DEVELOPMENT OF LARGE ARRAY AUTO WRITE-SCAN PHOTORESIST FABRICATION AND INSPECTION SYSTEM

by

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TABLE OF CONTENTS

LIST OF FIGURES ............................................................................................................ 8
LIST OF TABLES ............................................................................................................. 10
ABSTRACT ....................................................................................................................... 11
CHAPTER 1 – INTRODUCTION .................................................................................... 12
  1.1 A Starting Point ...................................................................................................... 12
  1.2 Maskless Lithography Tool ................................................................................... 14
  1.3 Automatic Inspection ............................................................................................ 15
  1.4 Thesis Statement ................................................................................................... 18
  1.5 Structure ................................................................................................................ 19
CHAPTER 2 – BACKGROUND ..................................................................................... 20
  2.1 Organization ......................................................................................................... 20
  2.2 Problems and Solutions ....................................................................................... 20
  2.3 Laser Scanning Microscopy ................................................................................... 24
  2.4 Automated Inspection Systems ............................................................................. 26
  2.5 Critical Concepts .................................................................................................. 27
  2.6 Review of Prior Literature for Experimental Design ............................................. 32
  2.7 Review of Image Registration Techniques ............................................................ 37
  2.8 Definition of Terms from Decision Theory ........................................................... 38
CHAPTER 3 – PRESENT STUDY ............................................................................... 40
  3.1 Thesis Statement ................................................................................................... 40
  3.2 Organization .......................................................................................................... 40
  3.3 Fabrication ............................................................................................................. 40
  3.4 Sensing Optical System Development ................................................................ 47
  3.5 LSMDD ................................................................................................................... 53
  3.6 Phase Contrast Imaging Experimental Setup ....................................................... 60
  3.7 Latent Imaging Experimental Setup ...................................................................... 64
  3.8 Optical Profiler and SEM ..................................................................................... 66
  3.9 Image Registration Routine Development ............................................................ 67
  3.10 Image Processing Routine .................................................................................. 70
CHAPTER 4 – EXPERIMENTS AND RESULTS ......................................................... 73
  4.1 Organization .......................................................................................................... 73
  4.2 Figures of Merit ..................................................................................................... 73
  4.3 Central Aperture Detection .................................................................................... 73
  4.4 Phase Contrast Edge Detection and Latent Imaging ............................................. 89
  4.5 Additional Research: Deconvolution Filtering ....................................................... 99
CHAPTER 5 – CONCLUSIONS ................................................................................. 106
  5.1 Thesis Re-Statement .............................................................................................. 106
  5.2 Results ................................................................................................................... 106
  5.3 Conclusions .......................................................................................................... 107
  5.4 Future Work .......................................................................................................... 108
  5.5 Final Remarks ....................................................................................................... 110
APPENDIX-A: JOURNAL ARTICLE ............................................................................. 111
APPENDIX-B: SUPPLEMENTAL TOPICS ................................................................. 135
B.1 MLT Description ....................................................................................... 135
B.2 OEDS Development ................................................................................. 136
B.3 Additional LSMDD Information ............................................................... 138
   B.3.1 LSMDD System Requirements .......................................................... 138
   B.3.2 Fault-Indicator Algorithms ............................................................... 140
B.4 Other Topics ............................................................................................. 143
   B.4.1 OptiScan Simulations ....................................................................... 143
   B.4.2 Additional Information: Machine Vision ........................................... 152
REFERENCES ................................................................................................... 154
LIST OF FIGURES

Figure 1.1 Typical PR Layering Process [4]. 13
Figure 1.2 Flow Chart for MLT Operation [1, 6]. 14
Figure 1.3 (a) Binary image of a tablet showing defects [9]. 17
Figure 1.3 (b) Illumination Design for Tablet Inspection [9]. 18
Figure 2.1 Diagram of an X-Ray Microscope [16]. 22
Figure 2.2 Diagram of CD-SEM [18]. 23
Figure 2.3 Example of LSM Instrumentation Setup [22]. 25
Figure 2.4 Example of Central Aperture Detection [23-24]. 28
Figure 2.5 Edge detection of an image using a Prewitt filter [26]. 29
Figure 2.6 Example of Phase Contrast Edge Detection [25, 27]. 29
Figure 2.7 Raw (Latent) Image vs. Developed Image [29]. 30
Figure 2.8 (a) gray scale image (b) 3D latent image using a PTM [30]. 31
Figure 2.9 Example of Latent Imaging Setup [28, 30]. 31
Figure 2.10 Annular Illumination with High NA Objective [31]. 33
Figure 2.11 Writing Diffraction Grating [32]. 35
Figure 2.12 Fiber-Optics Laser Scanning System [33]. 36
Figure 2.13 Example of ROC Curve. 39
Figure 3.1 First Printed Pattern. 41
Figure 3.2 Second Printed Pattern. 42
Figure 3.3 Third Printed Patterns. 42
Figure 3.4 Fourth Printed Patterns. 43
Figure 3.5 Fifth Printed Patterns. 43
Figure 3.6 Final Printed Pattern for Quantifying Results. 44
Figure 3.7 Pattern Fabrication Process. 45
Figure 3.8 Alignment Camera. 46
Figure 3.9 MLT Spot Scanning. 48
Figure 3.10 Beamsplitter and Mount. 49
Figure 3.11 Detector. 50
Figure 3.12 Sine Wave on Oscilloscope. 51
Figure 3.13 Diagram of OEDS Version 2 [1]. 53
Figure 3.14 Main Panel Display of LSMDD. 54
Figure 3.15 Scope Settings Dialog Box. 58
Figure 3.16 Bi-cell detector used in telecommunications [47]. 61
Figure 3.17 Proposed Setup for Phase Contrast Imaging Experiment. 62
Figure 3.18 Circuit used for phase contrast edge detection experiment. 63
Figure 3.19 Combination of exposures to form a pattern w/o development [50]. 65
Figure 3.20 First and second exposures on pattern [50]. 65
Figure 3.21 Alternative Optical Inspection. 67
Figure 3.22 Example of MATLAB Control Point Selection Tool [51]. 68
Figure 3.23 Pattern Comparison. 69
Figure 3.24 Image Processing Routine. 71
LIST OF TABLES

Table 3.5.1 Scope Settings. 55
Table 3.5.2 Colormap Options. 57
Table 3.5.3 Scope Settings. 58
Table 3.5.4 Image Buffer System Starting Parameters. 59
Table 3.5.5 Additional MLT Starting Parameters. 60
Table 3.9.1 Binary vs. Quantized Image Values 69
Table 4.3.1 Discriminability Values for ROC Curves, 1st Level [1]. 87
Table 4.4.1: Discriminability Values for ROC Curves, 1st Level. 96
Table 4.5.1 Discriminability Values for ROC Curves, 2nd Level. 103
Table 4.5.2: Discriminability Values for ROC Curves, 2nd Level. 105
Table B.3.1 Data Acquisition Requirements. 139
Table B.3.2 PC Requirements. 140
Table B.3.3 Software Requirements. 140
ABSTRACT

Current metrology methods involve technicians viewing through a microscope, increasing the time, cost, and error rate in inspection. Developing an automated inspection system eliminates these difficulties. Shown in this work is a laser scanning microscope (LSM) design for an opto-electronic detection system (OEDS), based upon the concept that intensity differences related to pattern defects can be obtained from reflections off fused silica samples coated with photoresist (PR) or Aluminum. Development of this system for data collection and processing is discussed. Results show that 2.1 μm resolution of these defects is obtainable. Preliminary results for larger-array patterns through stitching processes are also shown.

The second part of this work uses the concept of phase contrast edge detection. Looking at non-metallized patterns, one can use the property that phase changes induced by a refractive-index sensitive material can be seen with a multi-cell array, rendering the image visible by comparing the respective phases. A variety of defects and samples are shown. Extrapolating results to larger arrays is also discussed. Latent imaging, or imaging without development, is also evaluated. Future work in the areas of system commercialization, sample storage, and other mass-printing techniques are discussed.
CHAPTER 1 – INTRODUCTION

1.1 A Starting Point

Modern practices of optical metrology, in particular those of small-feature patterning and inspecting, typically involve the use of human viewing through a microscope [1]. As one can imagine, reliability of the observations are subject to operator fatigue and judgment errors. Moreover, as feature sizes decrease, and subsequently part sizes increase, both the time and cost in the inspection task in this work increase exponentially [2].

In particular interest is the patterning and inspection of photoresist (PR) features over a large area. As shown in Fig. 1.1, a substrate (i.e. fused silica) is coated with a thin layer of metal, followed by a layer of PR. Illumination of the exposure wavelength alters the chemistry of the PR. Liquid developer dissolves the exposed portions of the resist, leaving bare metal on top of the substrate. A solution specific to the metal is then applied to the sample, which etches the area of the metal coating not covered by PR, leaving a bare substrate in the exposed regions. Finally, residual PR is dissolved through submersion in a solvent [3].
Numerous stages in the photoresist etching process lead to many opportunities for defects. This fact is especially true for large-format arrays (i.e. 1 m class and above), since these parts are currently inspected by technicians through smaller microscopes, and as a result, errors in inspection are very likely to occur. Defects can be as small as 1 μm and lower, where the number of resolution elements on a single 1 m diameter part is over 700,000. Many of the mistakes are attributed to visual acuity, age, and the training level for the technician [5].
1.2 Maskless Lithography Tool

Much of the work done here involves the use of the University of Arizona’s Maskless Lithography Tool (MLT). The MLT consists of eight system blocks, shown in Fig. 1.2 [1, 6].

To begin, an Argon Ion laser beam (1) is sent through a series of reflection mirrors into a closed-loop laser beam stabilization servo system (2). This system compensates any beam drift present. To control the laser beam for binary patterning (i.e. on and off), there is a modulation sub-system (3). This modulation system can also serve to vary the power for grayscale (i.e. 0 to 255) patterning, if desired. The scanning system (4) uses an air-bearing rotating multi-faceted (12-sided) polygon to sweep the beam.
across the flat sample in one direction (fast scan direction) in such a manner that for every complete rotation of the polygon, the sample is transported in an orthogonal direction (slow scan direction) (5). The laser power servo system (8) uses a power detector to sample laser power at the writing plane. It also compares the generated signal from the detector with the set signal in the acousto-optic modulator (AOM) to obtain constant laser power at the start of each scan line. The input pattern (in bitmap format) is delivered from a graphical user interface (GUI) to software (7) that controls the input of the AOM. Position control electronics (6) accurately indicate pattern location to allow overwriting and stitching.

