filtering



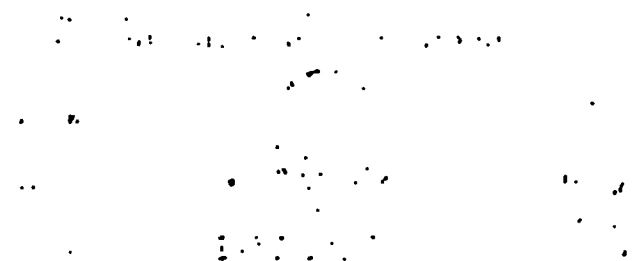
(b) Difference after integer pixel registration



(c) Difference after subpixel registration



(d) Difference after structural filtering



(e) Difference after morphological filtering

Figure 8.7. Effect of Noise Suppression on Currency Edge Noise.

Image from each noise reduction step is shown in (a) through (e).

Area Measurement

The area and density of the potential flaws found in the note image must be measured accurately in order to arrive at a valid flaw severity grade. The accuracy of the area measurement was verified by digitizing high-contrast flaws of known size and comparing the calculated sizes with the known values. A set of 14 simulated high-contrast flaws with root areas ranging from 0.005 to 1 in. per side was created on a transparent backing using a laser printer. The areas of the simulated flaws were estimated visually by comparing the length of each side to an NIST (NBS) traceable scale under a microscope. The error in the observed measurement is ± 0.0025 in. The simulated flaws were placed over a currency note and the flaw area was calculated with the inspection system. To prevent extraneous noises from interfering with the test, the surrounding area were masked. The results of the test are shown in Figure 8.8 and Table C.20. The data are given in units of square root area for convenience. The worst-case error in root area is 0.008 in.

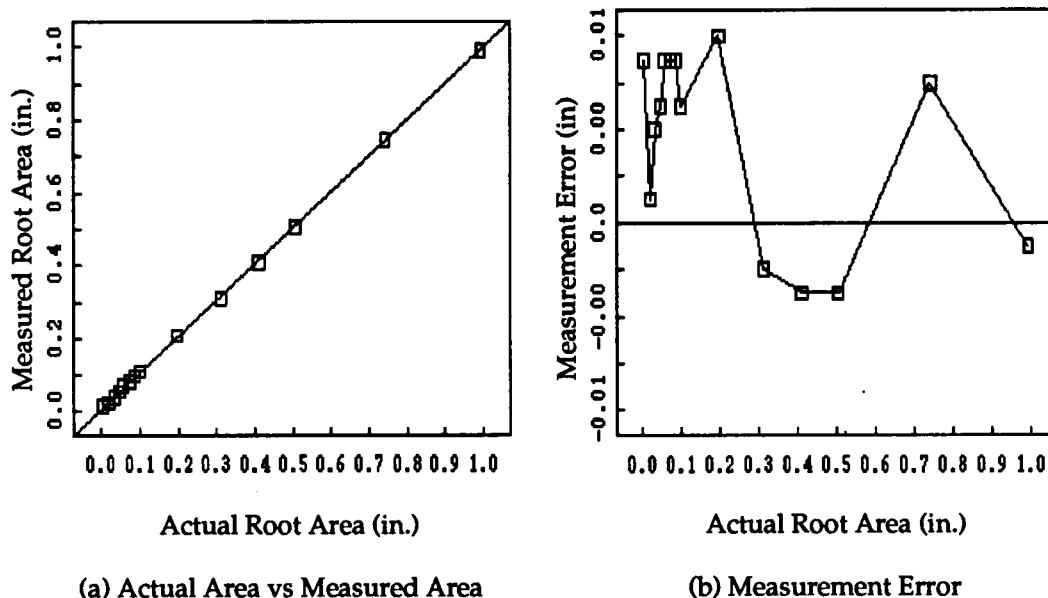


Figure 8.8. Measurement of Flaw Area.

(a) Plot of measured flaw area vs actual flaw area. (b) Measurement error from (a).

Density Measurement

The ability to convert images to equivalent halftone density was also determined by comparison to a known value. A clear acetate overlay was printed with a series of halftone density steps, each with an area of 19×19 mm. The halftone dot density of each step was measured with a reference densitometer. The overlay was placed over a uniform background and digitized, and the average density of each overlay square was calculated by the inspection system. The detection threshold was optimized manually to obtain good isolation of the low-contrast squares. The results of the density test (Figure 8.9 and Table C.21) show the worst-case error to be 0.04 density units.

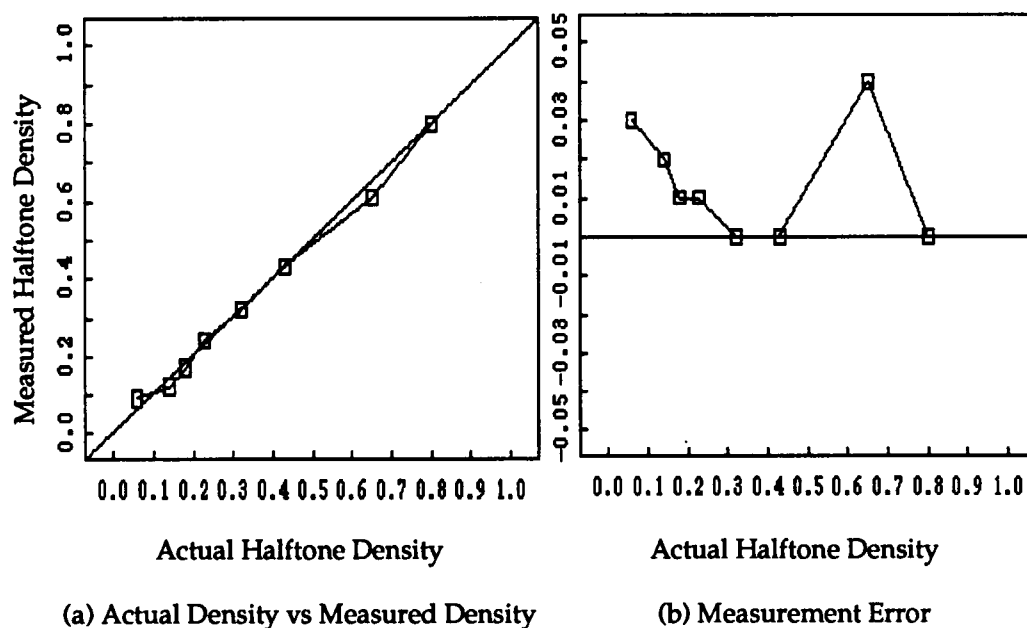


Figure 8.9. Measurement of Flaw Density.

(a) Plot of measured halftone density vs actual density. (b) Measurement error obtained from (a).

Flaw Perception

Flaw Location

The ability to determine the proper noticeability region was tested by evaluating flaws placed in known regions on a test note. A representative ink spot was added to one region at a time. The note was acquired and graded with the inspection system. The region of the added flaw was determined by the system and recorded. In all cases, the machine correctly identified the noticeability region containing the flaw.

Comparison To Human Perception

The final category of performance measurement is comparison of the machine flaw perception relative to the human observers. The basis of the comparison is the set of flawed exemplars used in the ORNL survey described in Chapter 3. There are three methods of determining the flaw severity grades: (1) the mean of the judge's scores, (2) the prediction of the judge's mean scores based on Eq. (3.1) using manually measured flaw parameters, and (3) the prediction of the judge's mean scores based on Eq. (3.1) using machine measured parameters. The flaw parameters which are required by Eq. (3.1) are flaw location, area, and density.

The plan is to grade the survey exemplars with the inspection system and compare the results with the grades assigned by the human judges for the same notes, as shown in Figure 8.10. The evaluation of machine performance is complicated because the machine is a direct implementation of method (2). It is unreasonable to expect the machine performance to exceed that of its underlying model. Therefore the machine performance will be determined relative to both methods (1) and (2). Let the judges mean scores be F_o , representing the severity ranking of the exemplars obtained from the responses of the human observers. Further, let the ranking of scores calculated from manually measured parameters be F_c and the ranking by the machine from automatically measured parameters be F_m . A flaw severity model has been empirically derived by correlating the manually measured flaw parameters to F_o . In order to characterize the accuracy of F_m as a predictor of F_o , the machine grades F_m will be compared to the judges scores F_o and to calculated scores F_c . The central hypothesis being tested is that, on average, a machine can reproduce the outcome of human currency evaluation.

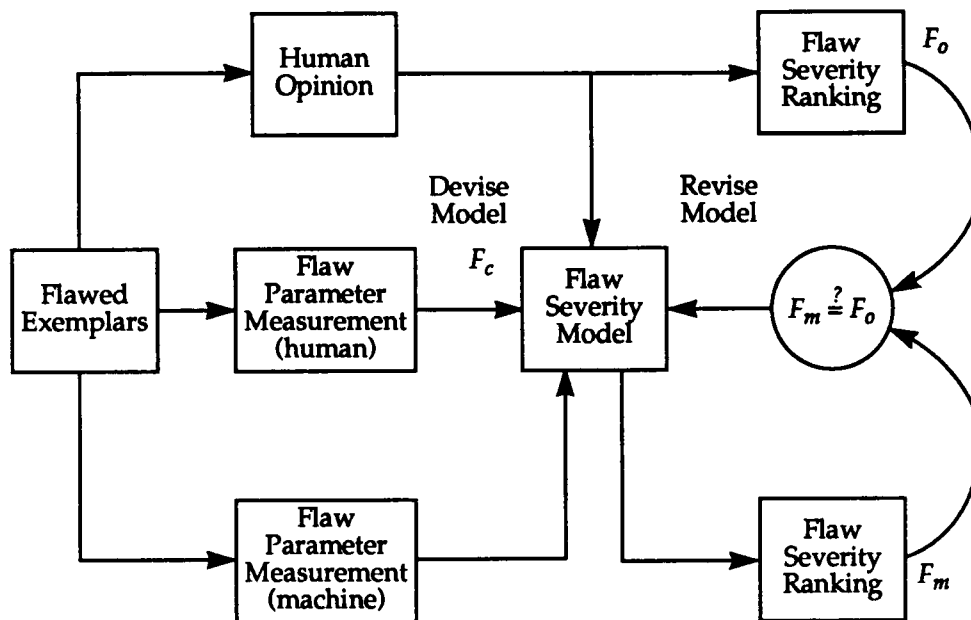


Figure 8.10. Process to Compare Human and Machine Perception of Flaw Severity.

The flaw exemplars in this comparison are the set of one dollar denomination notes used in the flaw survey. The one dollar notes were selected because they were most prevalent, and the reference images were available. Each exemplar contains a print defect, either natural or simulated, characteristic of intaglio sheet printing. The notes are classified according to the specific type of printing flaw it contains. During the survey, the judges were instructed to rate the notes based solely on their opinion of the designated flaw. For instance, if the evaluation centered on ink spots in the portrait region, the other flaws which might be present were disregarded. Likewise, when the flaw parameters were manually characterized to formulate the flaw model, only the designated flaws were measured. To ensure a comparison of similar features, only the flaws designated in the survey are evaluated by the inspection system.

Each note was acquired and evaluated in the normal manner, using the flaw detection algorithms to identify the candidate flaws on the note. A bounding rectangle enclosing the designated flaw was described by an operator. The inspection system then computed the flaw severity grade from the flaws within the bounding rectangle. The flaw parameters were extracted by the inspection machine.

There are $n = 99$ notes available, but 9 notes were not part of the original flaw model and did not have values of F_c assigned to them. Also, the inspection system failed to find any flaws on four notes; therefore these lacked values for F_m . In order to effect a fair comparison, the missing grades are assigned a value of 0.0, letting $n = 99$ rather than reducing the data set to include only those notes forming the union of F_m , F_c , and F_o .

The measurement process is characterized by fixed and random measurement errors (Jaech, 1985). The general model to relate the measured value to the predicted value is

$$(F_k)_i = \alpha_k + \beta_k (F_o)_i + \varepsilon_{ik}, \quad (8.4)$$

where $(F_k)_i$ is the flaw grade of the i th note measured by any method k , $(F_o)_i$ is the true value given by the judge's mean score, α_k and β_k are the measurement biases for method k , and ε_{ik} is the measurement error for method k . By forcing $\alpha = 0$ and $\beta = 1$, the measurement error ε_m is simply the difference between the measured grade F_m and the observed grade F_o ; that is,

$$\varepsilon_i = (F_m)_i - (F_o)_i. \quad (8.5)$$

The average measurement biases α and β , given in Eq. (8.5) was found to be -0.56 ± 0.09 for F_m and -0.26 ± 0.08 for F_c . The bias is a systematic error which is normally removed during calibration. Since the inspection system has not been calibrated to the observations, the data will be adjusted to remove the measurement biases α and β . The data are transformed by $aF_c + b$ and $cF_m + d$, where the constants a , b , c , and d are chosen to minimize

$$\sum_{i=1}^n [aF_c + b - F_o]^2 \quad (8.6)$$

and

$$\sum_{i=1}^n [cF_m + d - F_o]^2. \quad (8.7)$$

The transformation constants are determined by a least squares regression of F_o onto F_c and F_m . The values assigned are $a = 0.624408$, $b = 1.318464$, $c = 0.608159$, and $d = 1.544260$. The adjusted values have zero bias and unity slope.

The metrics used to compare the flaw grades are based on the difference of grades $F_m - F_x$, where F_x can be either the calculated or the observed grades. The following descriptive statistics are used in the comparison: (1) the *bias*, which is the mean difference,

$$bias = \frac{1}{n} \sum_{i=1}^n [(F_m)_i - (F_x)_i] , \quad (8.8)$$

(2) the mean absolute difference (*MAD*),

$$MAD = \frac{1}{n} \sum_{i=1}^n |(F_m)_i - (F_x)_i| , \quad (8.9)$$

(3) the mean square difference (*MSD*),

$$MSD = \frac{1}{n} \sum_{i=1}^n [(F_m)_i - (F_x)_i]^2 , \quad (8.10)$$

(4) *Min* and *Max*, the minimum and maximum differences respectively, (5) *P*, the proportion of time that

$$|F_m - F_o| < |F_m - F_c| , \quad (8.11)$$

(6) $P_{>\chi}$, the probability that the absolute difference will exceed flaw grade χ , and (7) *Corr*, the correlation coefficient of F_m with F_c and F_o .

In Figure 8.11, F_m is plotted against F_c and F_o . Figure 8.11a is a plot of the measured grades F_m to the observed grades F_o . The least squares regression of F_m on F_o is indicated by the solid line. In 8.11b, F_m is plotted against the empirical data F_c . Notice that there is a good fit of the machine measured grades to the human observations.

An analysis of the experimental data to determine if the inspection system performs as intended is given in the following chapter.

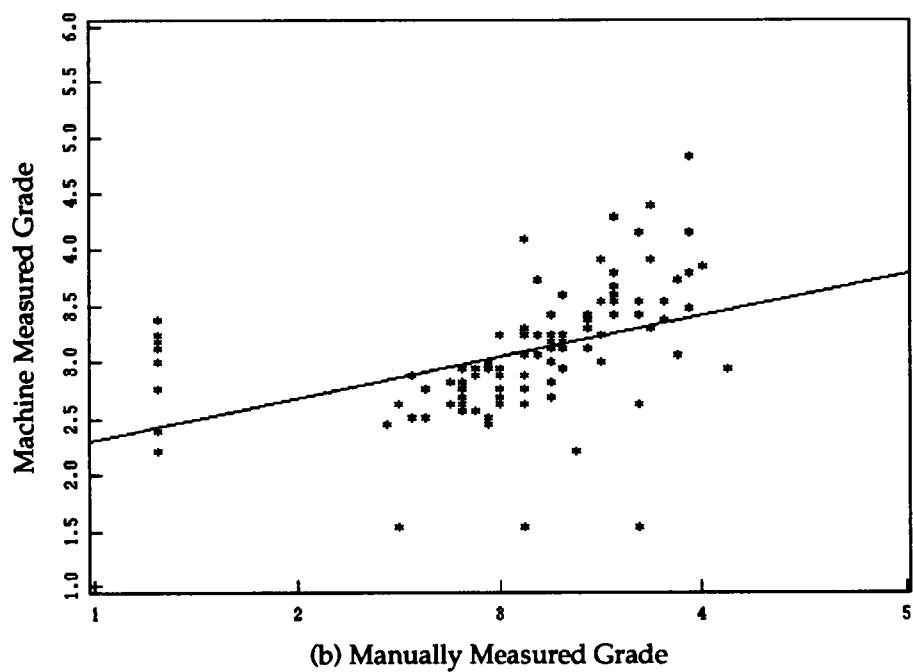
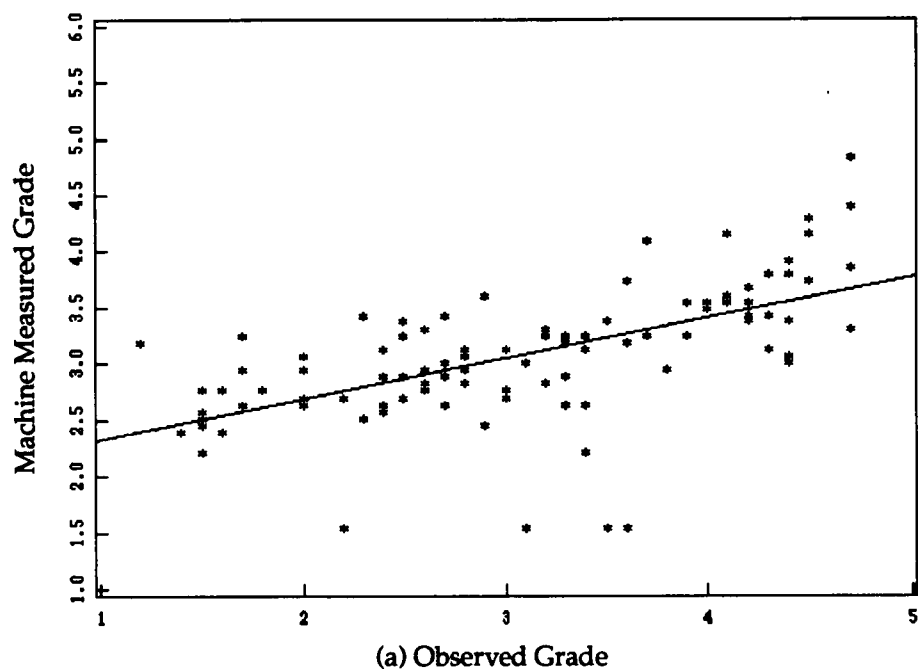


Figure 8.11. Comparison of Measured Flaw Grade to Human Observations.

The flaw grades measured by the inspection versus (a) the grades assigned by the human judges and (b) the grades calculated from the manually obtained parameters.

CHAPTER 9

CONCLUSIONS

Thus far, the theory, implementation, and performance of an automated currency inspection prototype has been described. There are several questions which will now be addressed concerning the interpretation of the experimental data. Does the inspection system fulfil its mission to reproduce the flaw evaluation of human observers? What are the strengths and limitations of the system? What is the potential for practical application?