1.3 Automatic Inspection

While the human observer inspection technique is in use today, it is very expensive and time consuming for large-format arrays. An automated fabrication inspection system can significantly reduce inspection time at an acceptable reliability, where inspection time is defined as the time required by a human observer to inspect 1 m class parts with 5 μm features, with acceptable reliability defined as the threshold at which an inspection system detects a minimum percentage of the total defects present.

Unlike human-based inspection systems, automated inspection systems offer several advantages: reduced inspection time, improved reliability, and technicians are freed from the dull labor of inspecting sample after sample, which can be very psychologically demanding [7]. Labor costs can be reduced, and the quality of the end-
product is improved. Moreover, the production environment is cleaner. Finally, an automated system is much easier to use for precise assembly.

Automated inspection systems have been in existence since the early 1980s [8]. Some of the earliest applications involved inspection of printed circuit boards. Defect features have included short or open circuits, over and under-etching, pad size violations, variations in the quality of the metal, and other examples [8]. Automated inspection systems operate using the following process [9]. Light source illuminates an object and its information. Whether from reflection, transmission, or combination thereof, that information is sent to an imaging sensor. The information is then digitized, and sent through a series of image processing logical routines to identify desired characteristics of the object (i.e. critical dimensions, defects, reflectivity, etc.). That output is sent to a computer for further analysis and display. A transporting mechanism holds the object, and a feedback mechanism from the computer allows for a specific scan pattern.

This process of automatic inspection can be done with a wide variety of techniques, including differential scanning, in which adjacent patterns are compared; optical spatial filtering, which uses Fourier techniques; reference comparison, in which a binary image is generated to highlight the defects between an ideal reference and a test sample; or design-rule verification, in which distances to specific features on the object are measured [8]. Other parts can be inspected as well, including solder joints, integrated circuits and qualities of surfaces.

Visual inspection is very important in industrial manufacturing processes, and has a wide variety of applications that impact people every day. An example is the visual
inspection of pharmaceutical tablets [9]. Using a simple illumination design with logical operators, one can determine if a particular tablet meets the necessary specifications. Examples of this task from the literature are shown in Figs. 1.3 (a) and (b).

Figure 1.3 (a) Binary image of a tablet showing defects [9].
In Fig. 1.3 (b), the object in question is a contact switch sealed in glass, and any asymmetries and cracks in the seal must be found [9]. A diffused back illumination system helps detect these asymmetries, and the light source itself serves the same function for the cracks present.

1.4 Thesis Statement

The availability of the MLT and its flexibility to incorporate additional optical components presents a unique opportunity to combine the laser writer instrument with an inspection tool. To the author’s knowledge, this combination has not been previously
discussed in the literature. The goal of this dissertation is to demonstrate the development and operation of a direct read-write-detect optical inspection engineering model for large-format arrays. The detection task is based on realistic array patterns. A single instrument is used to write the pattern in PR, and then detect the pattern for defects, where inspection speed and reliability are quantified.

1.5 Structure

This dissertation is organized in as follows. Chapter 2 discusses the background of direct read-write-detect systems, both in terms of a chronological development, as well as the physical principles that lay the foundation for them. Chapter 3 presents the current status of these systems. It also describes the aforementioned designed system, both in terms of its components and operation. Chapter 4 explains the experiments conducted to test the system and illustrates their results. Chapter 5 provides concluding remarks. The journal article related to this dissertation is shown in Appendix A, with supplemental topics discussed in Appendix B.
CHAPTER 2 – BACKGROUND

2.1 Organization

In order to have a clear understanding of the basis of this research, it is necessary to explain the experimental and mathematical background.

This chapter is organized as follows. It begins with a look at other techniques that have been used for imaging defects, and why the proposed system is better. Next, prior literature regarding laser scanning microscopes and automated visual inspection systems is discussed. Lithographic applications and image registration techniques are defined and explained. Finally, decision theory characteristics are discussed. Mathematical descriptions of theory where needed will be illustrated in parallel.

2.2 Problems and Solutions

In previous work, techniques that have been used to accomplish the goals of this work include the use of atomic force microscopes (AFMs), scanning electron microscopes (SEMs), transmission electron microscopes (TEMs), X-ray microscopes (XRM), and critical dimension scanning electron microscopes (CD-SEMs).

For AFMs, cantilevers are used to scan the surface. When the cantilevers reach a very close proximity to an object’s surface, the electrostatic forces between those two objects, primarily Van der Walls forces and electrostatic charging, cause the cantilever to shift. This process operates in accordance of Hooke’s Law. Differing applications can lead to two modes of operation: contact mode and non-contact mode [10].
SEMs work slightly differently, with electrons thermionically emitting from an electron gun, hitting the sample. As a result, the electrons lose energy in process [11]. The reflected energy from these reactions can be captured on a detector in the form of secondary electrons.

TEMs transmit light instead of scattering it through the sample. The transmission causes an image to form from the interactions of the electrons with the sample itself [12-13]. TEMs form their images by using information contained in the electromagnetic waves emanating from the sample. What is seen as an image from a TEM is the observed intensity of the image, which is the approximate time-average amplitude of a corresponding electron wavefunction. The intensity is given by the following equation:

\[
I(x) = \frac{k}{t_1 - t_0} \int_{t_0}^{t_1} \Psi \Psi^* dt
\]

(Eq. 2.1 [14])

where \( I(x) \) is the image, \( t_1 \) and \( t_0 \) are the beginning and ending times of the wavefront, respectively, and \( \Psi \) and \( \Psi^* \) are the wavefront and complex conjugate, respectively [14].

Soft X-rays can also be used. The major difference between X-Rays and SEMs and TEMs are the wavelengths used in image formation. XRM's use a wavelength band of 2.3 to 4.4 nm [15]. An example from the literature is shown in Fig. 2.1.
Finally, CD-SEMs perform similarly to SEMs, but have an added optical proximity correction, making them much more accurate [17]. A sample CD-SEM is shown in Fig. 2.2.
Each of these techniques present problems with the research performed in this dissertation. AFMs present challenges in that their resolution is limited by the size of the cantilever tips, inducing additional artifacts that need to be avoided [10]. Moreover, AFM scanning speeds are lower compared to other techniques, often taking minutes to complete what would otherwise be a real-time scan.

SEMs use a very narrow beam, which can increase the depth of field, showing otherwise unimportant features and creating confusion for the user [11]. Furthermore, SEMs also have the property of large vacuum chambers, which are not designed to
handle large-scaled samples, making the microscopes very expensive. Finally, SEMs are not designed to handle dielectric surfaces.

TEMs require extensive sample preparation, and can also limit the field of view (FOV) of the sample [12]. Moreover, TEMs also suffer from the same vacuum system problems and expense of their SEM counterparts. X-ray microscopes often display diffraction patterns, which can again reduce resolution while increasing the number of image artifacts [16]. Finally, CD-SEMs have similar issues to SEMs, including possible calibration with an AFM [17].

It should be stated that optical detection techniques could also have been used [19]. However, a system that can do all of the following is desired. First, the system needs to be able to write and inspect patterns on demand. Second, the system should require minimal sample preparation, including the use of a vacuum. The system must also be non-destructive, easy to use, and fast. For these reasons, a laser scanning microscope (LSM) approach has been selected.

### 2.3 Laser Scanning Microscopy

For many years, the technique of laser scanning microscopy has been used for a variety of applications, including material characterization and thermal measurements [20-21]. Unlike a scanning optical microscope, a laser scanning microscope produces an electrical signal, which is not restricted to visible light, and thus avails itself to a wider range of possible experimental techniques [20].
An example of an instrumental setup for LSM from the literature is shown in Fig. 2.3. Light from a gas laser is modulated, usually through an (AOM), which shapes the beam and allows it to be scanned across the sample [20]. Any reflected light is collected off the target sample into a detector as an electrical signal (i.e. voltage or current measurements). For further analysis signals are recorded simultaneously with the scan line and are recorded in an image buffer. Prior work has shown that for smaller samples, resolutions of 2 μm and better are indeed possible.

As discussed earlier, the system desired for this dissertation needs to do several things, including writing and inspecting patterns on demand, minimal sample preparation,
being vacuumless, non-destructive, easy to use, and fast. Each of these criteria is satisfied through the use of an LSM [1].

### 2.4 Automated Inspection Systems

Important to this work is the concept of automated visual inspection systems. As discussed in the previous chapter, automated systems offer the advantages of freeing technicians from dull labor, reducing labor costs, increasing the inspection speed, and resulting in an overall higher quality product [7]. Here, several types of automated inspection systems are discussed, as well as why one approach is selected. The processes of differential scanning, optical spatial filtering, reference comparison, and design-rule verification each have advantages and disadvantages, and are discussed here.

In differential scanning, a visual inspection system will take a sample, usually a printed circuit board, and scan that sample against an adjacent pattern [8]. This process works by using the periodic property of the photomask that made the pattern, and noticing differences between patterns next to one another. Differential scanning has the advantage that it is an easy approach to understand and implement. However, the technique lends itself to printing the same pattern numerous times, which might work well for a large firm (i.e. Intel™, AMD™), but for custom patterning is a significant drawback.

In optical spatial filtering, a lens is placed in the system, so that one can view the Fourier transform at the back focal plane [8]. This concept is very important, as filters can then be placed at the focal plane, changing the spectrum of the inputted pattern. If
any defects or deviations from the ideal pattern are present, those defects will appear as amplitude and phase differences in the transformed pattern. While very accurate for larger defects, optical spatial filtering inhibits the visualization of smaller defects.

Design-rule verification consists of any inspection that is restricted to checking the distances between known objects on the pattern, and making sure they meet some pre-defined tolerance [8]. As can be surmised, precisely aligning the pattern to a testing platform is not required, but larger defects can be missed. Moreover, if any of the features is distorted, the technique is practically unusable.

Finally, with a reference comparison, any sample to be inspected is scanned, with the resulting image compared to that of an ideal pattern [8]. Any differences between the images correspond to defects in the sample pattern. Features that are often used in this technique include pads, wiring tracings and annular rings, each exhibiting a wide variety of characteristics in the patterning process. Though an easier and faster technique to implement, reference comparisons often require large storage of data, and are sensitive to illumination conditions.

The reference comparison approach mostly closely matches the rubric created using the LSM design, and with the data storage system that will be discussed in the next chapter, the major drawbacks are significantly mitigated.

2.5 Critical Concepts

Before discussing the prior literature that has helped in the experimental designs, it would be useful to discuss the three important concepts that will form the basis for the
experiments in this work. These concepts include central aperture detection, phase contrast edge detection, and latent imaging.

Central aperture detection, or CAD, was first developed in the 1970s as a way of measuring the effectiveness and operation of video disks [23]. Specifically, CAD was originally used as a way to measure signal current coming into a detector from a coherent source (i.e. laser), where the uninterrupted beam was just large enough to fill the entire detector (i.e. photodiode). When half a wavelength covers half the beam area, the maximum efficiency of the technique is achieved. Today, CAD is widely used in optical data storage and telecommunications as a way of measuring the modulation transfer function and the image quality of those systems [24]. An example of a setup using CAD is shown in Fig. 2.4.

![Central Aperture Detection Diagram](image)

**Figure 2.4 Example of Central Aperture Detection [23-24].**

Phase contrast edge detection has its roots in edge detection itself, where areas of an image have a high gradient (or a large change in intensity over a small distance) [25].
These changes can be caused by a variety of phenomena, including surface orientation, depth, materials, and illumination of the scene. An example is shown in Fig. 2.5.

When one introduces a “phase congruency” component, or a restriction that any sinusoidal frequencies present in the image must have the same phase, then phase contrast edge detection exists [27]. This fact is important in that any errors in the detection technique due to “false positives” are eliminated due to any phase mixing or similar effects. An example setup using edge detection is shown in Fig. 2.6.
Finally, latent imaging originally comes out of the field of film photography, where a latent image is defined as the image present after film has been exposed to light, but before development [28]. A developer solution is needed in order to change the orientation of the electrons in the crystal in such a way as to increase the photographic sensitivity. An example of this result from the literature is shown in Fig. 2.7.

![Figure 2.7 Raw (Latent) Image vs. Developed Image][29]

However, the concept of latent imaging is not restricted to photography, but is very important in the fields of machine vision, lithography, and optical data storage [30]. This concept is very important because being able to study the latent image allows one to improve the lithographic process by measuring any defects in fabrication, especially with the shrinkage of features. An example of this idea, using a photon tunneling microscope, is shown in Fig. 2.8.
Figure 2.8 (a) gray scale image (b) 3D latent image using a PTM [30].

And shown in Fig. 2.9 is an example of a setup using latent imaging.

Figure 2.9 Example of Latent Imaging Setup [28, 30].
2.6 Review of Prior Literature for Experimental Design

In the course of this dissertation, several papers have been reviewed in order to improve understanding of the processes involved, as well as how to make certain enhancements (i.e. selecting the detector and accounting for stage movement). Here three foundational papers are discussed.

In 2001 several researchers at Osaka University in Japan designed an optical detection system for microdefects, similar to this project. Their technique, applied to silicon surfaces, is an improvement over prior methods of defect detection. These prior methods involve scattered light, where incident light illuminates the surface, and the reflected light gathered to generate an image and defects appear as artifacts. The authors note that the problems with these methods are (1) a difficulty sensitively detecting oriented microdefects such as scratches; (2) a long time to make defect measurements; and (3) a difficulty in being able to discern between different types of microdefects [31].

In the work of the Osaka University, the researchers employ what is called an “annular” illumination system. This system, shown in Fig. 2.10 from the literature, consists of an incident beam formed by passing a parallel laser beam through a ring slit focused with a high numerical aperture (NA) objective lens [31]:

...
In Fig. 2.10, it can be seen that the focused beam illuminates a polished silicon surface. The distance between the objective and the silicon wafer is one focal length. By having the light coming from a ring slit, the system is equivalent to that of oblique illumination from every direction. As a result, if a defect is perpendicular to an incident direction, light is scattered from the slit into the object lens and sent into a detector [31].

This work is important for this dissertation for two reasons. First, the concept of unrestricted use of scattered light off the samples for comparisons make it advantageous to use a reflection-based system. Moreover, the work of the Osaka researchers clearly shows that one wants to have a system that can distinguish between defects that are parallel to incident light as well as perpendicular to the light direction, which is possible using a reflection-based system [31].
Another article reviewed for information pertaining to this system design consists of using a real-time latent image to write patterns into photoresist. In this work by two scientists at De Montfort University in the United Kingdom, the goal was to see if a “latent image,” or image before development, could be used to write holographic diffraction gratings [32].

In the article, the authors discuss that when a substrate of PR is exposed to a pattern from a diffraction grating, the subsequent intensity pattern (in this case sinusoidal) results in a refractive index profile present in the PR itself. Consequently, the variation in the refractive index mimics the behavior of a weak phase grating. The grating, in turn, gives the latent image being sought [32]. A diagram showing the experiment itself is shown in Fig. 2.11:
As can be seen in Fig. 2.11 from the literature, the system operates in the following manner: An Argon-ion laser, operating at 458 nm, sends out a beam that is reflected by a pair of mirrors into a half-wave plate, changing the phase of the beam by $\pi$ radians. This resulting beam is sent through a beamsplitter, which uses two subsequent beams (458 and 633 nm, respectively), to write into the photoresist plate. In order to detect and further process the resulting image, a photomultiplier tube (PMT) is used for a detector [32].

This work is relevant to this project in a number of ways. It can be shown, at a specific location to be discussed later, a beamsplitter in the system can be utilized in
order to obtain reflected light from the returning beam path. Moreover, the idea of using other wavelengths of light to read the signal that are different from writing the signal, implied in the article [32], is a possible improvement in the system that can be investigated for a future project.

Lastly, work from a team at the School of Mechanical and Manufacturing Engineering at Dublin City University in Ireland was reviewed. The objective of this work is to look at surface defects using a fiber-optics scanning laser system. While laser scanning systems have been used in defect detection for quite some time, continuously inspecting a sample in real time still presents a challenge, particularly ensuring accurate measurements of defect features, substantially more difficult with moving objects [33].

To solve this problem, the researchers chose to use a fiber-based system, claiming it would reduce the time of measurements, and similarly increase their defect detection resolution. Moreover, the use of a fiber eliminates many alignment issues [33-34]. The versatility of the technique is also increased, along with the overall quality of the measurements. To illustrate this work, Fig. 2.12 from the literature is shown:

![Fiber-Optics Laser Scanning System](image)

**Figure 2.12 Fiber-Optics Laser Scanning System [33].**
As shown in Fig. 2.12, the system consists of a sample plate, illuminated with five fiber-lasers, integrated onto a three-dimensional translation stage. The reflected light is then sent to a signal detection box, consisting of PIN photodiodes. This data are sent to an acquisition card (DAQ) and processed. Driving circuits allow the stage to move in three orthogonal directions [33].

This article is particularly relevant to the research done for this project. Perhaps most importantly, patterns are scanned and data collected with a moving translation stage while they are written, affecting the data collection abilities of the system. With this advanced knowledge, it is easier to determine data processing requirements, both in terms of how the data is acquired, as well as how it is post-processed. Moreover, since driving circuits are also used, an additional consideration for this dissertation is given.

2.7 Review of Image Registration Techniques

Various techniques in order to register and calculate the associated errors between the original bitmap images and their experimental counterparts typically fall into the categories of Fourier Transforms [35-36], edge detection [37-39], visual alignment [40], and stochastic optimization [41].

Fourier transform techniques generally involve finding the associated frequencies of each image, and looking for the peak intensity in the Fourier domain [36]. From finding the peak, inverse Fourier transforms are applied to then align the images. The problem with this approach is that the images generally are only of the size of 500 x 500 pixels. As a result, the computation time necessary to run the necessary algorithms is
much smaller than what was used here (i.e. 40,000 x 12,000 pixels), and therefore is not as useful as other techniques. Similar issues arise with edge detection and stochastic optimization. These techniques all involve much smaller images, as well as a priori knowledge of information between pixels [37-40]. What this means is that interpolation and multiple-order partial derivatives would be necessary to run the algorithms in order to understand the changes on the surface. The feasibility of this on a 40,000 x 12,000 pixel image is very unlikely, and therefore was not pursued. As a result, the method of visual alignment with edge detection, or automatic cross correlation has been used, and is discussed in the next chapter.

2.8 Definition of Terms from Decision Theory

An important aspect of this work is how the defects are labeled as defects. A defect is classified as a feature that significantly deviates from the ideal case. Two types of defects are evaluated here (with specific classes discussed later). The two defect types are programmable defects, in which a feature is intentionally placed (i.e. lines, dots), and random defects, in which a feature is not intentionally placed (i.e. smudge, scratch). Image patterns in this dissertation consist of regularly spaced lines 10 pixels apart with varying thicknesses of 1 to 3 pixels in various directions. Programmed defects also include removal of a varying number of pixels, as well as placement of additional pixels along diagonals.

There are four basic classifications for programmable and random defects: (1) true positive, (2) false positive, (3) false negative, or (4) true negative [41-43]. From this
information, one graphs (1) vs. (2), and generates a receiver operating characteristic (ROC) curve, which varies with a given threshold applied by the user to determine if a feature is considered to be a defect. An example of an ROC curve is shown in Fig. 2.13.

An ROC curve varies with a given threshold that the user applies to determine whether or not a feature is considered to be a defect. The area under one of these curves is the discriminability [42]. In practical terms, discriminability defines the probability that a random pixel is a true positive as opposed to a false positive.
CHAPTER 3 – PRESENT STUDY

3.1 Thesis Statement

As stated in the opening chapter, the goal of this dissertation is to demonstrate the development and operation of a direct read-write-detect optical inspection engineering model for large-format arrays. The detection task is based on realistic array patterns. A single instrument is used to write the pattern in PR and detect the pattern for defects, with inspection speed and reliability quantified.

3.2 Organization

This chapter is written as follows. First, the fabrication techniques used are explained. Next, the development of the sensing system, culminating with the Laser Scanning Microscope Defect Detection (LSMDD) system, is discussed. Different procedures for the various experiments are discussed in sequence. Cross-characterization with an optical profiler and SEM is also discussed. Finally, the development of the image registration and fault-detection is explained. Mathematical definitions and theory for each step are outlined in parallel with these steps.