The analysis of machine performance is based on the set of measurement errors ϵ_i , where ϵ is the difference between the measured flaw grade and the observed grade given in,

$$\epsilon_i = (F_x)_i - (F_o)_i. \quad (9.1)$$

F_x represents either F_m , the grade resulting from machine-measured parameters, or F_o , the grade from manually measured parameters.

If the inspection system were ideal, the errors would be zero. Parameters such as the mean absolute difference (*MAD*) and the mean square difference (*MSD*) are indicators of the agreement between F_m and F_o .

We would like to test the machine performance in the following manner: if the errors are less than some value, $\epsilon < Z$, the measurements are accurate. There are complications which prevent applying this straightforward test. In a mathematical sense, the significance of any given measurement error is unclear. There is no historical data to base the choice of the maximum allowable error Z . The flaw grade scale was arbitrarily derived from the averages of widely differing opinions, which does not directly relate to conventional standards such as time or distance. At this time, the consequence of maximum allowable error is unclear. Any attempt to define the maximum allowable error would be arbitrarily based on a set of *ad hoc* rules.

Also, it is not clear that an error of 0.5 flaw grades means the same over the flaw scale. Is the difference between 1.5 and 1.0 notes the same as the difference between 4.5 and 4.0 notes? Recall that the local flaw equation

$$F_l = 3.93 \left[\sum_{j=1}^5 R_j \sum_{k=1}^m H_{jk}^{1.76} A_{jk}^{0.75} \right]^{0.2} \quad (9.2)$$

is a nonlinear function of the area, density, and location of a given flaw. It is clear from Eq. (9.2) that linear increments in flaw grade do not result from linear increments in the parameters. Therefore, it is difficult to objectively determine if the inspection system is accurate enough for practical application. Rather than trying to define a fixed error standard, the error probability distribution function will be used to establish the expected performance for any arbitrary error value.

Error Analysis

The fundamental means for determining the performance of the inspection system relative to human perception is by analysis of the descriptive statistics of the measurement error ϵ in Eq. (8.5). The errors in the grades derived from flaw model using manually measured flaw parameters are named ϵ_c , and the errors from the flaw model using machine-measured parameters are named ϵ_m . The analysis is complicated by the fact that the inspection system uses the manually measured parameters through its underlying model, the empirical flaw equation. Since the inspection system implements this model, it is reasonable to expect that in general ϵ_m will be limited by ϵ_c . The descriptive statistics of measurement errors of the inspection system ϵ_m and the model ϵ_c are given in Table 9.1. It can be seen that the differences between ϵ_m and ϵ_c are small.

Table 9.1. Descriptive Statistics for Measurement Error.

	MAD	MSD	σ_ϵ	P	$P_{>.25}$	$P_{>.50}$	$P_{>.75}$	$P_{>1}$	Min	Max	Corr
ϵ_c	0.55	0.49	0.70	0.55	0.78	0.46	0.26	0.10	-3.1	1.4	0.69
ϵ_m	0.63	0.60	0.78	0.45	0.76	0.52	0.34	0.19	-2.1	2.0	0.60

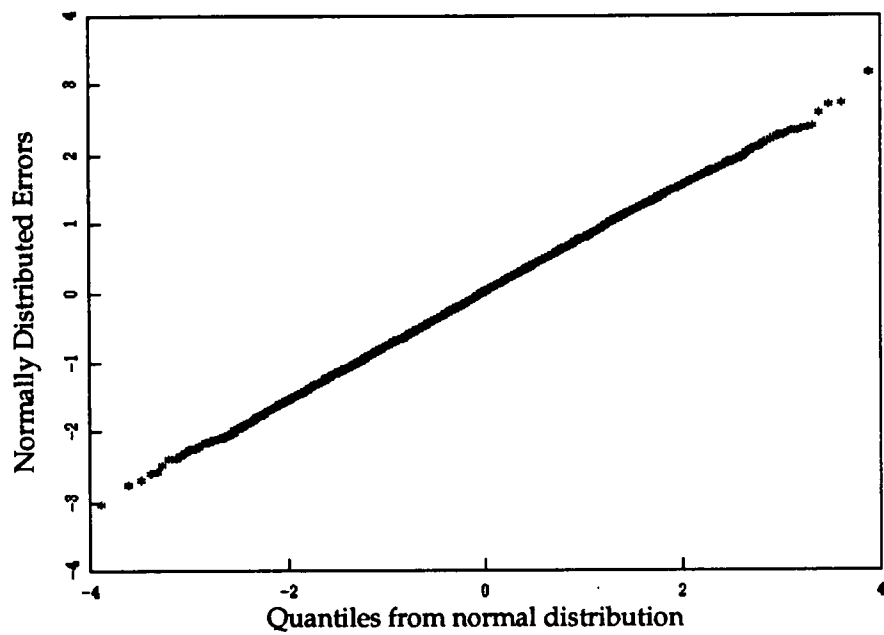
The first item to consider is the average error over the 99 samples. A large error would indicate a severe deviation from the ideal values. From the table, the average error for the inspection system is approximately 0.6 units as indicated by $MAD = 0.63$ and $MSD = 0.60$. The average error for the ϵ_c is approximately 0.5 as given by $MAD = 0.55$ and $MSD = 0.49$. The square root of the variance of errors for ϵ_c , given by σ_{ϵ_c} , is 0.70 and 0.78 for ϵ_m . By comparison, the average standard error among the 31 judges for any given note was 1.3.

Min and *Max* in the table indicate the extrema of the measurement errors. The minimum error and the maximum error for ϵ_c are -3.1 and 1.4 respectively. Similarly, the minimum and maximum errors for ϵ_m are -2.1 and 2.0 .

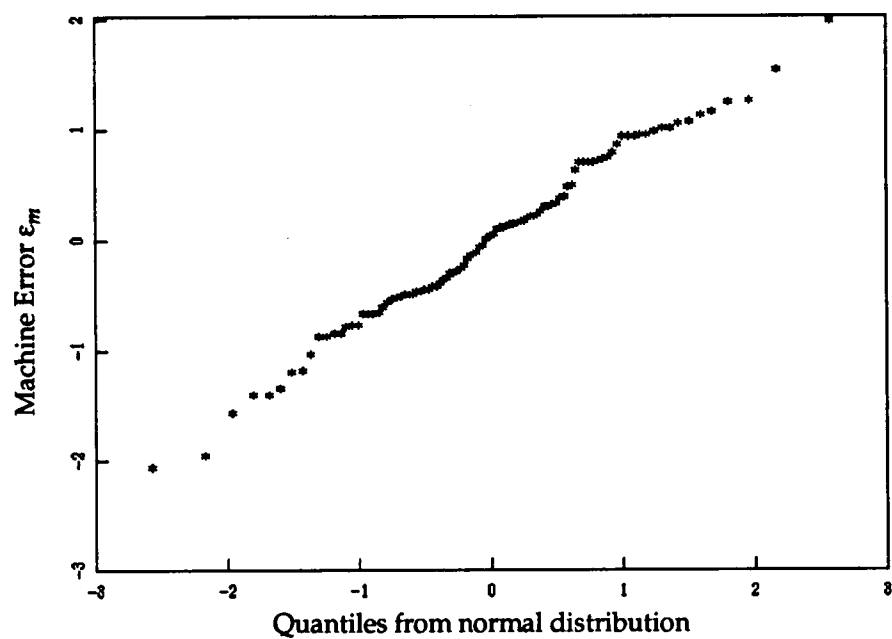
Another method which is frequently used to gauge the agreement between two sets of data is the correlation coefficient. The correlation coefficient is a number from 0 to 1 representing the relative goodness of fit. The correlation of F_m with F_o is 0.60. The correlation of F_m to F_c is 0.69. In both cases, the high correlation indicates good agreement of measured values to the expected values.

The final item to consider is the probability that a measurement will deviate from the expected value. This is given by $P_{>\chi}$, the probability that the measurement error will exceed χ . Thus the table indicates that the probability of the inspection system error exceeding 0.25 is 0.76. The error probability for several values of χ is given. If the machine errors are uncorrelated and random, the measurement errors should have a Gaussian (normal) distribution. In a normal distribution, the probability of an error exceeding one standard deviation, $P_{>1\sigma}$, is 0.32. Recall that standard deviation of ϵ_m is 0.78. The probability of an inspection system error exceeding one standard deviation is similar to that of a normal distribution which can be seen by, $P_{>.75} = 0.34 \approx P_{>1\sigma}$.

In statistics, one method to check the assumption of a normal distribution is to use the normal Q-Q plots shown in Figure 9.1. In a Q-Q plot, the data are sorted and plotted against the corresponding quantiles of a normal distribution. If the assumption is supported, the resulting plot will approximate a straight line (Chambers *et al.*, 1983). Anomalies in the data will appear as curvatures. In (a), 9900 points were drawn randomly from a normal distribution with zero mean and standard deviation of 0.78. Note the straightness of the plot. In (b) are the machine errors ϵ_m also plotted against the normal distribution. Here the plot is approximately straight, indicating a nearly similar (normal) distribution of error probability for ϵ_m .



(a) Normal Distribution with $\mu = 0, \sigma = .78$



(b) Measurement Error Distribution with $\mu = 0, \sigma = .78$

Figure 9.1. Measurement Error Distribution.

Since it is not possible to *a priori* specify the maximum error that can be tolerated, it is desirable to determine the likelihood of an error for any value. This can be accomplished with the error probability distribution function shown in Figure 9.2. The dotted line represents the error probability distribution for ϵ_c , and the solid line represents the machine error ϵ_m . This function was calculated from the experimental data described in Chapter 8. The error probability distribution shows the likelihood that the measurement error will exceed an arbitrary value χ . The probabilities given in Table 9.1 were calculated from this function. For example, the probability that the inspection system grade will deviate from the observed grades by 1 unit or more is ~ 0.2 . The significance of the chart is that the probability that the inspection system will incorrectly grade a note can be easily determined for any given maximum error value.

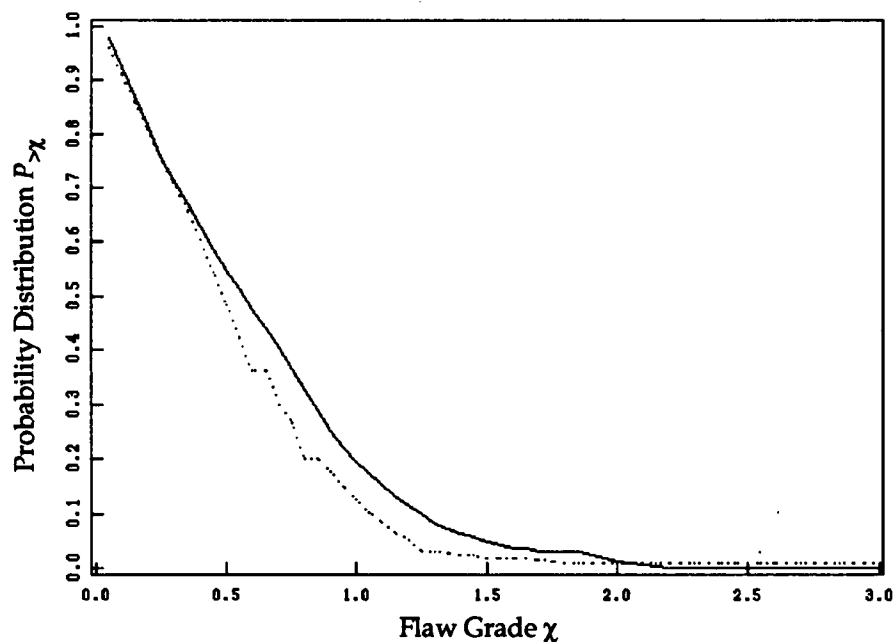


Figure 9.2. Measurement Error Probability Distribution Function.

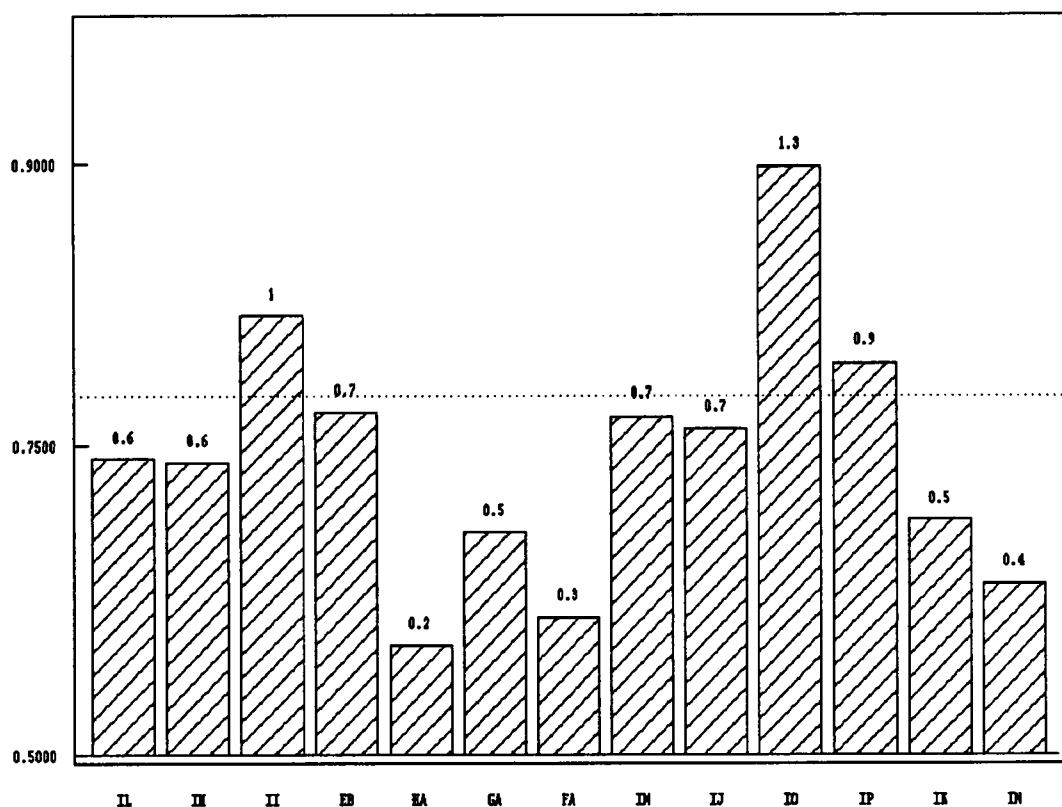
The probability that a measurement error will exceed χ is $P_{>\chi}$, shown above. The solid line is the inspection system error; the dotted line indicates the error in the manually measured grades.

Strengths and Weaknesses of the Inspection System

It is apparent from the previous discussion that the performance of the inspection system is closely linked to the flaw model. It was shown that, in general, the inspection system is a good, but not perfect predictor of human flaw evaluation. The relative strong points of the inspection system are illustrated by sorting the experimental data according to flaw type as shown in Figure 9.3. In this diagram, the mean absolute error is plotted for individual flaw types shown along the horizontal axis. The bar height indicates the error magnitude, also printed over each bar. The probability values corresponding to a normal distribution are shown vertically along the left axis. It must be emphasized that the sample sizes for individual flaw types are too small to give statistical significance to this chart. It is useful however, to graphically analyze the relative performance between flaw categories.

The relative strengths of the inspection system are deemed to be those flaw categories where the mean absolute error is less than the standard error of the set. In Figure 9.3, this corresponds to the flaw types with $MAD < 0.78$, shown by the dotted line. Conversely, the weaknesses are those flaw types where the $MAD > 0.78$.

There are three categories where the inspection system does not perform well: (1) slywipe streaks on portrait crosshatch, (2) slywipes on portrait, and (3) stains. The slywipe streaks in the portrait crosshatch region have the highest relative error, shown by the IO series exemplars. These flaws are long relatively narrow flaws which tend to merge into the background. The crosshatch background tends to be integrated optically because the camera does not fully resolve this area. It is desirable not to resolve each engraving line because it is much more difficult to accommodate the note-to-note variations in ink topology.



Legend

IL - Ink spot in open substrate
 IH - Slywipe in lathework
 II - Slywipe in portrait
 EB - Break
 HA - Portrait coat break
 GA - Portrait background break
 FA - Chip

IM - Cracked chrome
 IJ - Slywipe smear
 IO - Portrait background slywipe streak
 IP - Stain
 IK - Substrate flooding
 IN - Ball-up mark

Figure 9.3. Measurement Error by Flaw Type.

The mean absolute error of the inspection system by flaw type.

Slywipes in the portrait region had the second largest relative error, shown by the II series exemplars. The difficulty here seems to be related to differences in the way people perceive flaw boundaries compared to the machine. This problem is illustrated in Figure 9.4 showing an inkspot flaw over an engraved grid. The flaw boundary perceived by a person is the perimeter of the ellipse. The method of detecting flaws with machine vision perceives the flaw to be ink existing in areas where none should be. In other words, only the ink between the lines is actually a flaw from the machine's point of view. This causes the inspection system to generally underestimate the flaw area compared to humans.

The inspection system successfully graded each of the three exemplars of stains found in the IP series but with a grade significantly lower than the observed grade. In each of these exemplars, the flaw density determined by the machine was lower than that measured manually. This could be the result of higher reflectance from staining compared to ink, causing the inspection system to underestimate the flaw density.

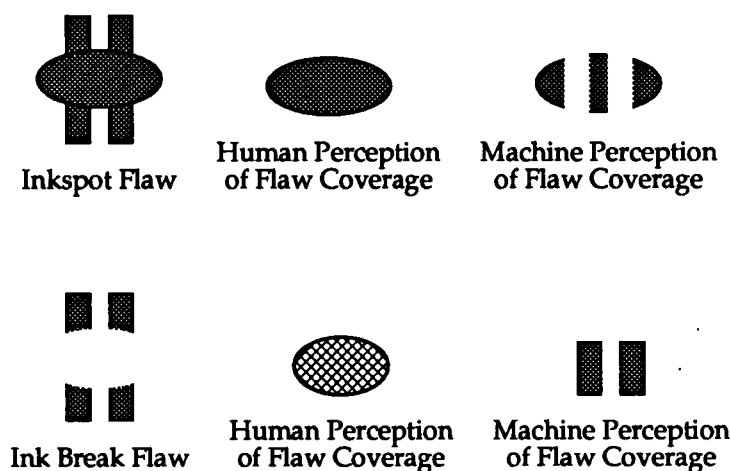


Figure 9.4. Human vs Machine Perception.

The figure shows the differences in perception for human and machine estimation of flaw coverage. Humans can readily discern flaw geometry, even in missing ink.

The strengths of the inspection system were the remaining ten flaw categories. This includes the following flaw types: (1) plate chip, (2) break in portrait background, (3) break in portrait coat, (4) slywipe in outer lathework, (5) slywipe smear, (6) flooding in substrate, (7) ink spot in substrate, (8) cracked chrome in lower right border, (9) break and board break, and (10) ball-up mark on right side. In each of these flaws, the inspection system performs within expectations.