3.3 Fabrication

As previously discussed, current trends in microlithography are leading to decreasing pattern feature sizes and larger print areas. In order to test procedures for this
coming reality, several patterns have been created that can be used both to test the initial setup of the optical detection system as well as to mimic the small lines and angles that might be found in other settings. A commercially purchased Edmund Optics® grating was also used to provide a starting point while other patterns were fabricated.

The patterns developed initially consisted of three different designs, each generated because of unique qualities that would be helpful in testing the sensing optical system. All of the patterns mostly featured alignment marks in various forms of a “+” sign (see Fig. 3.1) for alignment purposes on the MLT stage. The first pattern to be designed and successfully fabricated was a large window shape (see Fig. 3.5). This pattern was used for direct reading by the sensing optical system, as well as to show characterization of an additional photoresist pattern printed on top of the window (i.e. over fused silica) and the surrounding aluminum areas. Another grating pattern with a 50% duty cycle (allowing work with smaller feature sizes and checks for writing quality) was also fabricated. Moreover, a ‘Super Pattern’ was also developed to mimic what might be seen in an industry setting. The pattern had 6.3 μm wide lines and posed a challenge both in writing and scanning due to angles, curves and lines it contained.

![Figure 3.1 First Printed Pattern](Left: Super pattern with small features tiled across the surface and alignment markers on the outer edges. Center: Close-up of the small features on the Super Pattern. Right: Close-up of an alignment marker).
Over the course of this work, subsequent patterns have been developed in order to mimic not only features that could be printed on a substrate, but defects of various shapes, sizes, and orientations as well. Some of these patterns are shown in the following figures chronologically.

**Figure 3.2 Second Printed Pattern.**

**Figure 3.3 Third Printed Patterns** *(Left: without defects, Right: with defects).*
Figure 3.4 Fourth Printed Patterns  *(Left: without defects, Center: with dot defects, Right: with line defects.)*

Figure 3.5 Fifth Printed Patterns  *(Left: without defects, Center: with dot defects, Right: with line defects.)*
To best reflect the wide range of defects, the defect classes are broken down into two groups: lines and dots. Among the subgroups for each of these defect classes are intensity, size, shape, and orientation. These characteristics can be seen especially in Figs. 3.5-3.6, the final patterns designed to be printed. Note that contrast flipped versions of Fig. 3.6 (where the background and features have their intensities reversed) are also used in this work. The contrast flipped patterns also had their interior lines biased so as to prevent the lines from disappearing during development.

Producing the patterns is an arduous task because of several processes required to work in unison to form the final product. Fused silica is the chosen substrate because of the consistency it offers, even after experimentation with aluminum deposition and various types of PR. While costly, fused silica is also obtainable in large sizes that are needed to perform final testing with numerous samples.
The fused silica substrates are first cleaned in an ultrasonic methanol bath, followed by a vacuum-spinning process and washing with acetone, methanol, and isopropyl alcohol in that order [1]. Following a bake at 250 Centigrade, the substrates are spun-coat with a thin layer of 1822 PR. Next, a soft-baking and writing on the MLT takes place. After exposure, the substrate is placed into a 0.25 mol concentration sodium hydroxide solution where the exposed aluminum is etched to produce a window effect. PR that remains on top of the aluminum (protecting areas that not etched) are removed.

![Pattern Fabrication Process](image)

**Figure 3.7 Pattern Fabrication Process** (Left: Fused Silica coated first with Aluminum and then photoresist. Center: After printing with the MLT and developing; lighter regions are areas of exposed aluminum where printed photoresist had been developed away. Right: Windows created after etching way the exposed aluminum with sodium hydroxide; excess photoresist removed.)

It is then possible to either take images using the optical setup, or re-coat the pattern with new photoresist, and print and develop with a new pattern, characterizing those patterns above the aluminum with the optical setup. In order to print several overlapped patterns on top of one substrate, the sample must be physically situated on top of the MLT writing stage in the same position each time. Because of the difficulty in placing a sample by hand, an alignment camera system is used. The alignment camera apparatus consists of a source, camera, optical lens assembly, and periscope to illuminate the sample and collect live images (see Fig. 3.8). A vacuum system is also used to
prevent slippage during scanning. Software integrated into the MLT control system allows the operator to generate fiducial marks on top of sample and re-align to them at a later time. Alignment is then achieved by translation and rotation of the writing stage. The process manipulates the sample into a position that mimics the original orientation accurately to within 1μm.

Figure 3.8 Alignment Camera. (1. Camera. 2. Light Source. 3. Periscope.)
3.4 Sensing Optical System Development

Upon pattern fabrication, it is necessary to have an optical system that can detect the patterns, collect waveform shapes generated as a result of those patterns, and post-process them in order to reconstruct an image. For the purposes of completeness and to illustrate the system development, the design is discussed in chronological order.

For viewing the intensity differences due to the pattern defects, the original idea for imaging was to use reflected light at a specific point in the light path of the MLT. Inside the MLT itself, there is a 12-sided polygon that provides the scanning spot from which to write patterns. The spot scans the sample at a speed of approximately 17.5 m/s. Furthermore, since the MLT spot scans and writes at a small angle, so as to have a smooth continuous motion, the spot moves across the test surface in the orthogonal (or Y) direction by 2.1 μm after every rotation of the polygon. A diagram to illustrate this writing capability is shown in Fig. 3.9.
The position chosen to maximize the reflected light from the polygon is the area where the MLT light undergoes beamsplitting and modulating, as illustrated in Fig. 3.10. In particular, there is a position in the beam path where the light is collimated and aligned for writing with a camera. A beamsplitter is added to siphon light from the alignment camera to a sensor. A picture of this mount can be seen in Fig. 3.10.
As can be seen in Fig. 3.10, the mount consists of a beamsplitter with a turn knob for easy alignment. The mount is encased in a black cube to prevent stray light or mechanical vibrations. A pinhole is placed next to the cube for further stray light reduction. To secure the mount, the black cube is epoxied onto the steel MLT bench.

With the original mount described, it is possible to explain the detection system. Because the light entering the cube can be highly variable depending upon the type of pattern and test surface used (i.e. a voltage range of 0.1 to 0.1 V is not uncommon), a detector that can comfortably operate in that voltage range is needed. The original solution was a photomultiplier tube (PMT). A PMT made sense due to a large field of
view, lack of Johnson noise, and higher frequency response, particularly for small signals [44]. With an additional circuit board, the PMT was connected to both a power supply, and an output cable for data download. A close up of this can be seen in Fig. 3.11.

![Figure 3.11 Detector](image)

Figure 3.11 Detector (Close up view of the reflected light detector).

From the PMT, the data were sent into an oscilloscope for collections. In order to collect the data, an Infiniium ™ DSO8104A digital oscilloscope was originally used. Three different inputs were connected to the oscilloscope: the output from the PMT, a position origin signal for scan location, and a pulse signal for scans synchronization. A sample image of a waveform from the oscilloscope itself can be seen in Fig. 3.12.
The use of this oscilloscope to this point initially made the collection of data very convenient. The scope was programmed to collect automatically at specific time intervals and a set number of samples. From this collection, data was taken into a series of MATLAB™ programs (illustrated in Section D.3).

Upon system construction at this juncture, several problems were encountered. Firstly, the signal strength collected into the detector was very small, resulting in a lower signal-to-noise ratio (SNR). Moreover, the range of digital numbers (DNs) in the reconstruction images was limited, making resolution experiments very difficult.
To correct these problems, the opto-electronic detection system (OEDS) was modified by bypassing the AOM in order to raise the SNR. This is further illustrated in Section D.2.

After initial experiments showed a reduced light level on the MLT return beam path, it was concluded that a different detector was required, as well as a change in the detector location. Instead of placing the detector directly next to the beamsplitter, adjacent to the alignment camera, a beamsplitter was placed directly above the rotating polygon to send light into a silicon detector. A lens of f=50 mm was added to focus the beam onto the center of the detector. An additional operational amplifier was added in order to increase the gain of the signal, and hence match the dynamic range of the signal processing tools [44-45]. This setup is shown in Fig. 3.13.
3.5 LSMDD

Because of the extreme data and time requirements (i.e. 500 MB file representing a 0.25 x 0.4 mm area generated in 60 minutes), a special-purpose image buffer called the Laser Scanning Microscopy Defect Detection system (LSMDD) was developed (with construction done by AML Consulting [46]).
Consisting of an oscilloscope and processing computer, the image buffer system takes initial data from the silicon detector and amplifier, converting it into easy-to-use images from which further image processing and analysis can be performed [1]. The system has a Quad-core 2.6 GHz, 32 nm processor running Windows™ 7 Ultimate 64-bit, 12 GB of memory, 3, 1 TB hard drives for storage and data acquisition, and a LabVIEW™ interface. The image buffer system has inputs for trigger delay, sample rate and number of samples per scan line from the MLT, as well as the number of lines scanned. Data are saved as a binary file, allowing it to be sent to a program (such as MATLAB). The system software can show both waveforms and images, along with numerous scaling, colormap, and viewing options per the user’s preference.

Figure 3.14 Main Panel Display of LSMDD.
At this point, it would be prudent to discuss the image buffer’s interface and features, as well as show the different possible settings. As shown in the previous figure, the main display consists of a left sub-panel housing timing settings, file locations, data saving/loading buttons, the main acquisition and abort button controls, as well as a viewing window that displays either a waveform or image representation of the data.

Here are a list of the scope settings, and what they represent. (Note: all controls recognize SI suffixes such as ‘M’, ‘m’, ‘u’, ‘n’ (Mega, milli, micro, nano, respectively).

<table>
<thead>
<tr>
<th>Table 3.5.1 Scope Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Trigger Delay</strong></td>
</tr>
<tr>
<td><strong>Sample Rate</strong></td>
</tr>
<tr>
<td><strong># Samples / Line</strong></td>
</tr>
<tr>
<td><strong>Lines</strong></td>
</tr>
</tbody>
</table>

It should be further noted that, with regard to the sample rate, since the rate is limited to an integer number of internal timebase periods, the control will return the closest higher valid sample rate to the one entered. Moreover, with regard to the number of samples per line, that variable also represents the number of samples to acquire after each trigger.

In terms of file locations, the path to any saved data, or any data saved while in acquisition mode is in the following form:

```
[Main Data File Folder]/[date & time stamp]_[Alternate Text File Identifier]_[File Iteration #].bin
```

Clicking on “load data” opens a previously saved .bin file, while clicking on “save data” saves the current data to a binary file. “Loaded Data Path” will display the path of the currently open file, if applicable. “Run Script” takes the data from memory and sends it to a script in MATLAB™ to open the file.
For acquisition, one can click on “acquire.” This step arms the scope card and starts the acquisition loop. The loop waits for data to be loaded, and then transfers the data to a host memory location when prompted. The loop will continue to transfer data from the card (if available) until the specified number of triggers is reached, an ABORT button is pressed, or a timeout period has elapsed. In the cases of the latter two options, no data is retrieved.

For displaying data, there are tabs for both vertical and horizontal dimensions. In the case of the vertical, it can be toggled between volts and binary number, whether for the Y axis (if looking at a waveform) or the Z axis (if looking at an image). For the horizontal axis, the X axis is controlled, and will toggle between time (in seconds) and pixels. Clicking on “Full Data Set” will show a copy of the entire dataset into LabVIEW™, and can cause memory issues with large patterns.

If one switches from the display tab to the waveform tab, the acquired data is then shown in a linear manner, as it was collected. This step can help in determining the correct trigger delay and number of samples for each line. Finally, the “CTM” button brings the on-screen cursor to the middle of the screen.

There is also an image tab, in which the data sequence after each trigger line is shown. If one presses “Ctrl+Space”, this tab toggles between a cursor tool, hand tool, and zoom tool. Each one of these tools allows the image to be viewed in a different way. Larger datasets, as a result, can take additional time to refresh the image. If one presses “Autoscale”, the image is fully zoomed out.
Near the image tab is an auto-acquisition button, which functions very similar to the “Acquire” button. Here, however, the file is also auto-saved, incrementing the File Iteration number by 1, and arming the capture card for another acquisition sequence. One should note that, just like the singular acquisition, the auto-acquisition mode will end if the user presses the “Auto Acquisition” button a second time, presses the “ABORT” button, or if the timeout period has elapsed with no triggers sensed. Again, in the cases of the latter two options, no data is retrieved.

For purposes of basic, first-order comparisons, there are the “Open Ref” and “Compare down/up” controls. For “Open Ref,” a reference bitmap is opened to compare the acquired data. This bitmap can then be modified through using the “Compare down/up” button. In the case of the image buffer system, acquired data is 16-bit and reference data is 8-bit. “Compare Up” translates the 8-bit reference data to 16-bit before subtracting the acquired data, resulting in greater resolution at the expense of calculation speed for real-time comparison feedback. “Compare Down” does the opposite, reducing the bit-depth of the 16-bit acquired data down to 8-bit before subtracting from the reference data, resulting in less resolution in the comparison data but is quicker for real-time comparison. A very useful feature on the far right side of the main display is the colormap toggle switch. This tab can be used to select a colormap scheme to highlight different defects. The options are shown in the following table.

<table>
<thead>
<tr>
<th>Table 3.5.2 Colormap Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>IsoL</td>
</tr>
<tr>
<td>CubicL</td>
</tr>
</tbody>
</table>
Edge: Black-blue-cyan-white-yellow-red-black-divergent scheme. For ratio data (ordered, constant scale, natural zero).

TVS: Specialized colormap transitioning through yellow, orange, red, dark red, and purple.

TVS2: Specialized colormap emphasizing divisions below 10%.

Haxby: Lab-based colormap developed by Haxby.

Electric: Even transition from black to blue to white.

Hot: Even transition from black to red to yellow to white.

Jet: Same as Matlab default “Jet” colormap, dark red to yellow to dark blue.

Rainbow: Similar to 'spectrum' colormaps. Transition from black to red, yellow, green, cyan, blue, purple, and white.

Gray: Standard grayscale colormap.

Gray Saturation: Same as above but makes max value red.

Finally, it is important to show the different scope settings. A dialog box illustrating the settings is shown in the following figure.

![Figure 3.15 Scope Settings Dialog Box.](image)

Table 3.5.3 Scope Settings

<table>
<thead>
<tr>
<th>Channel</th>
<th>Specifies which channel the detector data is on.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>Selects between +/- 5V and +/- 1V. The +/-1V range will yield more voltage resolution for the detector signal as</td>
</tr>
</tbody>
</table>
long as the signal does not exceed 1V.

| Trigger Level | The trigger level in volts. |
| Trigger Source | Specifies which channel the trigger is on. |
| Trigger Slope | Select either rising or falling. |
| Timeout | Determines how long the acquisition loop will sit waiting for triggers before exiting. Units are seconds. |

In terms of a typical operation of the system, here are the steps, along with some starting settings, that should be used.

On the 81110A HP ™ Function Generator controlling the triggering signal, one should take off the terminator on the right-hand side of the BNC connection, and attach the BNC cable that leads to the image buffer system trigger signal. Next, one should take a BNC cable, and split the signal from the detector, sending that second cable to the front of the oscilloscope on the MLT. After that, one can then adjust the mirror that siphons light to the detector, and adjust it, watching Channel 2 on the oscilloscope, while a sample is in a print position. When the signal shows a complete drop, the sample is being imaged directly into the detector, and the mirror is in the correct position.

Once those steps are completed, one can use the image buffer system software (see Figs. 3.14 and 3.15), with the following starting parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trigger Delay</td>
<td>260</td>
<td>Microseconds (u)</td>
</tr>
<tr>
<td>Sampling Rate</td>
<td>30</td>
<td>Megasamples (M)</td>
</tr>
<tr>
<td>Samples / Line</td>
<td>40000</td>
<td>n/a</td>
</tr>
<tr>
<td>Lines</td>
<td>12000</td>
<td>n/a</td>
</tr>
<tr>
<td>Channel</td>
<td>Dev/ai0</td>
<td>n/a</td>
</tr>
<tr>
<td>Range</td>
<td>+/-5</td>
<td>Volts (V)</td>
</tr>
<tr>
<td>Trigger</td>
<td>50</td>
<td>Millivolts (m)</td>
</tr>
<tr>
<td>Trigger Source</td>
<td>Channel 1</td>
<td>n/a</td>
</tr>
<tr>
<td>Trigger Slope</td>
<td>Rising</td>
<td>n/a</td>
</tr>
<tr>
<td>Timeout</td>
<td>120</td>
<td>Seconds (s)</td>
</tr>
<tr>
<td>Parameter</td>
<td>Value</td>
<td>Units</td>
</tr>
<tr>
<td>-----------------</td>
<td>------------------------</td>
<td>-------</td>
</tr>
<tr>
<td>Position Origin</td>
<td>$x = 57, y = 88$</td>
<td>Mm</td>
</tr>
<tr>
<td>Copies</td>
<td>1</td>
<td>n/a</td>
</tr>
<tr>
<td>Pattern</td>
<td>Standard White Pattern</td>
<td>n/a</td>
</tr>
</tbody>
</table>

After this, one can simply hit “print” on the MLT window. A screen switch is required to see the image buffer system display, and f1 must be pressed for acquisition. Once the acquisition is complete, the image should appear in the image buffer system window.

### 3.6 Phase Contrast Imaging Experimental Setup

The second part of this dissertation consists of work with phase contrast imaging using edge detection. As discussed in the previous chapter, this technique works by using the idea that changes in refractive index can be used to show differences between various features in a sample [25]. A novel way to illustrate this concept within the LSMDD-MLT framework has been developed using a bi-cell detector.

A bi-cell photodetector has its roots in the telecommunications industry, specifically with multi-detector cells used for separating signals at different wavelengths in an optical fiber. By splitting the signals into different wavelengths, these signals land on different parts of a detector area [47-48]. An example from the literature is displayed in Fig. 3.16.
In the case of the current work, because of the “phase congruency” component introduces birefringent changes in the signal, different parts of the signal hit different parts of a detector area [25]. In order to notice these changes, and hence look at the defects between them and the original pattern, a bi-cell detector, or effectively a diffractive prism, is required [25, 47].

This concept is related to edge detection by the following. The birefringent changes are best shown as spatial variations in the signal due to polarization changes [47-48]. So, if the signal is viewed using an edge detector, the variations from the signal cause the defects to separate from the original image [49]. Hence, one cell in the bi-cell detector shows the original image, and the other shows the defects. The only difference in the setup between the central aperture detection and phase contrast edge detection is the switching of a prism and pair of detectors (or a bi-cell detector) for the single silicon detector. An example of the setup is shown in Fig. 3.17.
As shown in Fig. 3.17, the setup is as follows. Reflected light, containing the sum of two different phases, returns from the sample. The beam is then split using a prism, and sent to two different detectors (sitting on a single bi-cell detector). The signals from these detectors are then either added or subtracted from each other, with the difference in the phase edges visible on the imaging buffer system. The hardware used for this step is shown in Fig. 3.18. This procedure can be done in the cases of (1) pure PR on glass or (2) Aluminum and PR on a glass substrate, so long as there is gain and offset balancing through optimizing the circuit pots.
Figure 3.18 Hardware used for phase contrast edge detection experiment. Detector (top) and circuit (below). Circuit pots are shown as grey rectangles with white lettering.
3.7 Latent Imaging Experimental Setup

In the final part of this dissertation, latent image defect detection is investigated as an additional illustration of both central aperture detection and phase contrast edge detection. As discussed before, this concept originates from the field of film photography, but has expanded into many other fields [28, 30].

In order to be able to detect the defects without any development, the exposure of the pattern is changed. As discussed previously, typical patterning uses a single exposure and development to make the pattern on the sample visible. Here, that patterning becomes a two-step exposure process [50]. The first exposure, as before, causes a partial latent image of the desired pattern in the photoresist. However, instead of proceeding immediately to development, the pattern is exposed again, this time using a spatially-varying intensity, phase-only mask.

What this second exposure does is to combine with the first exposure to form a pattern where the minimum intensity required to etch the photoresist survives in all the needed areas [50]. If the window of exposure is varied near the saturation dose, the pattern can be modulated in such a way as to have it appear as though the entire pattern is etched. An example of this concept from the literature is shown in Fig. 3.19, while an example of an actual pattern from the literature is shown in Fig. 3.20.
Figure 3.19 Combination of exposures to form a pattern without development [50]. (a) aerial image intensity profile due to the first exposure, (b) intensity profile from the second exposure, (c) the combination of exposures.