The descriptive statistics indicate that the grades derived from manually measured parameters is a better predictor of the observed grades than the automatically measured method. For the exemplars tested thus far, the difference is small and is not statistically significant (Schmoyer, 1990). The closeness of the two methods warrants pursuing the automatic approach since it can likely be improved with further refinement of the local flaw model. Since the inspection system is an implementation of the flaw model, major improvements in performance could be realized by refining the model to directly relate machine acquired data to the human assessment of severity. Previously, this was not possible because a machine to acquire flaw parameters did not exist. The availability of the prototype inspection system now provides the tool for incorporating the characteristics of the machine into the model. Any new model would doubtlessly be of similar form, but with new coefficients to fit the machine data.

It should be apparent that machine vision is not likely to totally replace humans for the complex task of visual interpretation. The advantage offered by machine vision in currency inspection is a consistent application of a quantitative flaw standard. The ultimate currency inspection machine will indirectly incorporate a breadth of human opinions into a quantifiable decision boundary. The machine can then do what it does best, performing repetitive, labor-intensive tasks according to a sequential heuristic.

As currency inspection evolves from a research activity to reality, technological advances can be expected. Advances in computing technology will allow the inspection system of the future to operate faster and with more humanlike characteristics. The potential of new topics such as neural networks gives encouragement that the essence of human visual perception will one day be captured in a machine.

VLSI Implementation

Much recent research has been devoted to developing a computer vision system capable of discerning the contents of an arbitrary image. This continues to be a very difficult problem which will likely not have an immediate solution. In fact, researchers cannot agree on how the problem should be defined, let alone solved. It will remain unsolved until both our understanding of visual perception and the capabilities of computer technology are substantially advanced. Our knowledge of visual perception is being advanced by continuing research, while the computational power of computers is being increased through the use of very large scale integration (VLSI) technology.

The interpretation of a visual scene has been linked to the determination of the geometric shape of scene components (Austin, 1962). Marr (1982) extended the perception levels to include a representational hierarchy for extracting shape descriptions.

Image • The lowest level in the shape hierarchy is image representation by intensity values at each point in the image. The image acquired by the camera is a two-dimensional array of intensity values representing the three-dimensional volume projected into the lens. The biological vision system is able to automatically process the intensity matrix to extract image content while leaving the matrix itself unchanged. This is the essence of the early vision tasks, which extract higher information from the image projected onto the retina.

Primal Sketch • The vision system extracts the primal sketch from the image representation. The primal sketch represents a purely two-dimensional description of the image data from the zero-crossings, edge segments, and blob terminations.

2-1/2 D Sketch • The primal sketch is then used to obtain a surface description of the scene. The surface descriptors are determined from interpretations of shape descriptors such as texture and shading. The spatial coordinate system at this stage is centered at the viewer's perspective and the distances are given in those coordinates. The orientation and depth of visible surfaces are described by local surface orientation and distance from viewer.

3D Sketch • The highest level of shape representation describes the shape and organization of objects in the image with volumetric primitives such as generalized cylinders. The coordinates at this stage are object-centered rather than viewer-centered to eliminate the necessity for multiple views of the scene. A three-dimensional, spatial hierarchy is created for the original image.

Limitations of Early Vision

A high correspondence between low-level computer vision processing and early vision processing in humans was established by Marr and Hildreth (1980), who formulated an edge detection method based upon biological vision. Computer vision operations are divided into low, intermediate (mid), and high levels of computational complexity. In low-level processing, the image is treated as a set of data elements. The structure represented by the elements is not considered. Image operations are performed on a pixel-by-pixel basis. High- and low-pass filters for edge extraction and smoothing, zero-crossings, and texture are examples of low-level processing. In mid-level processing, the structure and organization of the data are represented by intensity histograms, feature lists, connected components, and frequency domain transforms. High-level processing requires a knowledge-based system to describe the scene through object and shape descriptors such as pattern matching, semantic nets, and inferences.

Early vision is the preliminary data reduction performed in the retina and optic nerve. The relationship between computer vision operations and the levels of shape representation is shown in Figure 9.5.

Computer Vision Levels	Shape Representation Levels	Attributes
Low	Image	2D Intensity Array
	Primal	Zero Crossings, Edge Segments, Blob Terminations
Mid	2 1/2 D	Viewer-Centered, Shading, Texture
High	3 D	Object-Centered, Generalized Cylinders

Figure 9.5. Computer Vision Operations.

Each level of shape representation in the biological vision system has a corresponding level in computer vision.

One important limitation of computer vision technology is due to the high data bandwidths required to access image memory. In a typical imaging operation, the image is processed pixel-by-pixel, sequentially scanning through the array. Since there are more elements in a high-resolution image, it takes longer to process the image. Processing time is proportional to the square of the increase in image size. With the current trend toward 1024 x 1024 images, the bandwidth must exceed 30-M pixels/s to process the image at conventional frame rates.

An approach to easing the bandwidth problem is to reduce the number of elements to be processed by performing low-level operations directly on the sensor. When low-level processing is performed on the sensor, several discrete integrated circuits could be combined on a single chip through VLSI technology. This would increase the communications bandwidth over interchip architecture by eliminating the capacitance of the printed circuit wiring paths connecting different chips.

There are particular tasks in image processing that are inherently well-suited for VLSI solutions. The low-level vision tasks in which the image data are organized in a regular pattern is especially amenable to implementation in a single-instruction, multiple-data (SIMD) or in a systolic array.

SIMD machines are closely related to the traditional Von Neuman architecture. In both instances, they implement a single state transition per execution step. Whereas Von Neuman machines usually change the program counter, arithmetic registers, or a stored data location, the SIMD machine can change many registers and data locations. A SIMD machine can be implemented as either a vector or a broadcast processor. In the vector processor, arithmetic units are configured into a pipeline and are linked to memory, which is accessed cyclically. In the broadcast processor, parallel arithmetic units have access to independent memory modules.

A systolic array is a network of small processors organized to emphasize local communication between processors. Logic and memory elements are combined into regular structures (Kung, 1982). In the systolic array, the data flow cyclically through the structure much akin to the way blood is pumped through the human heart. Many image-processing problems have been found to have systolic solutions, which can be implemented with a VLSI architecture.

VLSI Implementation Examples

The increased use of VLSI technology is generating many new integrated circuits beneficial to image processing. A survey of recent VLSI implementations for image processing and perception concludes the chapter.

Pattern Matching

A systolic array chip has been fabricated to match digital patterns between two inputs and generate an output indicating the presence of a match. The objective is to identify the occurrence of a predefined pattern within an arbitrary input string. Traditionally, patterns were matched by holding the pattern stationary, sliding the string past, and comparing the string with the pattern. If the string matched the pattern, a match was declared. This requires a global decision on the occurrence of a complete match. A systolic implementation was devised which allows local accumulation of matches by moving both string and pattern against each other (Foster *et al.*, 1980).

Object Location and Tracking

Fusion of image sensors with low-level processing on a single chip has begun appearing in the literature. An implementation that computes the position of an object in a 200×200 pixel array was reported by DeWeerth (1988). This device uses a clear window over the vertical parasitic transistor normally generated during the CMOS fabrication process. The parasitic transistor is also the current source of a transconductance amplifier, in which the current is proportional to incident light. The relative current through each pixel is used to determine the position of a bright spot on a dark background. The pixel array need not be transferred from the sensor because the low-level processing is performed on the chip.

A SIMD implementation of a real-time target tracking processor was described by Jaffee *et al.* (1989). This system is a massively parallel processor for 128×128 images at 100-Hz frame rates. Several image-processing functions such as moment and rotation correction are implemented in the SIMD format. The potential targets are isolated by thresholding the image into a binary representation and then labeling them with a clustering algorithm. The area centroid, image centroid, and location of peak intensity are found for each object. The coordinates of these three parameters are used to select and track the objects.

Memory Access

VLSI technology has also been extended to computer-generated images where the problem is related to memory-access time (Demetrescu, 1985). A major performance factor in computer graphics is the time required to access the internal image memory elements. A VLSI chip was developed which provides a significant speed improvement over conventional graphics systems. The scan-line access memory chip incorporates an internal processor to reduce the number of operations necessary to change a single pixel in the memory array. This permits faster access to the image memory and consequently higher operating speed.

Motion Detection

A method of motion detection that can be implemented with a VLSI systolic array was described by Catthoor and De Man (1987). The systolic array realizes an algorithm to minimize the distance between two image neighborhoods over time (Lin and Kwatra, 1984). The algorithm is implemented with a single chip featuring a dedicated shift register interface to eliminate the bottleneck in I/O communications.

Edge Detection

A method to implement the Robert's gradient operator was given by Gunzinger *et al.*, (1988) using a reconfigurable systolic array. In this method, the arithmetic operations are described in a planar data-flow graph. Each operation or node on the graph is replaced by a processing element consisting of an arithmetic processing unit, a matching unit to synchronize the data operands, and a network unit to communicate with the surrounding elements. The prototype operates at 10-M pixels/s and can be used for edge detection, filtering, and tracking at video frame rates.

Surface Orientation

The use of VLSI architecture is not limited to image irradiance data. It can also be used to extract a local surface orientation from an image obtained with a laser range finder. In the range image, the pixel values represent the distance to the object rather than the reflected intensity. An algorithm has been described for implementation in CMOS technology from a library of standard cells (Blanchet and Poussart, 1987). It operates on range image with a reconfigurable memory array to access the kernel data. A local surface orientation is determined from a tessellation of range pixels which approximates a surface plane.

BIBLIOGRAPHY

- American National Standards Institute, PH2.17, 1985.
- Austin, J. L. (1962) *Sense and Sensibilia*, Clarendon Press, Oxford.
- Ballard, D. H., and C. M. Brown (1982) *Computer Vision*, Prentice-Hall Inc., Englewood Cliffs, N.J.
- Bangs, J. A. (1986) "Prototype Currency Inspection Systems Bureau of Engraving and Printing," *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.
- Barnea, D. I. and H. F. Silverman (1972) "A Class of Algorithms for Fast Digital Image Registration," *IEEE Trans. Comput.*, Vol. C-21, pp. 179-186 February 1972.
- Barrow, H. G., and J. M. Tenenbaum (1981) "Computational Vision," *Proc. IEEE*, Vol. 69, No. 5, pp. 572-595, (May 1981).
- Batchelor, B. G., D. A. Hill, and D. C. Hodgson (1985) *Automated Visual Inspection*, IFS Publications Ltd. Kempston, Bedford, U.K.
- Batuscheck, C. M. (1987) "Correction of Video Camera Response Using Digital Techniques," *Optical Engineering*, Vol. 26, No. 12, (December, 1987).
- Benson, K. B. (1986) *Television Engineering Handbook*, McGraw-Hill, New York, N.Y.
- Blanchet, M., and D. Poussart (1987) "In-Memory VLSI Processor for Computing Local Surface Orientation of 3-D Range Images," *Proc. SPIE*, Vol. 849, *Automated Inspection and High Speed Vision Architectures*, pp. 27-34.
- Blazek, H. (1986) "Real Time Inspection of Currency," *Proc. SPIE*, Vol. 697, *Applications of Digital Image Processing IX*, San Diego, Calif., pp. 129-139, August, 1986.
- Boff, K. R., L. Kaufman and J. P. Thomas (1986) *Handbook of Perception and Human Performance*, Vol. 1, John Wiley and Sons, New York, N.Y., 1986.
- Carnes, W. R. (1979) "Specialized Electro-Optic Quality Control Systems in Document Processing and Printing," *Proc. SPIE*, Vol. 193, *Optical Systems Engineering*, pp. 184-193, 1979.
- Catthoor, F. and H. De Man (1987) "An Efficient Systolic Array for Distance Computation Required in a Video-Codec Based on Motion-Detection," *Systolic Arrays*, A. Hilger, Ed., Bristol, England.
- Chambers, J. M., W. S. Cleveland, B. Kleiner, and P. A. Tukey (1983) *Graphical Methods for Data Analysis*, Wadworth International Group, Belmont, Calif.
- Chapelle, W. E. (1988) "Radiometric Analysis of Machine Vision Cameras," *SME Conf. Lighting and Optics Machine Vision*, August 1988.
- Coggshall, G. (1981) "Currency Inspected at Rates of 192,000 Notes Per Hour," *Industrial Research and Development*, pp. 122-126 (November 1981).

- Collins, B. L., S. E. Mayerson, and J. A. Worthy (1985) *Noticeability of Features of Secure Documents* (NBSRI 85-3160), U.S. Dept. of Commerce: National Bureau of Standards.
- Currency Quality Standards Manual* (1980) Bureau of Engraving and Printing, March 1980.
- Demetrescu, S. (1985) "Moving Pictures," *Byte* (November 1985).
- DeWeerth, S. P. and C. A. Mead (1988) "A Two-Dimensional Visual Tracking Array," *5th MIT Conference on Advanced Research in VLSI*, Massachusetts Institute of Technology, Cambridge, Mass., March 28-30, 1988.
- Dunbar, P. (1986) "Machine Vision," *Byte*, pp 161-173 (January 1986).
- Fitzpatrick, J. E. (1986) "Quality Assurance Standards in Automated Inspection," *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.
- Foster, M. J. and H. T. Kung (1980) "The Design of Special-Purpose VLSI Chips," *IEEE Computer*, Vol. 13, pp. 26-40, (1980).
- Fridman, R. et al. (1987) "Report of the Committee on Machine Inspection Capabilities and Limitations," *International Workshop on Printing Flaw Standards for Machine Inspection, International Conference on Security Documents for the 21st Century*, San Diego, Calif., April, 1987.
- Gonzalez, R. C. and P. A. Wintz (1977), *Digital Image Processing*, Addison-Wesley Co. New York, N.Y.
- Graminski, E. L. (1986) "Historical Perspectives of Currency Inspection Methods," *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.
- Gunzinger, A., S. Mathis, and W. Guggenbuhl (1988) "A Reconfigurable Systolic Array for Real-Time Image Processing," *Proc. IEEE V3.4, CH2561*, pp. 2057-2060, September 1988.
- Gurley, T. M., and C. J. Haslett (1985) "Resolution Considerations in Using CCD Imagers in Broadcast-Quality Cameras," *SMPTE Journal*, pp. 882-895 (September 1985).
- Harding, K. G. (1988) "Optical Considerations for Machine Vision," *SME Conf. Lighting and Optics for Machine Vision*, August 1988.
- Hardy, A. C., and F. H. Perrin (1932) *The Principles of Optics*, McGraw-Hill, New York, N.Y.
- Harold, P. (1986) "Solid State Area-Scan Image Sensors Vie for Machine-Vision Applications," *EDN*, pp. 55-66 (May 15, 1986).
- Hecht, E. (1987) *Optics*, 2nd Ed., Addison-Wesley Inc., Reading Mass.

- Hill, D. A. (1984) "Solving Illumination Problems," *Proc 4th Int. Conf. Robot Vision and Sensory Controls*, pp. 75-83, London, U.K. (October 1984).
- Holt, J. (1985) "1985 Trends in Detector Technology," *Laser Focus/Electro-Optics*, pp. 76-90 (December 1985).
- Horn, B. K. P. (1977) "Understanding Image Intensities," *Artificial Intelligence*, Vol. 8, No. 2, pp. 201-231 (April, 1977).
- Horn, B. K. P. (1986) *Robot Vision*, McGraw-Hill, New York, N.Y.
- Howard, A. (1977) *Elementary Linear Algebra*, 2nd Ed. John Wiley & Sons, New York, N.Y.
- IRE Standards on Video Techniques: Measurement of Resolution of Camera System, *Proc. IRE* Vol. 19, No. 2, March 1961.
- Jaech, J. L. (1985) *Statistical Analysis of Measurement Errors*, John Wiley & Sons, New York, N.Y.
- Jaffe, R. C., W. T. Lin, C. Y. Ho, and D. S. Johnson (1989) "Applications of VLSI for Image Processing," *IEEE CH2673* pp. 2421-2424 (February 1989).
- Jatko, W. B. (1989) "A Survey of Camera Error Sources in Machine Vision Systems," *Proc. Sensors Expo*, pp. 301C-1-5, Helmers Pub. Co. Peterborough N.H., September, 1989.
- Jatko, W. B., M. A. Hunt and K. W. Tobin (1990) "Nonlinear Filter Derived From Topological Image Features," *Proc. SPIE*, Vol. 1295, Orlando Fla., April 1990.
- Johnson, C. K., R. E. Blake, et al. (1987) *Currency Flaw Evaluation in Theory and Practice*, Oak Ridge National Laboratory Report ORNL-6373, Oak Ridge, Tenn., December, 1987.
- Karohl, J. G. (1989) "U.S. Currency Inspection System," Presentation at Oak Ridge National Laboratory, Oak Ridge, Tenn., May 1989.
- Kuhl, A. (1986) "Automatic Printing Quality Control For Banknotes," *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.
- Kung, H. T. (1982) "Why Systolic Architectures," *IEEE Computer Magazine*, pp. 37-46, 1982.
- Kurtum, G. (1969) *Reflectance Spectroscopy*, Springer-Verlag, New York, N.Y.
- Lake, D. (1984) "Solid State Cameras," *Proc 4th Int. Conf. Robot Vision and Sensory Controls*, pp. 75-83, London, U.K. (October 1984).
- Lin, C. and S. Kwatra (1984) "An Adaptive Algorithm for Motion Compensated Colour Image Coding," *Proc. IEEE Globecom*, pp. 47.1.1-4.
- Lindsey, D. (1989) "Selecting Lenses For Machine Vision," *SME Conf. Lighting and Optics for Machine Vision*, June 1989.

- Longhurst, R. S. (1967) *Geometrical and Physical Optics*, 2nd Ed. Longmans, Green and Co., London.
- Luck, R. L. (1987) "Implementing an Image Understanding System Architecture Using PIPE," *Proc. SPIE*, Vol. 849, *Automated Inspection and High Speed Vision Architectures*, pp. 35-41.
- Maragos, P. (1987) "Tutorial on Advances in Morphological Image Processing and Analysis," *Optical Engineering*, pp. 623-632 (July, 1987).
- Marr, D. (1982) *Vision*, W.H. Freeman, New York, N.Y.
- Marr, D. and E. Hildreth (1980) "Theory of Edge Detection," *Proc. R. Soc. London*. B207, pp. 187-217.
- Martin, G. J., K. H. Womack and J. H. Fischer (1987) "A High Resolution CCD Camera for Scientific and Industrial Imaging Applications," *Proc., SPIE*. Vol. 818, San Diego, Calif., August 16-21, 1987.
- Martins, E. (1988) "Choosing CCDs for Machine Vision Applications," *Lasers & Optronics*, (June 1988).
- Matsukawa, I. (1986) "Needs, Experience and Plans In Automated Currency Inspection" *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.
- Miller, I. and J. E. Freund (1985) *Probability and Statistics for Engineers*, 3rd Ed. Prentice-Hall, Englewood Cliffs, N.J.
- Neuhauser, R. G. (1987) "Photoconductors Utilized in TV Cameras," *SMPTE Journal*, pp. 473-487 (May 1987).
- Nevatia, R. (1982) *Machine Perception*, Prentice-Hall, Englewood Cliffs, N.J.
- Newitt, J. H. (1985) "A Sensor Guide for Image Analyzers," *Sensors*, pp. 23-31 (January 1985).
- Nicodemus, F. E., J. C. Richmond, *et al.* (1977) "Geometrical Considerations and Nomenclature for Reflectance," *NBS Monograph 160*, National Bureau of Standards, U.S Dept. of Commerce, Washington D.C., October 1977.
- Ott, H. W. (1976) *Noise Reduction Techniques in Electronic Systems*, John Wiley and Sons, New York, N.Y.
- Parker, I. N. (1985) "VLSI Architecture," in *VLSI Image Processing*, R. J. Offen Ed., McGraw-Hill, New York, N.Y.
- Payne, R. (1986) "Fundamentals of Security Printing," *Proc. International Conference on Machine Inspection of Printed Security Documents*, Long Beach, Calif., September 25-26, 1986.
- Perron, M. (1986) "Needs-Experience and Plans For Automated Currency Inspection in The Bank of France" *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.

- Pratt, W. K. (1978) *Digital Image Processing*, John Wiley & Sons, New York, N.Y.
- Preston, K. (1972) *Coherent Optical Computers*, McGraw-Hill, New York, N.Y.
- Ray, R., J. Birk, and R. B. Kelley (1983) "Error analysis of Surface Normals Determined by Radiometry," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 5, No. 6, pp. 631-645 (November 1983).
- Reed, R. F. (1985) "Paper, Relative Humidity and Color Register," *Graphics Arts Technical Foundation Research Project Report*, 1985.
- Regone, K. A. (1986) "Present and Future Currency Examining Needs," *Proc. International Conference on Machine Inspection of Printed Security Documents*, Long Beach, Calif., September 25-26, 1986.
- Reutz, P. A., R. Jain, and R. W. Brodersen (1987) "Comparison of Parallel Architectures for Real-Time Image Processing ICs," *Proc. ISCalif.S*, December 1987.
- Rogers, T. J. (1987) "Future Production Systems Requirements: What Equipment Will Be Needed To Produce More Sophisticated Security Documents?," *Proc. International Conference on Security Documents for the 21st Century*, San Diego, Calif., April 1-3, 1987.
- Rose, A. (1983) "Vision: Human and Electronic," *Electronic Imaging*, pp. 57-61 (August, 1983).
- Rosenfeld, A. and A. C. Kak (1982) *Digital Picture Processing*, 2nd Ed., Vol. 2, Academic Press, Inc., Orlando, Fla.
- Saghri, J. A., P. S. Cheatham and A. Habibi (1989) "Image Quality Measure Based on a Human Visual System Model," *Optical Engineering*, Vol. 28, No. 7, pp 813-818 (July 1989).
- Savarese, J. A. (1981) "Currency Inspection," Perkin-Elmer Technical News Release, 1981.
- Schmoyer, R. (1990) Oak Ridge National Laboratory Internal Correspondence, Oak Ridge, Tenn., March 19, 1990.
- Sheingold, D. H. Ed. (1980) *Analog-Digital Conversion Notes*, Analog Devices Inc. Norwood, Mass.
- Silver, W. M. (1987) "Normalized Correlation Search in Alignment, Gauging, and Inspection," *Proc. SPIE*, Vol. 755, Los Angeles, Calif., January, 1987.
- Skifstad, K. and R. Jain (1989) "Illumination Independent Change Detection for Real World Image Sequences," *Computer Vision, Graphics and Image Processing*, Vol. 46, pp. 387-399 (1989).
- Smith, F. et al. (1987) "Machine Inspection Specification Recommendations Workshop Report," *International Workshop on Printing Flaw Standards for Machine Inspection, International Conference on Security Documents for the 21st Century*, San Diego, Calif., April. 1987.
- Smith, G. B. (1983) "The Relationship Between Image Irradiance and Surface Orientation," *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, June, 1983.

- Spidell, E. (1987) "Selecting the Optimum Image Sensor: Camera Tubes vs. Solid-State Arrays," *Laser-Focus/Electro-Optics*, pp. 158-163 (January 1987).
- The Bureau of Engraving and Printing Management Handbook* (1985), U.S. Government Printing Office (0-480-300: QL 3), Washington, D.C., 1985.
- Tobin, K. W., Hunt, M. A. and Jatko, W. B. (1989) "High Resolution Three Dimensional Image Registration," *Proc. SPIE*, Vol. 1153, San Diego, Calif., pp. 541-551 August 1989.
- Westphal, H. and H. Nagel (1987) "Exploiting Reflectance Properties to Analyze Images of Moving Objects Needs Local Constraints," *Computer Vision, Graphics and Image Processing*, Vol. 38, pp. 90-98 (1987).
- Wyszecki, G., and W. S. Stiles (1982) *Color Science: Concepts and Methods, Quantitative Data and Formulae*, John Wiley & Sons, New York, N.Y.
- Yde, L. (1986) "Banknote Inspection At The Danmarks National Bank," *Proc. International Conference On Machine Inspection Of Printed Securities Documents*, Long Beach, Calif., September 25-26, 1986.
- Young, M. (1986) *Optics and Lasers*, 3rd Ed, Vol. 5, Springer-Verlag, New York, N.Y.
- Zisk, S. H. and N. Wittels (1987) "Camera Edge Response," *Proc. SPIE*, Vol. 850, *Optics, Illumination, and Image Sensing for Machine Vision II*, November 1987.
- Zuech, W. and R.K. Miller (1987) *Machine Vision*, Prentice-Hall, Englewood Cliffs, N.J.

APPENDICES

APPENDIX A

Hardware Diagrams

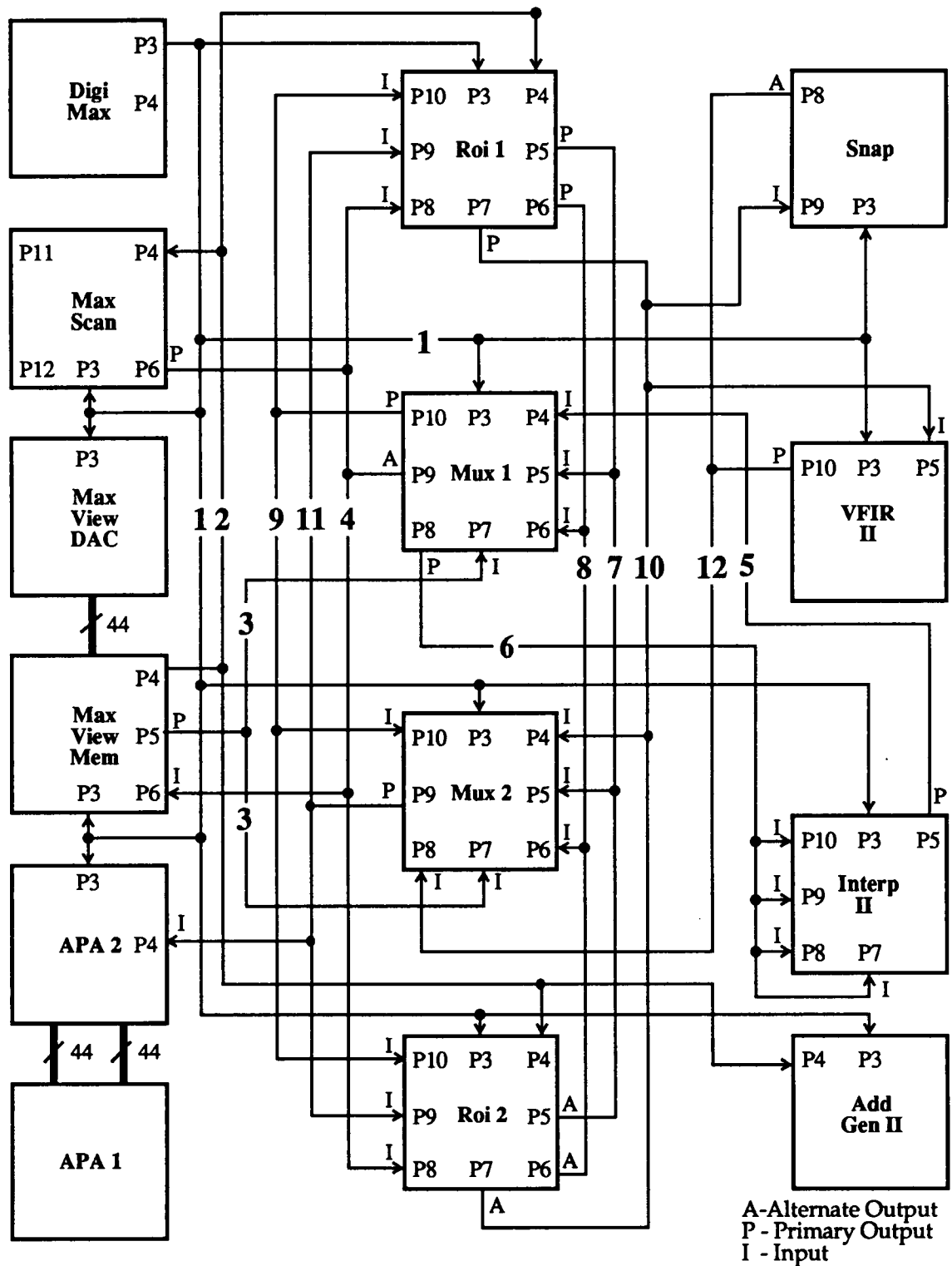


Figure A.1. Interconnection Diagram.

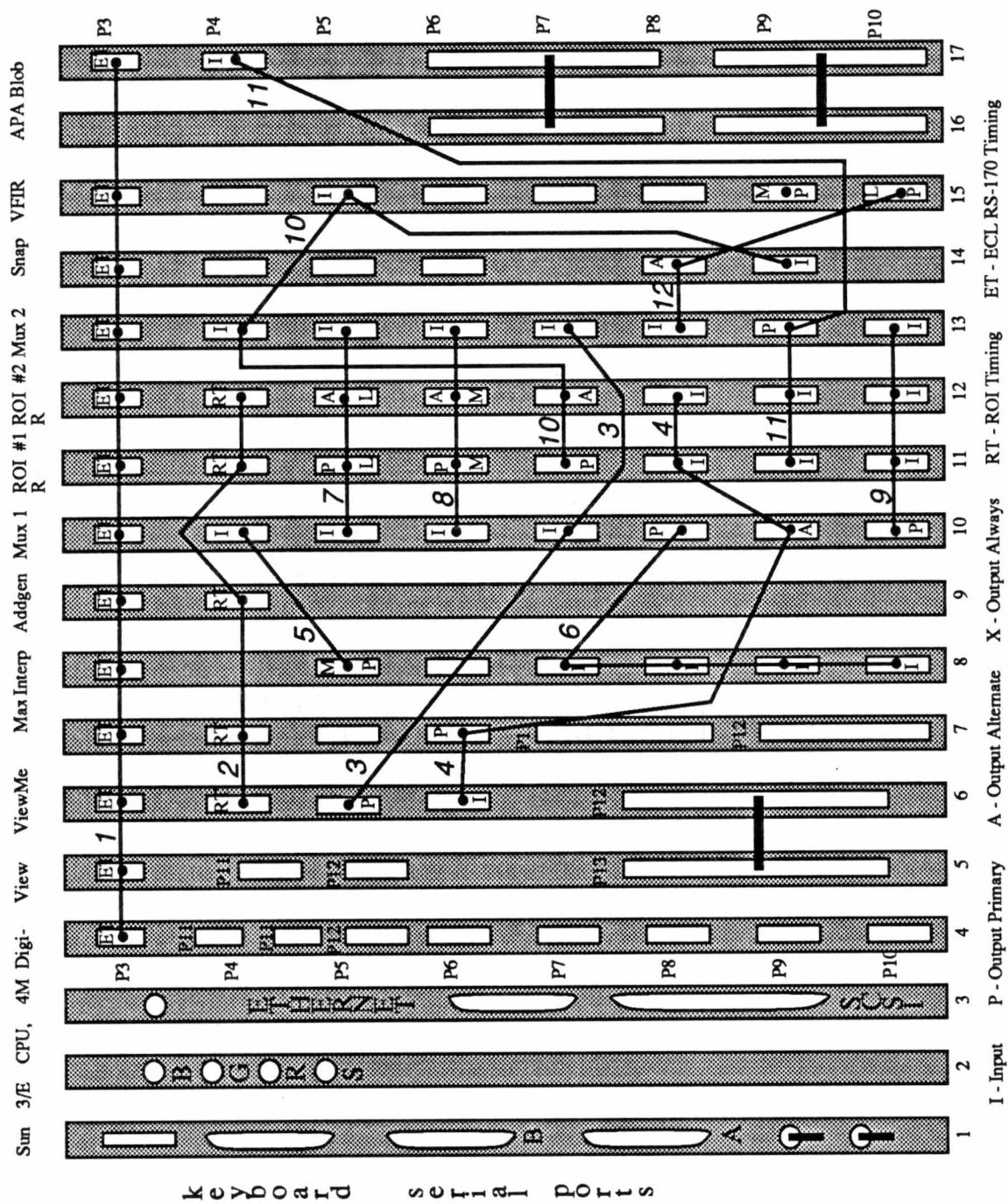


Figure A.2. Front Panel Layout.

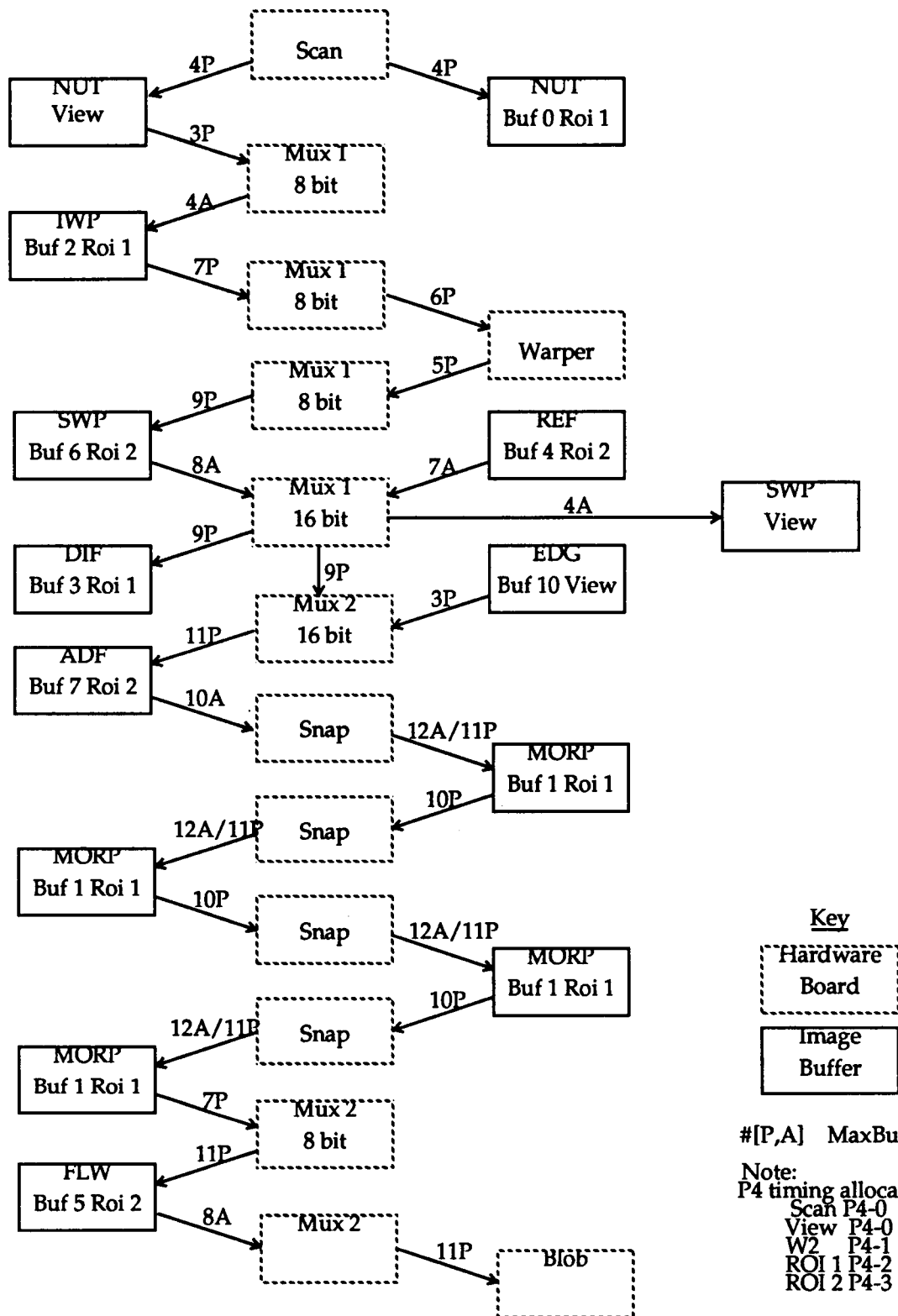


Figure A.3. Image Pipeline.

APPENDIX B

Software

Data Structures

Data related to flaw parameters for each note are collected into a set of data structures for convenience. There are four main data structures consisting of related variables grouped together under a common heading. The data structures are referred to as (1) *Board*, (2) *Calibration*, (3) *Note*, and (4) *FlawTable*.

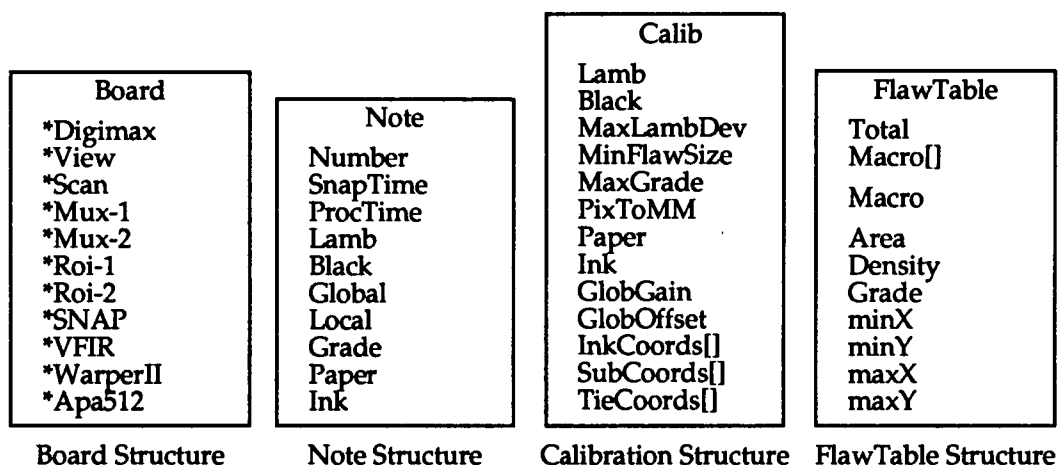


Figure B.1. Software Data Structures.

The *Board* data structure holds the software pointers to the file descriptors of each hardware board in the system. The file descriptors are themselves data structures containing system information regarding the amount of memory, register sizes, and physical addresses for each board. The pointer for each file descriptor in the *Board* data structure is set during initialization.