Figure 3.20 First and second exposures on pattern [50].
As one can see from Fig. 3.20, if the exposures are combined in a specific way and optimized for the best quality, they can generate patterns that do not require development. As a result, both the central aperture and phase contrast edge detection techniques already discussed can be used to not only view developed images, but also latent images as well. This point, to go back to an earlier remark in Chapter 2, also makes this method work much easier to accomplish, and more reliable.

3.8 Optical Profiler and SEM

In order to confirm the results of the image buffer system, it is necessary to use a method of cross-characterization. For this task, use of both a Veeco™ NT9800 Optical Profiler (see Fig. 3.21), an optical interferometric system that provides height information and surface topography with angstrom resolution, and a standard SEM, is employed.
3.9 Image Registration Routine Development

The technique used for image alignment is automatic cross correlation \([37-39]\). Automatic cross correlation obtains any scale factor, translation, and rotation angles of an unregistered image, making the needed changes for registration \([1]\). The Image Processing Toolbox in MATLAB\(^{\text{TM}}\)’s gives the user the ability to define a series of “control points,” or similar objects, to be matched between two images. This process involves the selection of the control points, spatial transformation structure creation, and performing that transformation. An example of the tool is shown in Fig. 3.22.

Figure 3.21 Alternative Optical Inspection (Left: Veeco\(^{\text{TM}}\) NT9800 Optical Profiler. Right: 3-D Rendering of Text (“UA”) and an alignment marker that has been printed. Color is used to indicate height differences. Residual photoresist on top of the aluminum is seen in red, green and light blue. The aluminum below the photoresist can be seen in dark blue).
Once the control points are chosen by the user, the program employs nearest-neighbor algorithms to determine the correlation matrices in nearby pixels [1]. Whichever pixel gives the highest value is used to form a transformation matrix, which is then multiplied onto the unregistered image, resulting in a re-registered image [51]. This technique is very useful in that it allows the user to only need to define control points within a specific region of interest in the entire array, avoiding unnecessary computation.

Lastly, difference images, particularly for simulations to be discussed in the next chapter, are shown in both a “binary” and “quantized” format. What these formats mean are that there are a different number of possible values for the difference images, based upon how well the defects can be displayed. Shown next is a table of the possible values,
followed by a simulated example of the difference between a “binary” difference image and a “quantized” one.

Table 3.9.1 Binary vs. Quantized Image Values

<table>
<thead>
<tr>
<th>Values (DN)</th>
<th>Binary</th>
<th>Quantized</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>255</td>
<td>255</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>171</td>
</tr>
<tr>
<td>3</td>
<td>n/a</td>
<td>85</td>
</tr>
<tr>
<td>4</td>
<td>n/a</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 3.23 (a) Original Pattern (b) Pattern with defects (c) Difference between A and B in binary, (d) Difference between A and B quantized.
3.10 Image Processing Routine

Figure 3.24 describes the image processing routine [1]. Following an acquisition, the AOM input bitmap, which is what was used to generate the PR pattern, is loaded (3.24a), along with the raw measured image (3.24b). A smaller section of the image, defined as the smallest repeatable feature in the overall pattern is then analyzed (3.24c). This image is then resized to match the dimensions of the input bitmap (3.24d). Using a series of control points (using either x’s in the image corners or the corners of the inner square), 3.24a and 3.24d are registered to each other (3.24e). It should be noted that after each step, the processed image is normalized on an 8-bit scale. A sequence of a background removal tool (3.24f), 2D median filter (3.24g), and 1D median filter (3.24h) on the columns, is applied to the measured image, helping to make it more closely match the reference image. Similarly, the input bitmap has applied to it a Gaussian blur filter (3.24i) and image shift correction (3.24j) to make it more closely match the measured image. Finally, a contrast reversal on the processed measured image is performed, depending on the color of the background (3.24k). This image is subtracted from (3.24j), giving a difference image (3.24l). An 8-bit threshold is applied, which produces the positive image (3.24m) that contains both true and false positives. A programmed defect map, containing only those defects is loaded (3.24n), and is then multiplied by the positive image in order to determine the number of true positives (3.24o). The defect map’s complement is multiplied by the thresholded image to find the number of false positives (3.24p). A more detailed description of the routine can be found in Appendix A.
Figure 3.24 Image Processing Routine [1]. Following an acquisition, the AOM input bitmap, which is what was used to generate the PR pattern, is loaded (a), along with the raw measured image (b). A smaller section of the image, defined as the smallest repeatable feature in the overall pattern is then analyzed (c). This image is then resized to match the dimensions of the input bitmap (d). Using a series of control points (using either x’s in the image corners or the corners of the inner square), 3.24a and 3.24d are registered to each other (e). It should be noted that after each step, the processed image is normalized on an 8-bit scale.

A sequence of a background removal tool (f), 2D median filter (g), and 1D median filter (h) on the columns, is applied to the measured image, helping to make it more closely match the reference image. Similarly, the input bitmap has applied to it a Gaussian blur filter (i) and image shift correction (j) to make it more closely match the measured image. Finally, a contrast reversal on the processed measured image is performed, depending on the color of the background (k). This image is subtracted from (j), giving a difference image (l). An 8-bit threshold is applied, which produces the positive image (m) that contains both true and false positives. A programmed defect map, containing only those defects is loaded (n), and is then multiplied by the positive image in order to determine the number of true positives (o). The defect map’s complement is multiplied by the thresholded image to find the number of false positives (p). A more detailed description of the routine can be found in Appendix A.

The flowchart can be summarized in the following equation:

\[
\mathcal{Z} = D - D_{\text{Ideal without Threshold, Binary}} = D_{\text{8-Bit Binary Threshold, Binary}}
\]  

[eq. 1]
where $Z$ represents the nonlinear MATLAB program, $I_{LSMDD}$ represents the AOM input bitmap, $I_{Ideal,without}$ the ideal bitmap, and $D$ represents the true positive defect image. It is important to note that much of the image processing routine helps to model the printing and scanning behavior of the imaging system by removing elements that impede proper defect identification.
CHAPTER 4 – EXPERIMENTS AND RESULTS

4.1 Organization

In this chapter, the results of the work done for this dissertation are presented. It is organized in the following manner. First, the figures of merit are discussed. Secondly, the experimental results with the data collected from testing the central aperture detection technique are shown. Next, the phase contrast edge detection results are shown, with latent imaging results shown for illustration.

4.2 Figures of Merit

Before going into any of the experimental results, it would be wise to briefly discuss the figures of merit that will be used to judge the quality of the results. These figures are the ROC curves and discriminability, previous discussed in Section 2.8. The discriminability represents the probability that, for a given threshold and random pixel, of finding a true positive versus a false positive.

4.3 Central Aperture Detection

In the first part of this work, the goal is to develop a proof-of-concept system that could both print grayscale patterns, as well as read and image them for the display of any present defects. For purposes of organization, results are shown in chronological order.

For purposes of displaying a proof-of-concept, a previously discussed ‘Super Pattern’ is used, designed to mimic several types of pattern scenarios that might be found
in an industry environment. The ‘Super Pattern’ is shown in Fig. 4.1a. Furthermore, in order to print several overlapped patterns on top of one substrate, the use of an alignment camera system is implemented. As stated earlier, the process manipulates the sample into a position that mimics the original orientation on the stage accurately to within 1μm.

### Figure 4.1 Super Pattern

<table>
<thead>
<tr>
<th>(a)</th>
<th>(b)</th>
<th>(c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Super Pattern design layout, including lines at angles and rounded shapes.</td>
<td>Intensity data collected from the Veeco System of part of the Super Pattern, as indicated by the yellow rectangle.</td>
<td>Intensity data collected from reflected light using the OEDS.</td>
</tr>
</tbody>
</table>

Following pattern creation, it is necessary to use a method of characterization in addition to the OEDS that is under development. For this task, we make use of a Veeco NT9800 Optical Profiler and standard SEM to provide both height information and surface topography with angstrom resolution. It is possible to demonstrate consistency between the intended pattern design (Fig. 4.1a), intensity measurements made by the optical profiler (Fig. 4.1b), and intensity information gathered from the OEDS (Fig. 4.1c).

Simulations of the entire system are performed first in order to get an understanding of what should happen in the subsequent experiments. An object-oriented design program for this purpose is written using MATLAB™ [51]. Called “OptiScan,” this program allows physical optics simulation of various optical and electromagnetic
phenomena easily and robustly. These simulation setups and results are shown below for all parts of this work, with the major difference between the central aperture detection part and the phase contrast / latent imaging parts being an additional layer on the detector to represent a pair of silicon detectors (or a bi-cell detector), and light split using a prism.

Figure 4.2 Diagram of OEDS in OptiScan.
From the results of the simulations (see Appendices A, B), we have shown that we can view and detect defects as small as 1.5 μm in diameter, which is well below the 2.1 μm threshold that the MLT prints.

In order to determine where the defects in the images are present, a “fault-detection” algorithm that highlights differences between our measured samples and a “master image” (or the original bitmap pattern) has been developed. The algorithm works as follows. After loading a previously generated image file, the original bitmap pattern is also loaded. The images are then registered to one another using a series of control points. This procedure is simulated in OptiScan, with many simulated LSMDD images having translations of 5 pixels, rotations of 1 degree, and scaling introduced, and then re-registered. This procedure is repeated for a more realistic test pattern. (see Fig. 3.5), including added defects. Simulation results with the translations, rotations, and scaling can be seen in Fig. 4.3. Results with more defects are shown in Figs. 4.4 and 4.7-4.8.

**Figure 4.3 OptiScan Results.** Top left: Image with no defects. Bottom Left: Image with defects, translation, rotation, and scaling. Right: Differences between top left and bottom left. As one can see, the defects appear clearly in the difference image, and the rotations, translation, and scaling has been removed.
Figure 4.4(a) OptiScan Results (Each pixel represents 1.5x1.5 μm). (a) Image without defects. (b) Image with dot defects. (c) Difference between (A) and (B). The goal here is to show that intentional defects placed in an image can be detected. Defects shown in (b) also appear in (c) as highlighted differences. This same identification method is used in initial experimental data.
Figure 4.4(b) OptiScan Results (Each pixel represents 1.5x1.5 μm). (a) Image without defects. (b) Image with line defects. (c) Difference between (A) and (B). The goal here is to show that intentional defects placed in an image can be detected. Defects shown in (b) also appear in (c) as highlighted differences. This same identification method is used in initial experimental data.