The *Calibration* data structure contains the constants determined during calibration. This structure is loaded from the disk during initialization and retains its data after the program is halted. The elements of this structure are as follows:

<i>Lamb</i>	Grey level intensity of the Lambertian reflector. It represents the highest pixel intensity in the image.
<i>Black</i>	Grey level intensity of the black reference reflector. It represents the lowest possible pixel intensity in the image.
<i>MaxLambDev</i>	The maximum permitted spatial deviation of the Lambertian intensity.
<i>MinFlawSize</i>	The minimum flaw size allowed for local flaws.
<i>MaxGrade</i>	The maximum flaw severity grade computed by the system. The range of possible grades is 0 - MaxGrade.
<i>PixToMM</i>	Pixel scaling factor to convert from pixels to note area in square millimeters.
<i>Paper</i>	The average reflectance of the reference substrate region.
<i>Ink</i>	The average reflectance of the reference note ink region.
<i>GlobGain</i>	The slope of the straight line relating global grade to reflectance difference.
<i>GlobOffset</i>	The offset of the global grading line.
<i>InkCoords[]</i>	An array containing the spatial coordinates of the regions used to determine the average ink reflectance.
<i>SubCoords[]</i>	Array containing the spatial coordinates of the regions used to determine the average substrate reflectance.
<i>TieCoords[]</i>	Array containing the spatial coordinates of the regions used to determine the spatial position.

The *Note* data structure contains the parameters measured for the current note under test. This structure is cleared prior to processing each note and the elements are entered as they are measured. The elements of the *Note* structure are as follows:

<i>Number</i>	The identification number of the current note.
<i>SnapTime</i>	The time the camera was snapped to acquire the note image.
<i>ProcTime</i>	The processing time expended for the current note.
<i>Lamb</i>	The value of the Lambertian reflector for the current note.
<i>Black</i>	The value of the black reflector for the current note.
<i>Global</i>	The global flaw severity grade of the current note.
<i>Local</i>	The local flaw severity grade of the current note.
<i>Grade</i>	The composite flaw severity grade of the current note.
<i>Paper</i>	The average reflectance of the current note substrate region.
<i>Ink</i>	The average reflectance of the current note ink region.

The *Flaw* data structure is referred to as the *FlawTable* and is the list of valid, local flaws found on the current note. This structure is necessary to temporarily hold the flaw locations until they can be processed. As the spatial coordinates of each flaw are determined by the APA 512 connectivity analysis boards, they are held in the *FlawTable*. The elements of the *FlawTable* are

<i>Total</i>	The number of flaws elements in the table.
<i>Macro[]</i>	Definition of the elements measured for each macroflaw found in the image.
<i>Area</i>	The number of pixels found in the macroflaw.
<i>Density</i>	The average density of the macroflaw.
<i>Grade</i>	The partial flaw grade computed for the macroflaw.
<i>minX</i>	The horizontal coordinate of the upper left corner of the macroflaw bounding rectangle.
<i>minY</i>	The vertical coordinate of the upper left corner of the macroflaw bounding rectangle.
<i>maxX</i>	The horizontal coordinate of the lower right corner of the macroflaw bounding rectangle.
<i>maxY</i>	The vertical coordinate of the lower right corner of the macroflaw bounding rectangle.

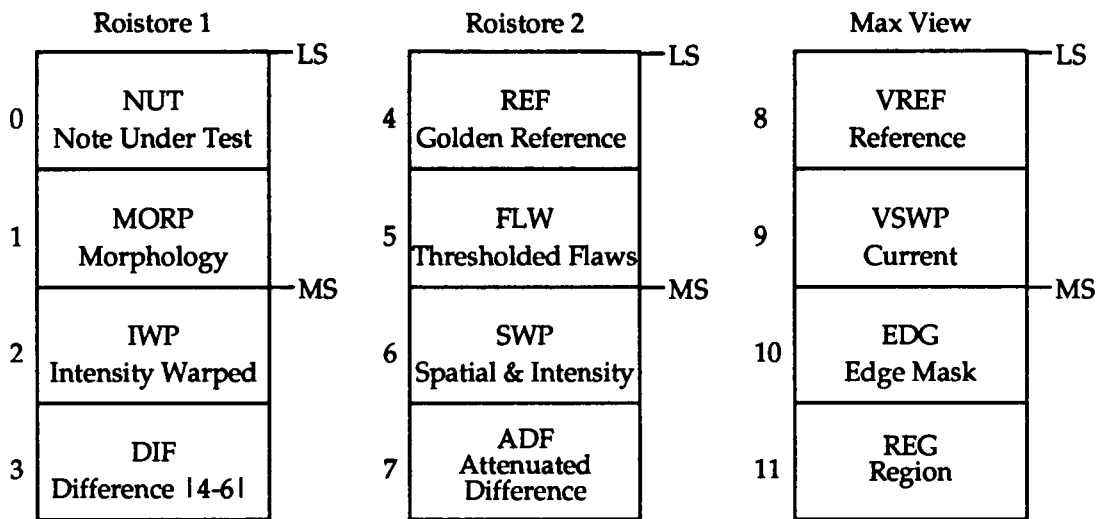


Figure B.2. Frame Buffer Memory Map.

Illustration of the memory mapping for the twelve frame buffers in the inspection system. Each buffer is 1024 x 512 pixels.

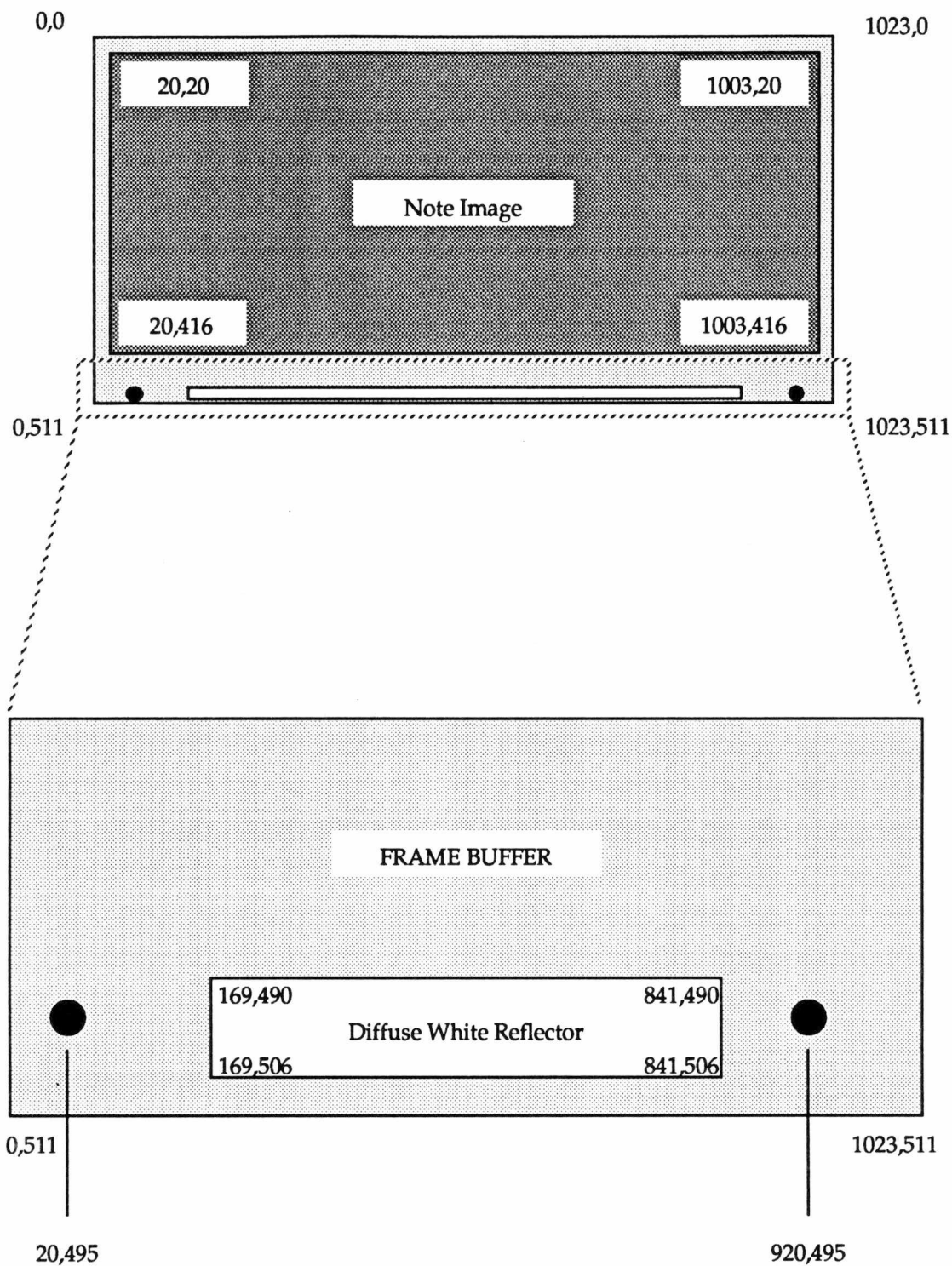


Figure B.3. Frame Buffer Coordinates.

Coordinates of the reference image buffer are shown in the upper illustration. The expanded inset below shows the coordinates of the white and black standard reflectors.

Flow Charts

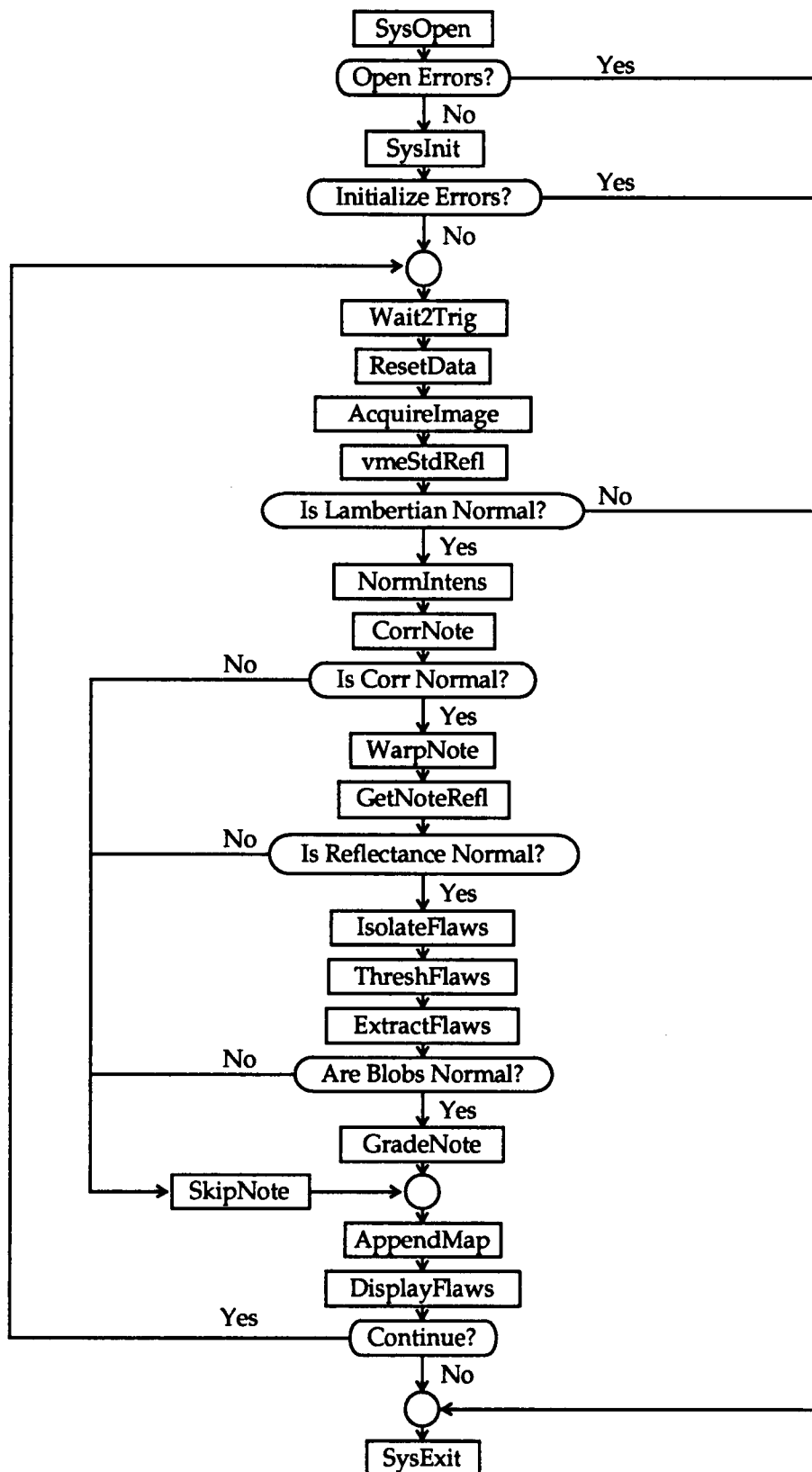


Figure B.4. Main Flowchart.

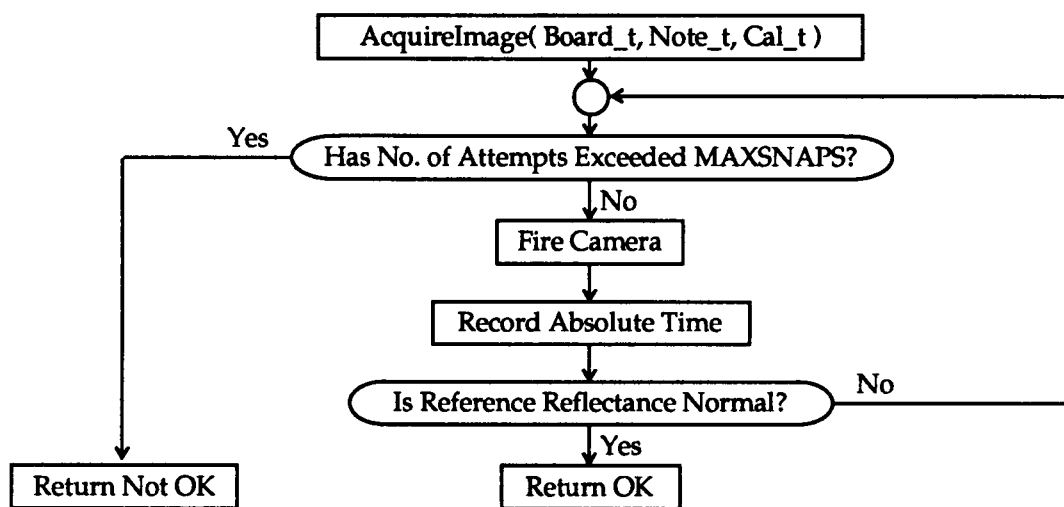


Figure B.5. `AcquireImage` Flowchart.

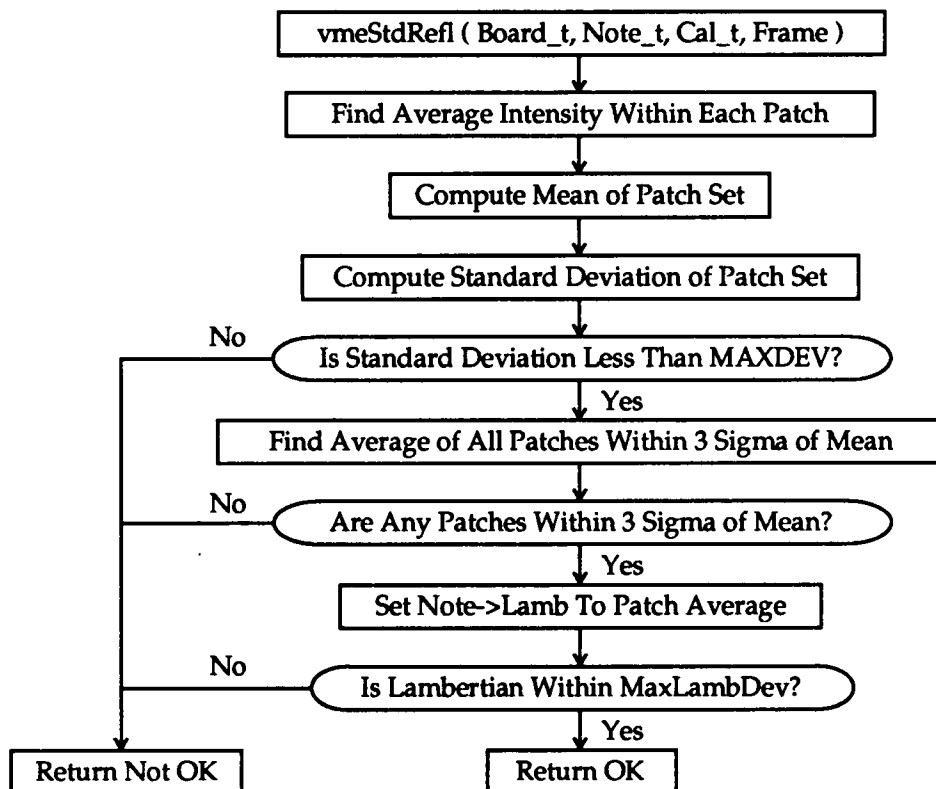


Figure B.6. VmeStdRefl Flowchart.

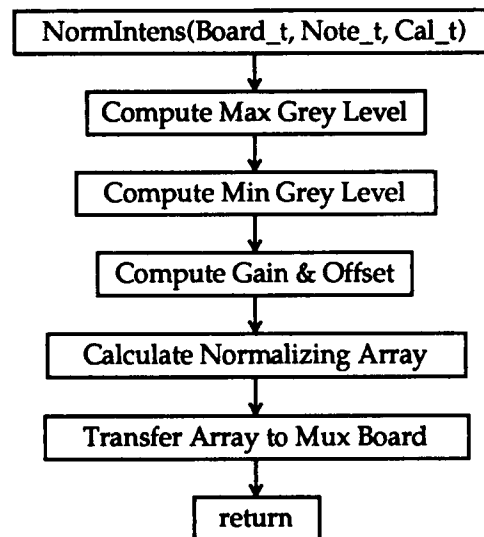


Figure B.7. NormIntens Flowchart.

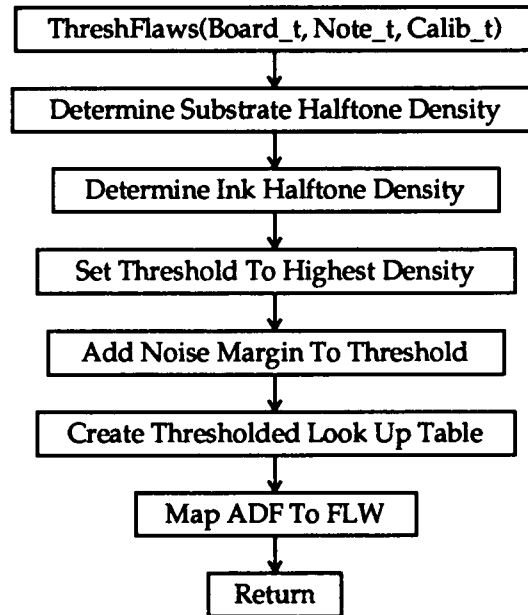


Figure B.8. ThreshFlaws Flowchart.

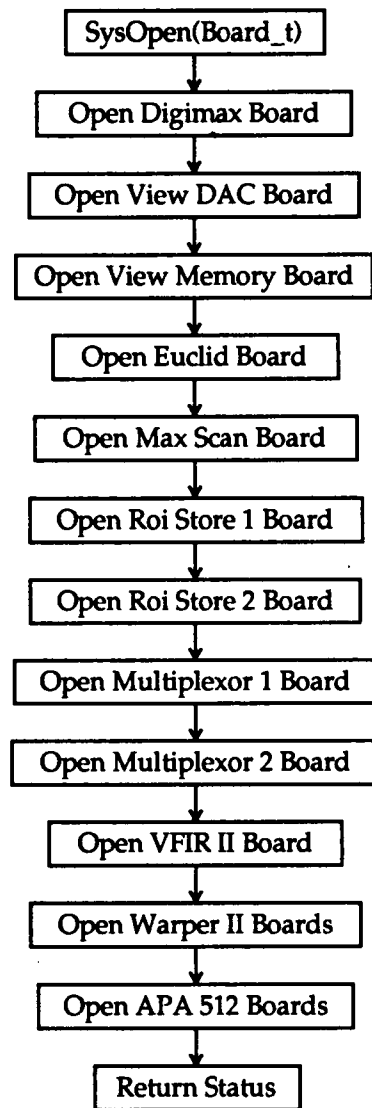


Figure B.9. SysOpen Flowchart.

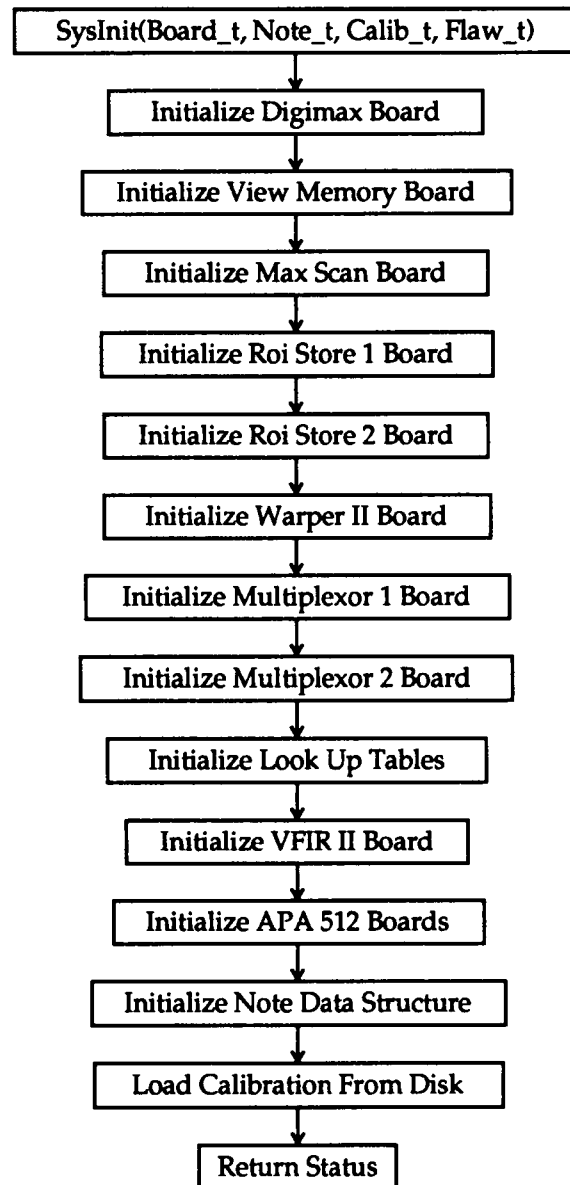


Figure B.10. SysInit Flowchart.

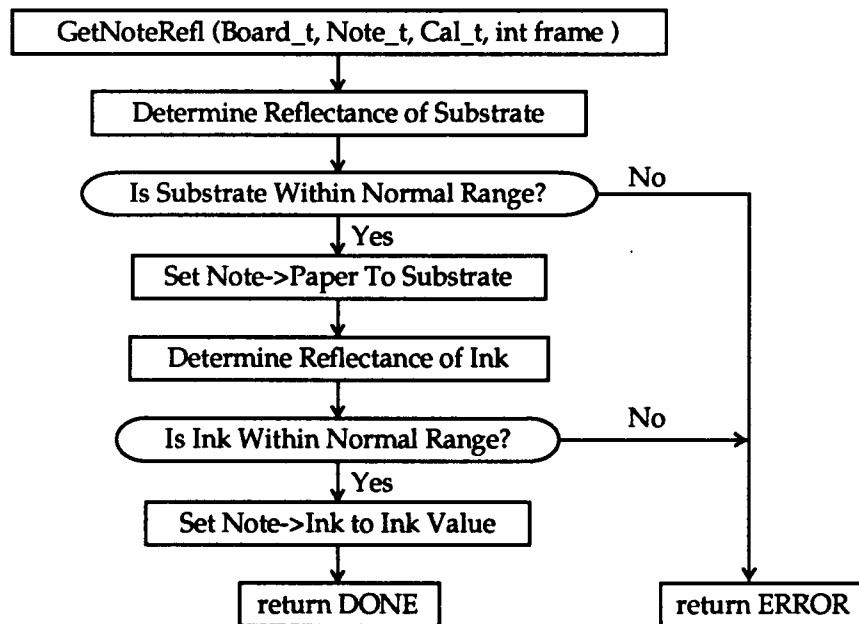


Figure B.11. GetNoteRefl Flowchart.

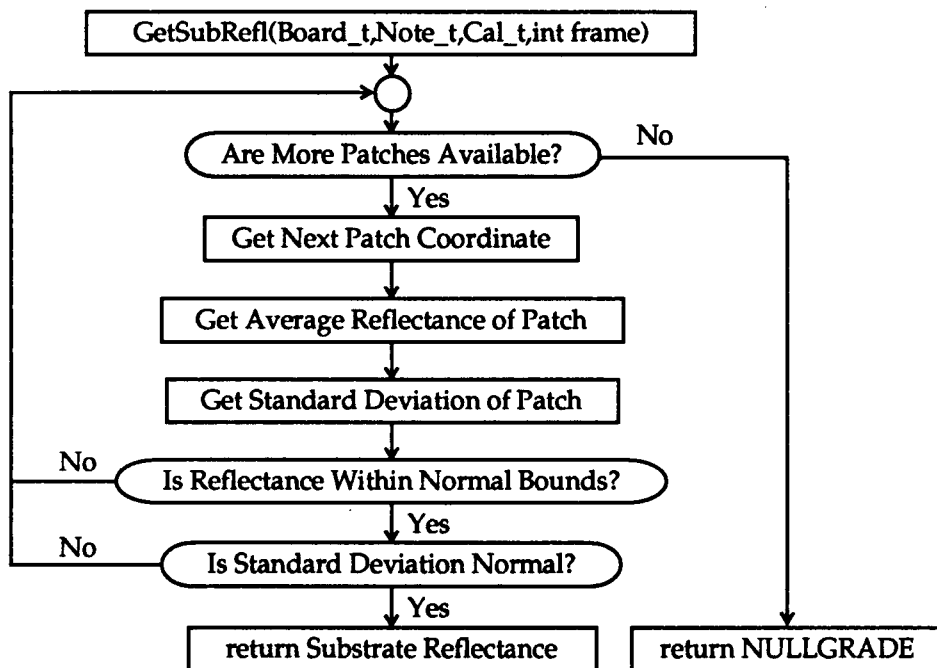


Figure B.12. GetSubRefl Flowchart.

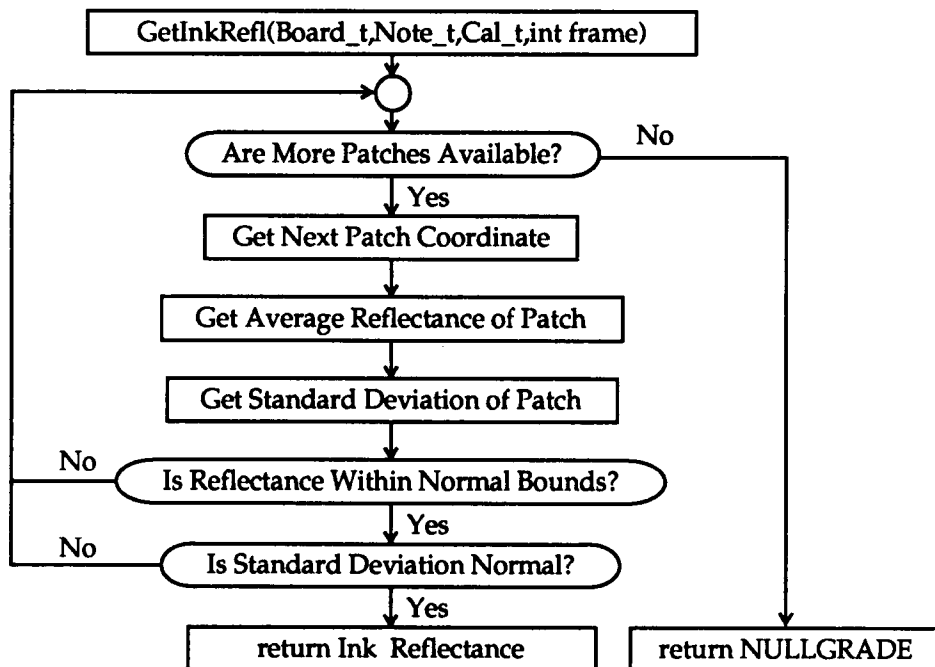


Figure B.13. GetInkRefl Flowchart.

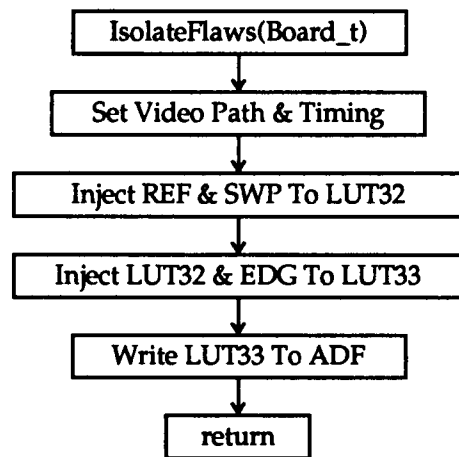


Figure B.14. IsolateFlaws Flowchart.

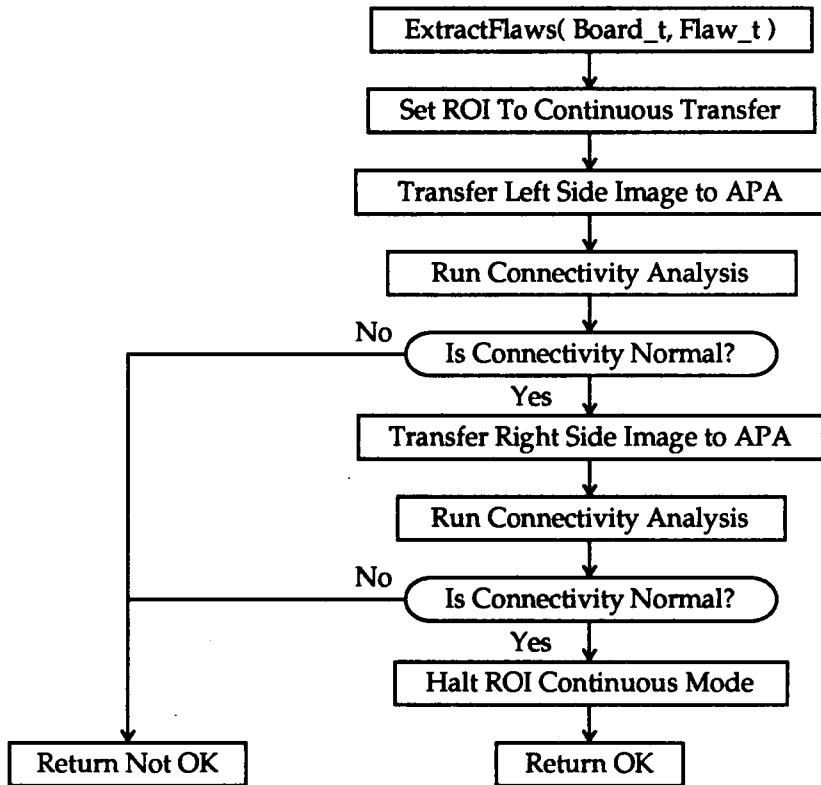


Figure B.15. ExtractFlaws Flowchart.

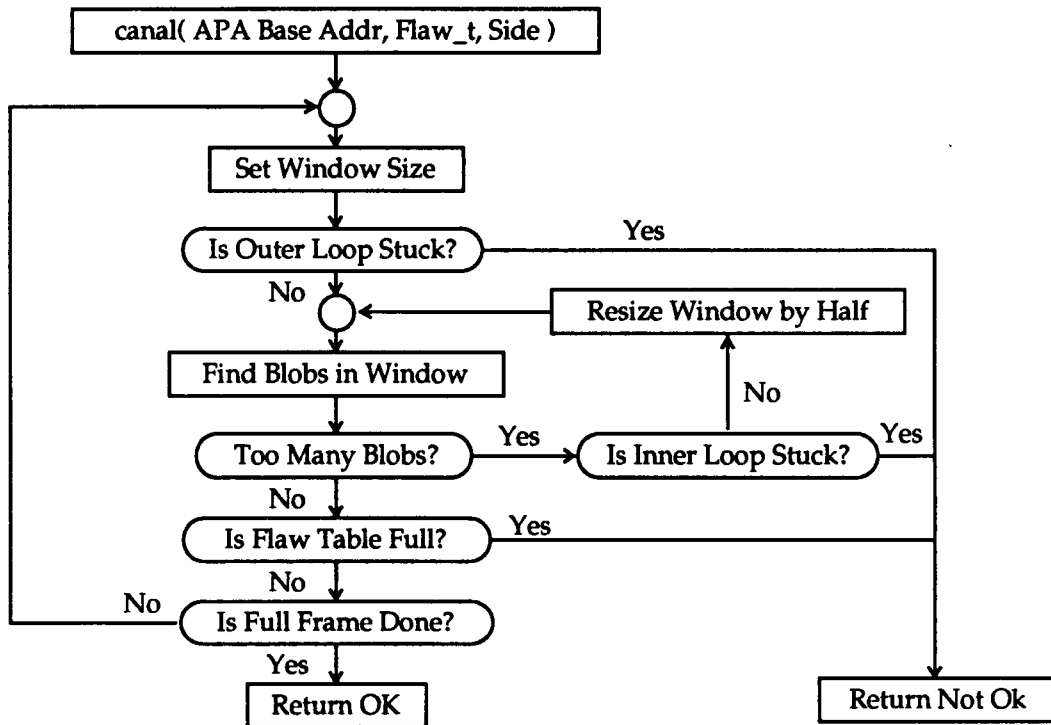


Figure B.16. Canal Flowchart.

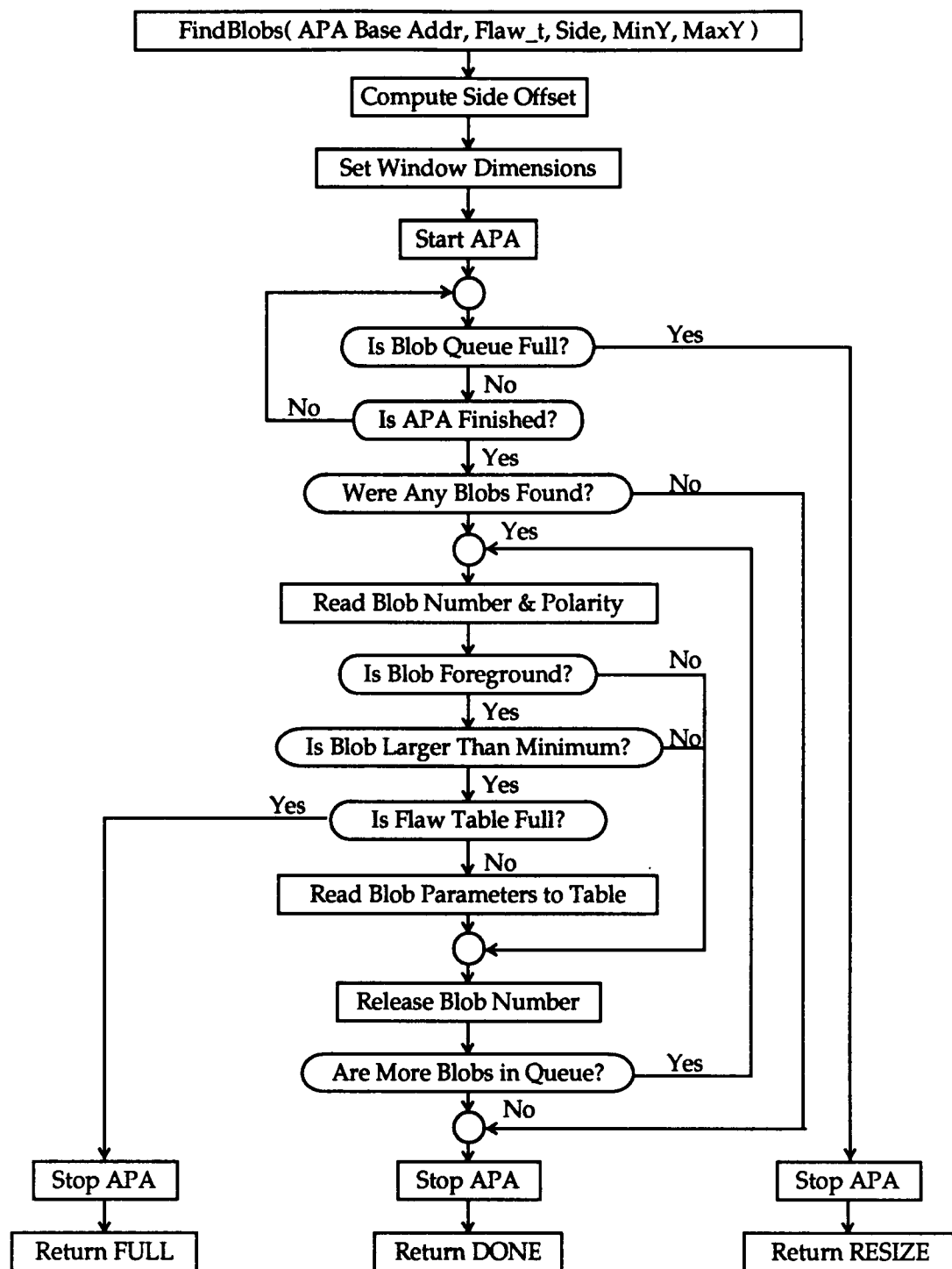


Figure B.17. FindBlobs Flowchart.