As one can see, for both original images, the line and dot defects are detected very well. Each of these cases shows that all the defects are detected for the selected area.
In the previous chapter, LSMDD images were also discussed. In Figs. 4.5 and 4.6, some of the initial results from those tests are shown.

**Figure 4.5 LSMDD Results.** This image is for Power = 450mW, starting position of (x=96, y=110), 30 megasamples/sec, 15000 samples/line, 18000 lines, Electric Colormap.
Note the detail shown in these images. A scratch that was not intentional shows up in both pictures, indicating that printing defects are present and can be seen. In Figs. 4.7 and 4.8, differences between reference bitmaps and measured data are shown.
Figure 4.7  Experimental Test Pattern. (a) The reference bitmap image. (b) The measured image. (c) The difference between C and A. (d) The difference between C and A quantized.

Note in the previous figures that intentional defects were added to the bitmap, and can be seen in the difference imaging. Other printing defects can also be seen, particularly in the “river-like” feature in Fig. 4.7. In Fig. 4.8, comparisons between another set of reference and measured images are shown, using the bitmap in Fig. 3.6.
As one can see in Fig. 4.8, the defects do not show up very well, even though they are present. To help make the defects more apparent, a convolution blur filter (of 7x7 pixels) is applied to Fig. 4.8a, and the quantization feature is dropped. The results with the filter are shown in Fig. 4.9.
As is shown in Fig. 4.9, the defects appear much more clearly than in Fig. 4.8. For further image processing, the mean level of a floor value (or the average value of the background of an image over a small portion of the sample) is calculated and then removed. Furthermore, pixels with values within 1 standard deviation are revalued to that.
mean. After testing, it was found that a removal of the background $1.5 \times \text{mean}$ and a standard deviation (in each direction) multiplied by 3 gave the biggest contrast to see defects. This result is shown in Fig. 4.10.

Figure 4.10  Experimental Test Pattern. (a) The reference bitmap image. (b) The measured image. (c) The difference between C and A. (d) The difference between C and A quantized.
Next is another set of images, with more quantifiable defects, followed by their respective detection rates. Note that in some cases either the reference bitmap image or the measured image has undergone a contrast flip to better match the images.

Figure 4.11  Experimental Test Pattern [1]. (a) The reference bitmap image. (b) The measured image. (c) The difference between C and A. (d) The difference between C and A quantized.
As was discussed in Section 2.8, another way of quantifying the ability to pick out defects is to generate a series of ROC curves. By subtracting out an image with the non-defective pixels, it is possible to count the number of true positive pixels. Knowing the total number of nonzero pixels present allows one to also find the number of false positive pixels. Effectively, in terms of algorithm construction, a threshold is set, and two
data maps are created: one above threshold and one below. These maps are multiplied by a known defect map, thereby removing incorrect positives. Data were collected by looking at different DC offsets (of 50 mV per division) with the op-amp circuit discussed in Chapter 3, as well as different substrates. Examples are shown in Figs. 4.13-4.14.

![Figure 4.13 ROC Curves for different DC Offsets using Al on glass [1].](image)

Discriminability values for these curves are shown in Table 4.3.1 [1].

<table>
<thead>
<tr>
<th>Figure</th>
<th>+4 DC</th>
<th>+2 DC</th>
<th>+0 DC</th>
<th>-2 DC</th>
<th>-4 DC</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.13</td>
<td>0.613</td>
<td>0.726</td>
<td>0.497</td>
<td>0.646</td>
<td>0.670</td>
</tr>
<tr>
<td>4.15</td>
<td>0.729</td>
<td>0.624</td>
<td>0.690</td>
<td>0.709</td>
<td>0.648</td>
</tr>
</tbody>
</table>
As one can see, changes in DC offsets affect the quality of the ROC curve. Moreover, aluminum substrates perform much better than pure PR on glass. Note that the aluminum on glass experiments involved only removing defects, and not the background. In order to see the effects of the opposite, or “reverse-contrast,” please see Fig. 4.15.
Averaging the discriminability values for each offset gives values of 0.63 for a black background and 0.67 for a white background. This improvement is substantial, considering the images used had a low quality [1].

Finally, these results could be extrapolated to the time required to test a 1 m class sample. With a coverage area of 1 in$^2$ in about 12 seconds, the LSMDD could an entire sample in 18,600 seconds, or approximately 5.5 hours [1].

### 4.4 Phase Contrast Edge Detection and Latent Imaging

In this second part of this dissertation, the objective is to detect defects on a sample by looking at the phase changes over that sample. This objective is achieved done by viewing “phase congruency” component, which introduces birefringence in the signal, making different pieces of the signal land at different points on the detector [46-47].

---

**Figure 4.15 ROC Curves for different DC Offsets using Al on glass (reverse contrast) [1].**
make these changes visible, and allow any defects to be viewed, a bi-cell detector (or
diffractive prism) is needed, where one half of the detector to view image components
with one phase, and the other half to view the other phase.

To begin, simulations are run to show that defects can be seen. As with the central
aperture detection work, OptiScan is used to perform these simulations. The basic setup
is the same, except for the target and detector. In the case of the target, it now appears as
a phase object, with uniform amplitude of 1. An example of the new simulation is shown
in Fig. 4.16.
Figure 4.16 OptiScan Target Design. (a) Magnitude (b) Phase.
For the detector, the single detector that is used for central aperture detection is now split into two detectors, each taking an area of half of the original area. These detectors are denoted by the white areas in Fig. 4.17.
Figure 4.17 OptiScan Detector Design. (a) Detector A (b) Detector B.
A test of this simulation shows the difference, both “raw” and “quantized” for a horizontal edge of rectangle in the upper left quadrant of Fig. 4.10. The results are shown in Fig. 4.18.

Figure 4.180 OptiScan Results. (a) Detector A (b) Detector B (c) A-B (d) (A+B)/2.
As one can see from Fig. 4.18, the only difference between (A) and (B) is the intentional defect in the bottom left corner.

The results of these simulations show that defects as small as 1.5 μm in diameter can be viewed, which is well below the 2.1 μm threshold that the MLT prints. This technique works for a variety of defect types as well.

As with previous central aperture detection work, the basic setup is the same, except for the target and detector. In the case of the target, it now appears as a phase object, with uniform amplitude of 1. For the detector, the single detector is now split into two detectors, each taking an area of half of the original space. The figures or merit that are used in this work are the ROC curves and discriminability, which give a probability, for a given threshold and a random pixel position, of finding a hit, or true positive, versus a false alarm, or false positive.

ROC curves are found in Fig. 4.19. The discriminability values are found in Table 4.4.1.
Figure 4.19 ROC Curves for Phase Contrast Detection. In order to generate these curves, the image with defects is subtracted from the difference image. This leaves only the true positive pixels, which are counted. Knowing the total number of non-zero pixels gave the number of false positive pixels. Discriminability values here range from 0.608 to 0.781.

Table 4.4.1: Discriminability Values for ROC Curves

<table>
<thead>
<tr>
<th>Figure 4.21</th>
<th>Addition</th>
<th>Subtraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Level, B</td>
<td>0.781</td>
<td>0.619</td>
</tr>
<tr>
<td>1st Level, W</td>
<td>0.611</td>
<td>0.608</td>
</tr>
</tbody>
</table>
From the previous graphs and tables, some interesting phenomena become apparent. The dark field ROC curves appear better than the bright field curves. A possible reasons for this include the background removal eliminating more low-value pixels in the dark field images than high-value pixels in the bright field images.

Finally, preliminary results for latent imaging are found in Fig. 4.20. While an image is apparent due to the outline of the sample, future work will need to refine processes to improve the image quality.

Figure 4.20 Preliminary Results for Latent Imaging. Here is an image from attempts to performing scanning before any development. Future work will need to refine processes to improve the image quality.
On a final note, it needs to be elaborated upon why measured images, one with and one without defects, are not used in the image processing routine. As is shown with a simple example in Figure 4.21, the image processing routine works best when an ideal image is compared to a measured image. The reasons for this are the following: First, power variations in the laser (i.e. curvature of the scan line, banding effects, etc.) are added to one another viewing the difference of two measured images, making it harder to remove the effects. Moreover, the image registration is much more difficult, primarily due to degradation of the alignment marks. Third, random defects appear more frequently, creating more false positives. Lastly, true positives can be reduced by random defects in one image cancelling the programmed defects in the other. Having an ideal image serve as a reference minimizes these problems [1].
**Figure 4.21 Comparison of Image Subtractions.** Two measured images (above) are subtracted (bottom left), and compared to ideal vs. measured (bottom right). Using an ideal image provides substantially better results than two measured images for the detection system.

### 4.5 Additional Research: Deconvolution Filtering

In an attempt to improve the discriminabilities of the ROC curves, additional filtering techniques were investigated, and the best results came from use of a regularized deconvolution filter is employed. The goal of this filter is to determine the likelihood of a random process by applying a linear, time-invariant filter on an image containing noise [41, 53]. This definition implies understanding the signal and associated noise, in order to
minimize a root-mean-square (RMS) error between the random process and the desired result. In image processing, a regularized deconvolution filter is advantageous for deblurring images, given that it can attenuate certain frequencies that are signal-to-noise ratio (SNR) dependent [53]. When applied to an image, as is shown in Fig. 4.22, a regularized deconvolution filter changes the local variance in an array, containing both the signal and noise terms, to minimize the RMS error. This process manifests itself by suppressing the noise pixels iteratively, while dilating the perceived signal pixels accordingly due to highlighting pixels in either the horizontal or vertical direction during the deblur process [54-56]. As a result, the overall effect is achieving better signal identification. Moreover, using the regularized deconvolution filter normalizes the numbers of signal and noise pixels between 0 and 1, preventing statistical discontinuities.
Figure 4.22 Illustration of Regularized Deconvolution Filter. (a) true positives detected after signal processing (b) false positives detected after signal processing (c) true positives detected after filtering (d) false positives detected after filtering.
As stated before, use of a deconvolution filter proved to be advantageous, given its adaptive variance correction for deconvolving images, over other techniques, including a nearest-neighbor search, active contour, and image segmentation [51-52]. The use of the deconvolution filter, through changes in the local variance in an array containing both signal and noise terms, minimizes RMS error, thereby dramatically improves the discriminability. Any additional pixels created by dilation from the deconvolution filter are normalized out by using a dilated pixel defect map. Concavities emanating from the dilation filter causing a classifier inversion are corrected by using (1-p(tp),1-p(fp) points in the graphs [57-59].