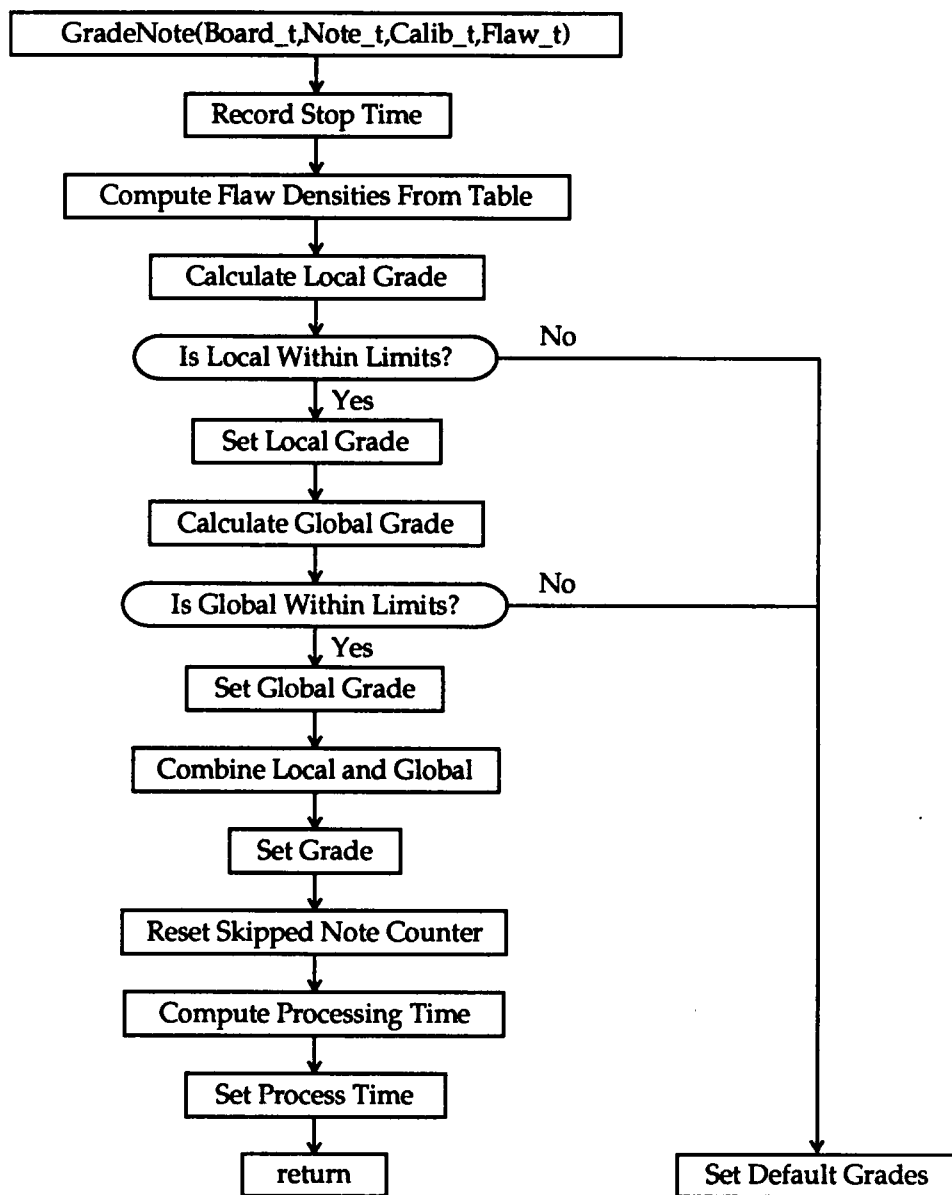


Figure B.18. GradeNote Flowchart.

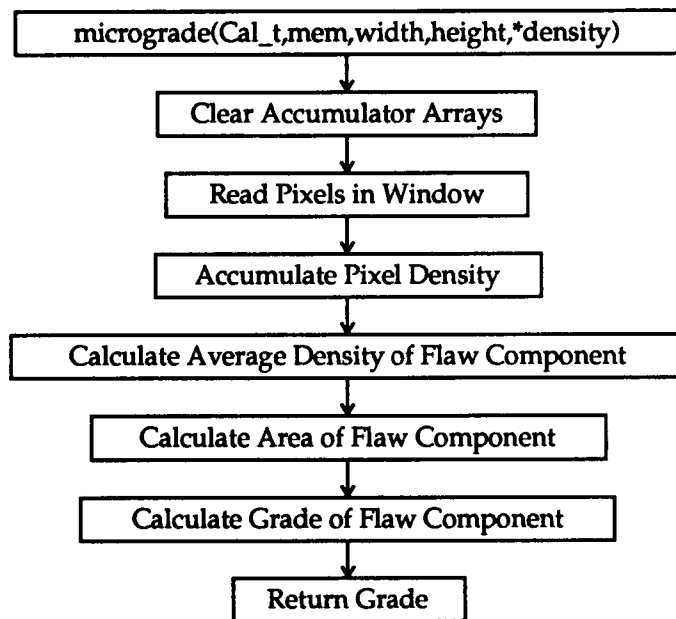


Figure B.19. Micrograde Flowchart.

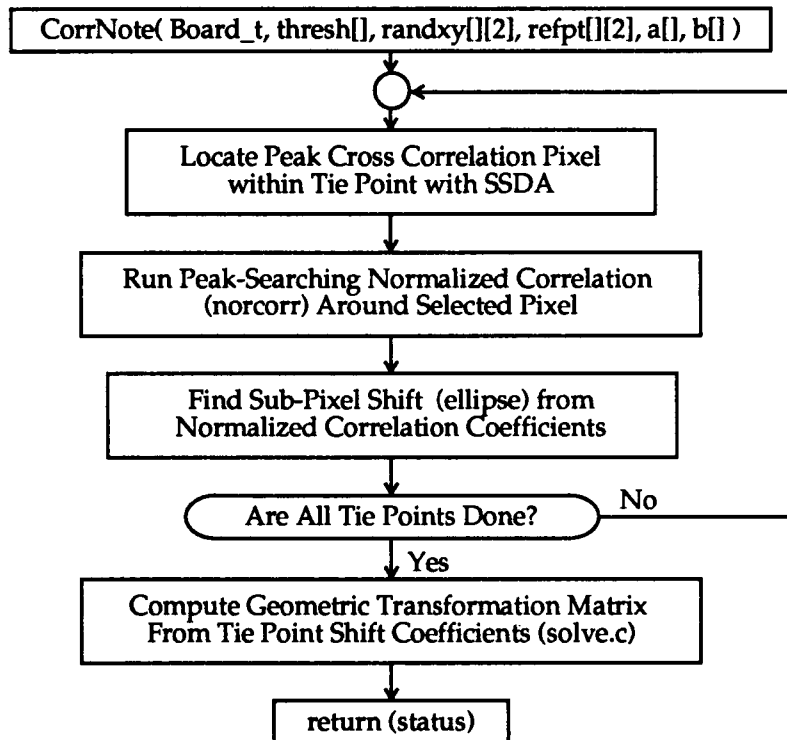


Figure B.20. CorrNote Flowchart.

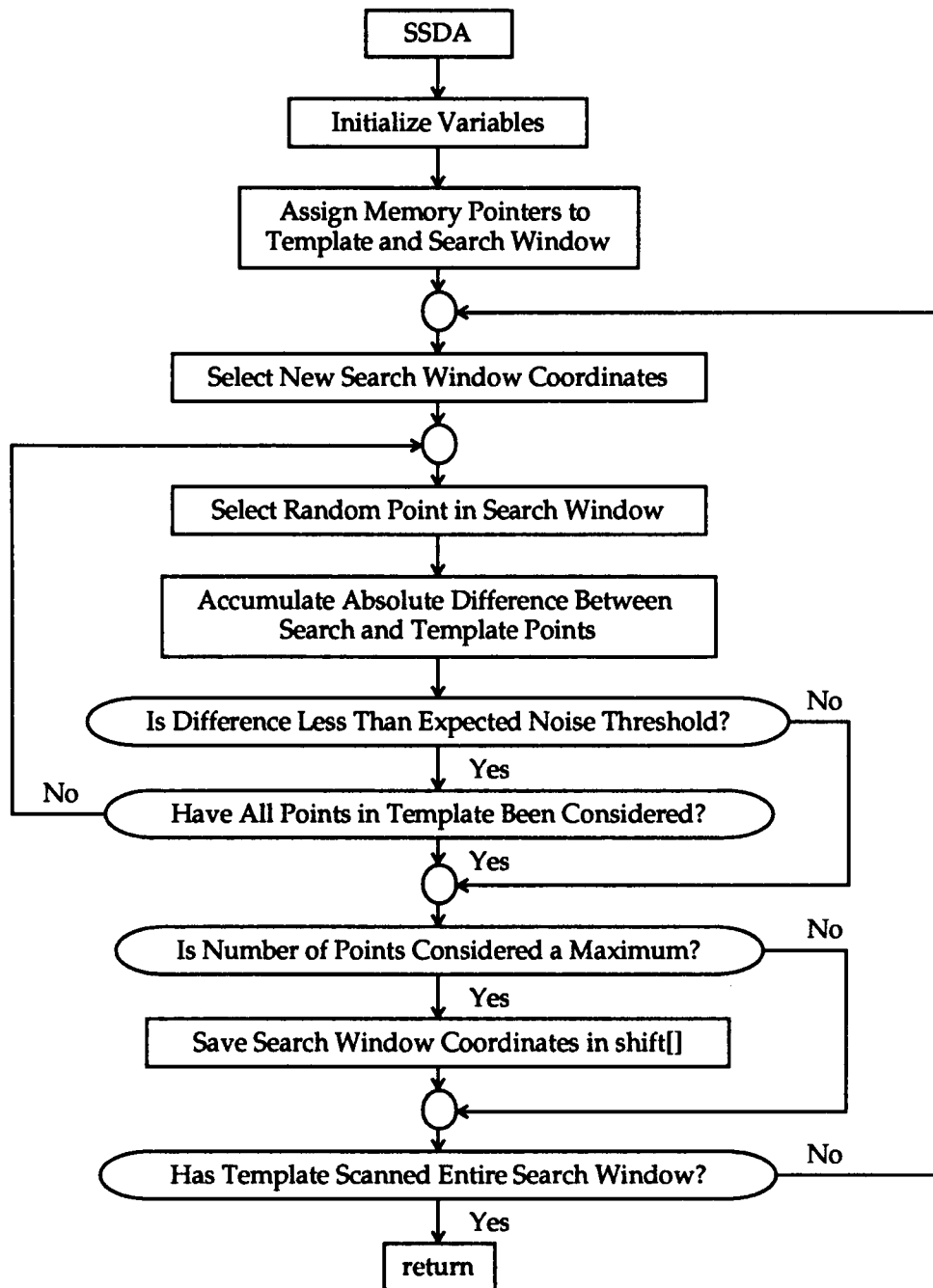


Figure B.21. SSDA Algorithm Flowchart.

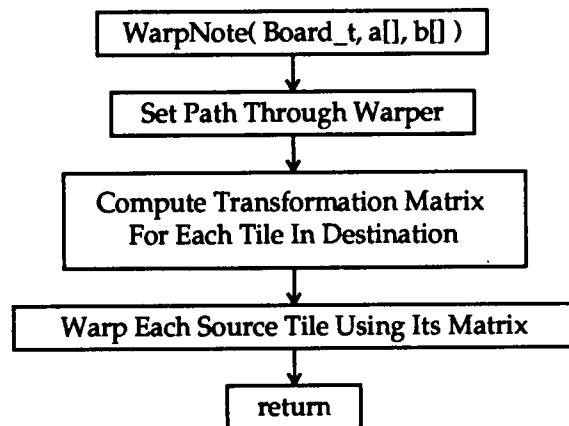


Figure B.22. WarpNote Flowchart.

APPENDIX C

Data Tables

Table C.1. Grayscale Reflectance.^a

Step		Measured Reflectance	
Density	Reflectance	Dark Field	Light Field
0.0	1.0	0.93	0.95
0.05	0.90	0.90	0.89
0.15	0.71	0.67	0.69
0.30	0.50	0.49	0.51
0.45	0.35	0.35	0.36
0.60	0.25	0.24	0.25
0.75	0.18	0.17	0.18
0.90	0.13	0.12	0.13
1.05	0.09	0.09	0.10
1.20	0.06	0.06	0.07
Mean Error:		-0.015	-0.004
Standard Deviation:		0.023	0.019
Δ Dark-Light Mean Shift:		0.011	
Standard Deviation:		0.009	

^a Grayscale is measured using Kodak R-9 Photographic Reflectance Scale. Scene illumination = 215 footcandles. Lens aperture = f/5.6. Dark field background reflectance = 0.05, light field background reflectance = 0.89.

Table C.2. Intensity Normalization in 100% Image Irradiance.^a

Actual Reflectance	Measured Reflectance		Reflectance Error
	Unnormalized	Normalized	
1.0	0.92	0.96	-0.04
0.90	0.85	0.89	-0.01
0.71	0.66	0.69	-0.02
0.50	0.48	0.51	0.01
0.35	0.34	0.36	0.01
0.25	0.24	0.25	0.00
0.18	0.17	0.18	0.00
0.13	0.12	0.13	0.00
0.09	0.09	0.09	0.00
0.06	0.06	0.07	0.01
Mean Error:	-0.004		
Standard Deviation	0.016		

^a Comparison of grayscale reflectance using Kodak R-9 Photographic Reflectance Scale. Scene Illumination = 215 footcandles. Lens Aperture = f/5.6. White Field Background R = 0.89.

Table C.3. Intensity Normalization in 50% Image Irradiance.^a

Actual Reflectance	Measured Reflectance		Reflectance Error
	Unnormalized	Normalized	
1.0	0.46	0.97	-0.03
0.90	0.42	0.89	-0.01
0.71	0.32	0.69	-0.02
0.50	0.23	0.49	-0.01
0.35	0.16	0.35	0.00
0.25	0.11	0.24	-0.01
0.18	0.07	0.17	-0.01
0.13	0.05	0.11	-0.02
0.09	0.03	0.08	-0.01
0.06	0.02	0.06	0.00
Mean Error:	-0.012		
Standard Deviation:	0.009		

^aComparison of grayscale reflectance using Kodak R-9 Photographic Reflectance Scale. Scene Illumination = 215 footcandles. Lens Aperture = f/8. White Field Background R = 0.89.

Table C.4. Intensity Normalization in 25% Image Irradiance.^a

Actual Reflectance	Measured Reflectance		Reflectance Error
	Unnormalized	Normalized	
1.0	0.20	0.96	-0.04
0.90	0.19	0.88	-0.02
0.71	0.14	0.66	-0.05
0.50	0.10	0.46	-0.04
0.35	0.06	0.31	-0.04
0.25	0.04	0.21	-0.04
0.18	0.03	0.13	-0.05
0.13	0.02	0.07	-0.06
0.09	0.01	0.03	-0.06
0.06	0.01	0.02	-0.04
Mean Error:	-0.044		
Standard Deviation:	0.012		

^aComparison of grayscale reflectance using Kodak R-9 Photographic Reflectance Scale. Scene Illumination = 215 footcandles. Lens Aperture = f/11. White Field Background R = 0.89.

Table C.5. Reflectance Variation Due to Intensity Normalization.^a

Reflectance	Standard Deviation Illumination Level		
	100%	50%	25%
1.0	0.009	0.015	0.030
0.90	0.010	0.016	0.027
0.71	0.008	0.013	0.034
0.50	0.008	0.014	0.024
0.35	0.008	0.011	0.030
0.25	0.007	0.014	0.022
0.18	0.007	0.011	0.029
0.13	0.005	0.011	0.045
0.09	0.005	0.012	0.026
0.06	0.007	0.013	0.009
Mean:	0.007	0.013	0.028

^aComparison of the spatial standard deviation of grayscale reflectance using Kodak R-9 Photographic Reflectance Scale. Scene Illumination = 215 footcandles. Lens Aperture = f/5.6. White Field Background R = 0.89. The standard deviation is calculated over the 16 x 16 pixel region.

Table C.6. Shot to Shot Reflectance Variation.^a

Shot	Reflectance			
	Unnormalized		Normalized	
	White	Black	White	Black
1	0.860	0.014	0.899	0.021
2	0.860	0.014	0.899	0.021
3	0.860	0.014	0.900	0.021
4	0.860	0.015	0.899	0.021
5	0.860	0.014	0.900	0.021
6	0.856	0.014	0.899	0.021
7	0.860	0.014	0.901	0.021
8	0.857	0.014	0.900	0.021
9	0.857	0.014	0.899	0.021
10	0.859	0.014	0.901	0.021
11	0.860	0.014	0.900	0.021
12	0.860	0.014	0.900	0.021
13	0.860	0.015	0.900	0.021
14	0.859	0.014	0.901	0.021
15	0.860	0.014	0.900	0.021
16	0.859	0.014	0.901	0.021
Mean	0.859	0.014	0.900	0.021
Standard Deviation:	0.0014	0.0003	0.0007	0.000

^a Variation in reflectance of nominal white and black references. Scene Illumination = 215 footcandles. Lens Aperture = f/11. White Field Background R = 0.89.

Table C.7. Correlation Measurement.

(Correlation Data From Note in Memory and Repeated Correlation on Static Image)

Tie Point					
0	1	2	3	4	5
X Axis					
0.011157	0.012645	0.034795	0.003821	0.033932	0.041620
Y Axis					
-0.001125	-0.018214	0.045503	0.062455	-0.010543	-0.033863

Table C.8. Correlation Measurement ($x = 0.0$ pixels, $y = 0.0$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.025607	0.015226	-0.006216	0.032422	-0.035637	0.033355
0.010546	0.013310	-0.004640	0.006200	-0.055418	0.020679
0.026079	0.012214	0.021612	0.018067	-0.033093	0.036471
0.036468	0.029481	0.017772	0.016705	-0.022996	0.034670
0.010551	-0.007231	-0.015724	0.001289	-0.058510	0.007197
Y Axis					
0.011267	0.071181	-0.004348	-0.071116	0.025262	-0.026388
-0.004712	0.044001	-0.015417	-0.085934	0.013522	-0.054902
-0.006192	0.035590	-0.032577	-0.096447	0.002415	-0.056027
-0.033427	0.027429	-0.033198	-0.113507	0.001441	-0.065255
-0.015915	0.045394	-0.028082	-0.106129	0.005989	-0.058045

^aCorrelation of 6 tie points in test image to reference image. Test image was translated $x = 0.0$ pixels; $y = 0.0$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.9. Correlation Measurement ($x = 0.0$ pixels, $y = 0.168$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.033036	0.054136	0.026933	0.045610	-0.002739	0.055124
0.042911	0.054588	0.044448	0.043679	0.008857	0.067415
0.011773	0.021661	0.002364	0.023140	-0.021890	0.057660
0.031943	0.045854	0.014172	0.033639	-0.011897	0.039666
0.012679	0.018434	-0.004267	0.025072	-0.042747	0.025018
Y Axis					
0.118280	0.189124	0.163915	0.110166	0.189247	0.084175
0.105617	0.178633	0.134614	0.079493	0.157641	0.065630
0.125116	0.170937	0.106969	0.085389	0.132468	0.065519
0.115654	0.176310	0.115662	0.109748	0.160410	0.054402
0.116393	0.181295	0.121633	0.101928	0.143524	0.058367

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.0$ pixels; $y = 0.168$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.10. Correlation Measurement ($x = 0.0$ pixels, $y = 0.336$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.048965	0.052201	0.031004	0.055496	-0.005048	0.072324
0.020583	0.057884	0.014404	0.036407	0.012126	0.067387
0.016209	0.033875	0.027799	0.056498	0.014320	0.052041
0.021808	0.031192	0.016028	0.038120	0.000016	0.040269
0.034092	0.052428	0.019472	0.042678	0.002025	0.059139
Y Axis					
0.229877	0.294086	0.301633	0.228979	0.304417	0.199486
0.241261	0.303989	0.304441	0.277041	0.302633	0.195296
0.248171	0.308954	0.305133	0.254770	0.348923	0.246679
0.226207	0.293029	0.279812	0.271680	0.293689	0.183695
0.225674	0.282536	0.276861	0.279690	0.305490	0.202588

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.0$ pixels; $y = 0.336$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.11. Correlation Measurement ($x = 0.0$ pixels, $y = 0.504$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.028606	0.038901	0.014250	0.035863	0.011977	0.061043
0.026974	0.032576	0.020322	0.049534	0.005109	0.082054
0.027507	0.046450	0.039532	0.036894	0.006961	0.085389
0.030801	0.026930	0.045786	0.054484	-0.012527	0.051549
0.019950	0.032203	0.028662	0.063233	-0.007716	0.064483
Y Axis					
0.481127	0.521330	0.551712	0.539105	0.518922	0.441160
0.506380	0.500000	0.562436	0.520083	0.512469	0.431159
0.469140	0.499871	0.547691	0.527564	0.527265	0.450327
0.444993	0.489264	0.535549	0.427941	0.525310	0.423306
0.476321	0.495815	0.546343	0.461849	0.523838	0.445800

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.0$ pixels; $y = 0.504$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.12. Correlation Measurement ($x = 0.168$ pixels, $y = 0.0$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.119551	0.085974	0.125690	0.153493	0.157573	0.108192
0.105931	0.083524	0.110220	0.125001	0.142733	0.091523
0.096857	0.093706	0.102589	0.133090	0.152679	0.108156
0.107707	0.085354	0.108332	0.115201	0.159095	0.102915
0.130284	0.090590	0.122295	0.125549	0.164119	0.105016
Y Axis					
-0.017624	0.071022	-0.006632	-0.095412	0.022959	-0.025793
-0.014626	0.056421	0.010358	-0.102667	0.025627	-0.031860
-0.032019	0.059966	-0.005422	-0.098720	-0.015567	-0.036225
-0.021305	0.056491	-0.029351	-0.122801	0.003292	-0.042925
-0.015301	0.061175	-0.003480	-0.095386	0.029028	-0.025658

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.168$ pixels; $y = 0.0$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.13. Correlation Measurement ($x = 0.336$ pixels, $y = 0.0$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.273639	0.241387	0.258629	0.274888	0.298332	0.246207
0.274736	0.227087	0.273258	0.265326	0.300594	0.230194
0.273540	0.235177	0.282650	0.281978	0.305311	0.244051
0.312346	0.255704	0.293491	0.278130	0.322994	0.263023
0.318149	0.251231	0.295467	0.287785	0.318880	0.268766
Y Axis					
-0.000864	0.051187	0.004409	-0.108216	0.027676	-0.031232
-0.032425	0.062879	0.009293	-0.118522	0.023301	-0.028568
-0.020713	0.048891	0.009404	-0.112708	0.017423	-0.047708
-0.023206	0.048270	-0.012129	-0.106607	0.022676	-0.023123
-0.012312	0.051708	0.008791	-0.113071	0.016270	-0.049367

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.336$ pixels; $y = 0.0$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.14. Correlation Measurement ($x = 0.504$ pixels, $y = 0.0$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.478085	0.375242	0.469155	0.477448	0.482061	0.420781
0.483527	0.390507	0.469230	0.471229	0.466058	0.420434
0.488615	0.395395	0.468856	0.469771	0.476534	0.420886
0.500000	0.417273	0.479960	0.469535	0.490459	0.436221
0.474444	0.400489	0.464832	0.469892	0.491594	0.425144
Y Axis					
	-0.033643	0.034506	-0.030117	-0.126949	0.013629
-0.044234					
-0.038586	0.040424	0.005928	-0.113361	0.009417	-0.033118
-0.052018	0.028790	0.000073	-0.139181	0.008017	-0.043428
-0.053780	0.036982	-0.005957	-0.130363	-0.012622	-0.056180
-0.044061	0.033448	-0.016362	-0.139803	-0.005064	-0.035124

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.504$ pixels; $y = 0.0$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.15. Correlation Measurement ($x = 0.168$ pixels, $y = 0.168$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.120609	0.104639	0.131625	0.117934	0.179671	0.136091
0.166680	0.148705	0.171815	0.150853	0.218326	0.193618
0.102393	0.146093	0.150339	0.123326	0.204509	0.152343
0.174877	0.169899	0.178532	0.159667	0.229170	0.183216
0.139650	0.142770	0.149625	0.128705	0.197796	0.168308
Y Axis					
0.112723	0.160539	0.116583	0.094680	0.153253	0.038305
0.126900	0.174310	0.125638	0.111308	0.161410	0.049677
0.110870	0.164695	0.142900	0.082669	0.151818	0.050408
.114846	0.167401	0.126650	0.102003	0.153464	0.034199
0.098799	0.161180	0.127665	0.094587	0.143801	0.028718

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.168$ pixels; $y = 0.168$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.16. Correlation Measurement ($x = 0.336$ pixels, $y = 0.336$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.301109	0.299277	0.303169	0.311045	0.366449	0.319464
0.291467	0.287712	0.298487	0.291362	0.360126	0.318978
0.273675	0.313470	0.348199	0.307425	0.383261	0.308164
0.297264	0.291421	0.325124	0.295961	0.379482	0.344528
0.320645	0.319879	0.337645	0.322561	0.412953	0.343297
Y Axis					
0.278444	0.311208	0.318727	0.274419	0.341234	0.244060
0.274074	0.292130	0.296802	0.256849	0.326683	0.195512
0.228409	0.298495	0.333840	0.255264	0.308981	0.219897
0.269015	0.295757	0.309747	0.278920	0.313076	0.211025
0.287755	0.304790	0.293479	0.265529	0.338895	0.215949

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.336$ pixels; $y = 0.336$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.17. Correlation Measurement ($x = 0.504$ pixels, $y = 0.504$ pixels).^a

Tie Point					
0	1	2	3	4	5
X Axis					
0.500000	0.479300	0.500000	0.500000	0.500000	0.500000
0.500000	0.500000	0.524990	0.500000	0.500000	0.500000
0.500000	0.482651	0.556198	0.500000	0.500000	0.500000
0.516884	0.500000	0.512699	0.500000	0.500000	0.500000
0.503603	0.500000	0.531355	0.500000	0.500000	0.500000
Y Axis					
0.497169	0.500000	0.500000	0.483533	0.500000	0.457143
0.462584	0.499203	0.500000	0.488407	0.500000	0.451358
0.500000	0.500000	0.500000	0.500000	0.500000	0.484352
0.500000	0.513481	0.500000	0.494207	0.500000	0.462246
0.500000	0.518440	0.500000	0.500000	0.500000	0.460357

^a Correlation of 6 tie points in test image to reference image. Test image was translated $x = 0.504$ pixels; $y = 0.504$ pixels. Values in table indicate the displacement measured by the sequential correlation program over 5 iterations. 1 pixel = 0.00598 in.

Table C.18. Effect of Noise Suppression Filter Without Registration.

Shift (mils)	Image Energy			
	$\epsilon_{\text{Uncorrected}}$	$\epsilon_{\text{Topology}}$	$\epsilon_{\text{Morphology}}$	$\epsilon_{\text{Thresholded}}$
0.0	0.0	0.0	0.0	0.0
1.7	0.0044	0.0017	0.0002	0.0001
3.4	0.0046	0.0017	0.0002	0.0001
5.0	0.0049	0.0018	0.0002	0.0001
6.7	0.0051	0.0018	0.0002	0.0001
8.4	0.0055	0.0020	0.0002	0.0001
10.0	0.0059	0.0021	0.0002	0.0001
11.7	0.0061	0.0022	0.0002	0.0001
13.4	0.0065	0.0024	0.0002	0.0001
15.0	0.0067	0.0025	0.0003	0.0001
16.7	0.0069	0.0027	0.0003	0.0002

Table C.19. Effect of Noise Suppression Filter With Registration.

Image	Image Energy			
	$\epsilon_{\text{Registered}}$	$\epsilon_{\text{Topology}}$	$\epsilon_{\text{Morphology}}$	$\epsilon_{\text{Thresholded}}$
1	0.0223	0.0098	0.0006	0.0003
2	0.0171	0.0075	0.0003	0.0001
3	0.0202	0.0079	0.0006	0.0003
4	0.0156	0.0071	0.0003	0.0002
5	0.0248	0.0117	0.0009	0.0005
6	0.0311	0.0124	0.0010	0.0006
7	0.0264	0.0119	0.0008	0.0006
8	0.0227	0.0110	0.0008	0.0005
9	0.0209	0.0119	0.0011	0.0008
10	0.0245	0.0126	0.0015	0.0010
11	0.0245	0.0126	0.0015	0.0010
12	0.0252	0.0154	0.0026	0.0021
13	0.0131	0.0057	0.0005	0.0003
14	0.0202	0.0073	0.0003	0.0002
15	0.0278	0.0097	0.0011	0.0002
16	0.0196	0.0065	0.0003	0.0001
17	0.0267	0.0069	0.0003	0.0001
Mean	0.0225	0.0099	0.0009	0.0005
%	1.0	0.44	0.04	0.0220

Table C.20. Area Measurement.^a

Actual $\sqrt{A}$	Avg # Pixels	Camera $\sqrt{A}$	Error
0.005	4.5	0.012	0.007
0.022	15.3	0.023	0.001
0.034	43	0.038	0.004
0.048	83	0.053	0.005
0.059	126.3	0.066	0.007
0.074	194.7	0.081	0.007
0.088	266	0.095	0.007
0.101	333.3	0.106	0.005
0.197	1231.7	0.205	0.008
0.313	2854.7	0.311	0.002
0.411	4905.7	0.408	0.003
0.506	7456.3	0.503	0.003
0.741	16411.3	0.747	0.006
0.992	28877.3	0.991	0.001
Mean Error:	0.003		
Standard Deviation:	0.004		

^a Area of a high-contrast square region is measured with the camera. Illumination = 215 fc.
Equivalent pixel size = 5.8 mil/pixel side.

Table C.21. Density Measurement.^a

Actual H	Camera H	Error
0.06	0.09	0.03
0.14	0.12	0.02
0.18	0.17	0.01
0.23	0.24	0.01
0.32	0.32	0.00
0.43	0.43	0.00
0.65	0.61	0.04
0.80	0.80	0.00
Mean Error:	0.005	
Standard Deviation:	0.021	

^a Density of a square, fixed-area, halftone overlay is measured with the camera. Illumination = 215 fc. Equivalent pixel size = 5.8 mil/pixel side. Overlay area = 19 x 19 mm.

Table C.22. Perceptual Comparison: Ink Spot on Open Substrate.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
II1	1.7	1.1	1.9	1.8
II2	1.5	0.9	2.1	2.0
II3	2.0	1.1	2.4	1.9
II4	1.8	1.1	2.7	2.0
II5	2.0	1.3	2.9	2.5
II6	2.3	1.3	2.6	1.6
II7	2.6	1.5	2.7	2.3
II8	2.4	1.5	3.2	2.6
II9	2.8	1.4	2.7	2.3
II10	3.2	1.3	2.9	2.9

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.23. Perceptual Comparison: Slywipe in Lathework.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ih1	1.5	1.0	2.1	1.6
Ih2	2.3	1.5	3.1	3.1
Ih3	2.4	1.5	2.4	1.8
Ih4	2.5	1.6	2.7	2.8
Ih5	2.7	1.5	3.1	2.4
Ih6	2.7	1.6	3.4	3.1
Ih7	3.3	1.5	3.8	1.8
Ih8	3.4	1.5	2.9	1.8
Ih9	3.7	1.3	2.9	2.8
Ih10	4.1	1.2	3.6	3.4
Ih11	4.4	1.0	4.2	3.7
Ih12	4.4	1.1	3.5	3.9

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.24. Perceptual Comparison: Slywipe in Portrait.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
li1	1.2	*b	*b	2.7
li2	1.5	1.1	2.5	1.7
li3	1.6	1.0	*b	2.0
li4	2.0	1.2	2.3	1.8
li5	1.7	1.2	2.5	2.3
li6	2.0	1.4	2.4	2.3
li7	1.7	1.2	*b	2.8
li11	2.8	1.6	3.2	2.3
li12	3.6	1.5	3.0	3.6
li13	3.4	1.6	3.3	1.1
li14	4.3	1.0	3.6	3.7
li16	4.3	0.8	3.6	3.1

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

^b * Denotes exemplar not included in derivation of flaw model.

Table C.25. Perceptual Comparison: Break.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Eb1	1.5	1.0	1.8	1.5
Eb2	1.5	0.9	2.0	1.6
Eb3	2.5	1.5	2.7	1.9
Eb4	3.0	1.7	2.9	2.0
Eb5	4.4	1.3	4.1	2.5
Eb6	4.3	1.3	3.4	2.6
Eb8	4.7	0.8	3.9	4.7

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.26. Perceptual Comparison: Portrait Coat Break.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ha1	2.2	1.3	2.4	1.9
Ha2	2.2	1.3	1.9	0.0
Ha3	2.5	1.4	2.0	2.2
Ha4	2.6	1.4	2.4	2.0
Ha5	2.8	1.6	3.1	2.1
Ha6	2.7	1.6	2.6	2.4
Ha7	2.8	1.5	3.1	2.6
Ha8	3.0	1.6	*b	2.6
Ha9	3.4	1.5	2.7	2.8
Ha10	3.2	1.5	3.0	2.8
Ha11	3.3	1.6	3.2	2.7
Ha12	3.7	1.4	2.9	4.2
Ha13	4.1	1.3	3.8	4.3
Ha14	4.5	1.0	3.6	4.5
Ha15	4.7	0.9	4.2	5.4

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

^b * Denotes exemplar not included in derivation of flaw model.

Table C.27. Perceptual Comparison: Portrait Background Break.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ga1	2.0	1.2	2.6	2.3
Ga2	2.9	1.6	3.2	3.4
Ga3	2.6	1.6	3.4	2.9
Ga6	3.3	1.5	3.2	2.8
Ga7	3.5	1.6	3.4	3.0
Ga9	4.1	1.2	3.8	3.3
Ga10	4.0	1.4	3.5	3.3
Ga11	4.4	1.1	3.9	3.9
Ga13	4.5	1.1	4.2	4.3

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.28. Perceptual Comparison: Lower Right Cracked Chrome.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Im1	1.4	*b	*b	1.4
Im2	1.6	1.2	*b	1.4
Im3	1.5	1.1	*b	1.1
Im4	2.9	1.5	2.6	1.5

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

^b * Denotes exemplar not included in derivation of flaw model.

Table C.29. Perceptual Comparison: Chip.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Fa1	2.4	1.5	2.5	2.2
Fa2	2.8	1.6	3.0	2.5
Fa4	3.4	1.5	3.2	2.6
Fa5	2.7	1.5	2.7	2.2

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.30. Perceptual Comparison: Slywipe Smear.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ij1	2.6	1.3	2.3	2.1
Ij2	3.2	1.5	2.4	2.1
Ij3	3.9	1.2	3.5	2.8
Ij4	4.5	0.7	4.1	3.6
Ij5	4.7	0.6	3.9	2.9
Ij6	4.7	0.6	4.3	3.8

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.31. Perceptual Comparison: Portrait Background Slywipe Streak.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Io1	2.5	1.5	*b	3.0
Io2	3.1	1.5	2.9	0.0
Io3	3.5	1.4	2.9	0.0
Io4	3.6	1.6	3.8	0.0
Io5	3.8	1.3	4.5	2.3
Io6	3.9	1.4	4.0	3.3

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

^b * Denotes exemplar not included in derivation of flaw model.

Table C.32. Perceptual Comparison: Stain.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ip1	4.0	1.4	4.2	3.2
Ip3	4.4	1.1	*b	2.4
Ip4	4.2	1.1	3.6	3.3

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

^b * Denotes exemplar not included in derivation of flaw model.

Table C.33. Perceptual Comparison: Substrate Flooding.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ik1	3.1	1.4	3.5	2.4
Ik2	3.0	1.4	3.1	1.9
Ik3	3.7	1.4	3.1	2.8
Ik4	3.6	1.3	3.1	2.7
Ik5	4.2	1.3	3.8	3.1
Ik6	4.2	1.0	3.6	3.5
Ik7	4.4	0.9	3.4	3.0

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.34. Perceptual Comparison: Right Side Ball-up Mark.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
In1	2.4	1.5	2.4	1.7
In2	2.7	1.6	2.7	1.8
In3	3.3	1.5	2.9	2.2
In4	4.2	1.1	4.0	3.0

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.35. Perceptual Comparison: Light Print.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Ba6	1.5	0.9	1.8	1.5
Ba13	4.0	1.4	3.6	3.2

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

Table C.36. Perceptual Comparison: Mash.^a

Note	F_{obs}	σ_{Fobs}	F_{model}	F_{meas}
Aa1	2.7	1.5	*b	2.1
Aa2	2.9	1.3	*b	2.2
Aa3	2.8	1.2	*b	1.9
Aa4	4.4	1.0	*b	4.5

^a F_{obs} is the grade obtained from human observers participating in the ORNL flaw severity survey. σ_{Fobs} is the standard deviation among the 31 judges. F_{model} is the grade calculated with the flaw severity model in Eq. (3.1) from visually estimated parameters. F_{meas} is the grade determined with the automated inspection system. Notes are categorized by flaw types as delineating by the note identification number.

^b * Denotes exemplar not included in derivation of flaw model.

VITA

William Bruce Jatko was born in Selma, Alabama on September 19, 1949. After graduating from A. G. Parrish High School in 1967, he received an Associate Degree in Electronic Servicing from W. R. King State Technical School in 1969.

In 1970, he began working as a broadcast technician at WTVK television in Knoxville, Tennessee. He became chief engineer for a commercial teleproduction studio, in 1976. In 1978, he enrolled at the University of Tennessee while continuing his full-time position. In 1982, he received the B.S. degree in Electrical Engineering and accepted a position as development engineer at the Oak Ridge National Laboratory. While an undergraduate, he was nominated to Phi Eta Sigma, Eta Kappa Nu, Tau Beta Pi, Phi Kappa Phi and Golden Key honor societies.

He began graduate school in Electrical Engineering at the University of Tennessee that same year on a part-time basis. He received the MSEE degree in 1985 and was accepted into the doctoral program, also in Electrical Engineering.

He is presently employed in the Instrumentation and Controls Division at the Oak Ridge National Laboratory. His areas of interest include video instrumentation, automated inspection, and image analysis.

He is married to the former Beverly Porter of Spring City, Tennessee. They have a daughter, Stacey, and a son, Brandon.