![ROC Curves - Black Background 2nd Level](image)

Figure 4.23 ROC Curves for different DC Offsets using Al on glass (deconvolution filtered).
Discriminability values for figures with filtering can be found in Table 4.5.1.

<table>
<thead>
<tr>
<th>Figure</th>
<th>+4 DC</th>
<th>+2 DC</th>
<th>+0 DC</th>
<th>-2 DC</th>
<th>-4 DC</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.23</td>
<td>0.745</td>
<td>0.728</td>
<td>0.742</td>
<td>0.775</td>
<td>0.766</td>
</tr>
<tr>
<td>4.24</td>
<td>0.786</td>
<td>0.740</td>
<td>0.770</td>
<td>0.765</td>
<td>0.796</td>
</tr>
</tbody>
</table>

Comparing the discriminability values in Tables 4.3.1 and 4.5.1, we find a significant improvement due to the deconvolution filtering. Averaging the discriminability values for each offset using the 1st Level discriminability gives values of 0.63 for a black background and 0.67 for a white background, while the 2nd Level discriminability gives values of 0.75 for a black background and 0.77 for a white background. This means that we see an average of 19.1% and 13.4% improvement using the deconvolution filtering for the black and white backgrounds, respectively.

In the case of the phase contrast edge detection, the regularized deconvolution filter improved the discriminability of the ROC curves by an average of 11.2%. Only in
the case of the dark field addition did the discriminability actually go down. The author believes this result is due to the fact that the image associated with that particular ROC curve was of sufficient quality that no further processing was needed.

Figure 4.25 ROC Curves for different DC Offsets (deconvolution filtered). Here, a second-level discriminability using a regularized deconvolution filter is shown. The graphs are on an inverse scale due to a threshold-intensity reversal. Discriminability values range from 0.641 to 0.811.
<table>
<thead>
<tr>
<th>Figure 4.22</th>
<th>Addition</th>
<th>Subtraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>2nd Level, B</td>
<td>0.641</td>
<td>0.810</td>
</tr>
<tr>
<td>2nd Level, W</td>
<td>0.811</td>
<td>0.664</td>
</tr>
</tbody>
</table>

While the regularized deconvolution filter does appear to improve the discriminabilities, it does have a couple of features that will need to be investigated. First is the classifier inversion. The author believes that the classifier inversion is due to the dilation of pixels, which is a direct consequence of the filter itself. In more specific terms, it appears that the filter adds true negatives to the true positives, and false negatives to false positives, primarily based upon the locations of the additional pixels. This fact in effect creates a cross-conditional scenario where the percentages of true and false positives are switched, which becomes visible with ROC curves falling below the diagonal line. In order to correct the inversion, \((1-p(tp),1-p(fp))\) points are used in the graphs. Further investigation has appeared to confirm this theory in terms of the percentages of true and false positives by looking at images that better match the new data points. These can be generated by subtracting these ‘negative maps’ (or defect maps run through the filter) from the filtered images.
CHAPTER 5 – CONCLUSIONS

5.1 Thesis Re-Statement

As stated in Chapter 1, the goal of this dissertation has been to demonstrate the development and operation of a direct read-write-detect optical operational engineering model. We wanted to show that we can write a pattern onto PR and read the pattern to evaluate the printing.

5.2 Results

We first showed that development of the system in terms of data collection and processing resulted in 2.1 μm resolution of defects is obtainable. Based upon the idea that light can reflect off a photoresist-laden fused silica sample containing defects, allowing height and depth information to be obtained through intensity changes, we have shown that defects with sizes approaching 2 μm can be resolved in various shapes, sizes, and orientations. The subsequent image processing routine involves matching the images as closely as possible before performing a threshold analysis, allowing the user to determine the location and size of defects. Discriminability values were found to be between 0.50 and 0.73. Finally, extrapolation to larger array samples shows this system could be used for industrial size patterning evaluation.

We also looked at other detection approaches; in particular, phase shifts caused by changes in index of refraction can be used to indicate height and intensity information.
Here we employed phase contrast edge detection in order to completed construction and operation of the OEDS. ROC curves and discriminability values confirmed the results. Discriminabilities ranged from 0.61 to 0.78. Preliminary results for latent imaging were also promising, with an image able to be produced. However, substantial work will be needed to improve those results.

5.3 Conclusions

There are several conclusions that can be made from the previous work. First and foremost, it is possible to inspect for defects on the same machine that prints patterns. This fact is the main goal of this dissertation, and the research has demonstrated this statement to be a reality.

However, there are some less significant conclusions that can also be drawn. The detection systems that were employed in this research are still very noise sensitive. The noise is due to the ambient light and electronics present in the MLT lab. Running the experiments without the lights on (or at the very least a lower level) did help the situation, but better stray light control will be needed in any future experiments.

The immense data volume that is collected in order to analyze the defects was an early problem that needed to be overcome before any other experiments could continue. With this fact being the case, data storage is an unanticipated but critical consideration to the research done, and should be strongly evaluated in any future work done in this area, particularly with respect to composite image reconstruction.
Finally, in order to get the best results possible, the fabrication quality needs to be very high. Over the course of this project, many of the fabrication procedures have been revised (and altogether changed in some cases), which requires much time and effort. This work included the design of the patterns fabricated, the metallization of those samples, and the storage of the samples for later use. The improvement in this area, the author is convinced, is directly proportional to the increased resolution of the defects, especially in the later stages of the project.

5.4 Future Work

Looking at the work completed, and seeing what might be possible as a result of it, two major ideas come to mind. First and foremost, methods to improve the image quality, and hence the discriminability, should be investigated. It appears that the bandwidth of the electronic filters are not of high enough quality to provide crystal clear images that one might expect. Moreover, further image processing improvements, such as the regularized deconvolution filter, should be further tested to understand their limitations, particularly with regard to classifier inversions.

Secondly, possibly commercializing the system with a standard software and hardware package for use in industry would be a logical next step. Obviously any commercialization would need to take into account costs, supply-chain management, and other business factors, as well as on the experimental side the adaptation of fabricators to an all-in-one system.
Moreover, an optimization of the image processing routine would be beneficial. If a commercialization of this work were undertaken, the system would need to demonstrate reliable and accurate behavior, much more so than suffices for a ‘proof-of-concept’ endeavor. This work would further require the MLT to be much better understood.

Fourthly, working on a system that could automatically have the resist stored in some kind of storage tank would be very beneficial, allowing a simple series of commands to be entered by the user and removing human error and inconsistencies one step further. Substantial testing would be required, particularly with resist being stored for longer periods of time.

Finally, this work could be applied to other types of lithography and mass micro-printing systems. One great example would be that of “Dip Pen Lithography.” In this process, an AFM transfers ions to a gold surface via a cantilever. This cantilever acts as a “pen” in applying the charged particles to the substrate or “paper.” This research would be very applicable in that one of the advantages of this process already is that of direct placement, meaning nanometer-scale registry is possible. Moreover, Dip Pen Lithography is scalable, or force dependent, and lending to parallel depositions of material [60].
5.5 Final Remarks

As we have shown in this dissertation, the concept of automating the fabrication and inspection process for micro-lithographic components is no longer a blueprint, but a real system with real capabilities. At this point, the author would like to close with a quote from Henry Wadsworth Longfellow:

“Each morning see some task begun,
Each evening sees it close;
Something attempted, something done.”
APPENDIX-A: JOURNAL ARTICLE

This manuscript is in preparation for submission to Optical Engineering in April 2014.
Central Aperture Detection for Auto Direct Read-Write Photoresist Fabrication and Inspection

Justin M. Sierchio, Melissa Zaverton, Lee Johnson, Victor Densmore, Thomas Milster

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Abstract. We show the design for a Laser Scanning Microscopy Defect Detection system (LSMDD) based upon the idea that light can reflect off a photoresist-laden fused silica sample containing defects, allowing height and depth information to be obtained through changes in light intensity. Image registration using pre-defined points are employed. Image processing techniques involving median and deconvolution filtering are used. Results show that 2.1 μm resolution of these defects is obtainable, and receiver operating characteristic curves are used for quantifying results. Discriminabilities of 0.73 are achieved. Preliminary results for larger-array patterns through stitching processes are also shown.

Keywords: photoresist, central aperture, inspection system, direct read, fabrication

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1 Introduction

Patterning and inspection of micro-scale photoresist (PR) features over large areas (i.e. > $10^5$ mm$^2$) presents challenging problems for minimization of defects and defect detection. A typical process is shown in Fig. 1, where a substrate (i.e. fused silica) is coated with a thin layer of metal, followed by a layer of PR. Illumination at the exposure wavelength alters the PR chemistry. Liquid developer dissolves the exposed portions of the resist, leaving bare metal on top of the substrate. A solution specific to the metal is then applied to the sample, which etches the area of the metal coating not covered by PR, leaving a bare substrate in the exposed regions. Finally, residual PR is dissolved by submersion in a solvent.
Steps in the patterning process lead to many opportunities for defects to occur, especially for large-format arrays, e.g. 1 m class and above. Defects as small as 1 μm are typical, where the number of 1 μm pixels on a single 1 m diameter part is over 700,000. Metrology techniques for small-feature patterning and inspecting of custom, large area patterns usually involve human viewing through a microscope, which results in reliability of the observations being subject to operator fatigue and judgment errors. Additionally, as feature sizes decrease and part sizes increase, both the time and cost in the inspection task in this work increase substantially. Many mistakes in visual identification of defects are attributable to visual acuity, age, and the level of training for the technician.
**Fig. 1** Photoresist etching process\textsuperscript{2}. Here is an example of the photoresist etching process, in which resist is irradiated with a UV light source through a pattern mask, either removing the exposed area (positive resist) or keeping it (negative resist). The final patterns are then developed, leading to a “lift-off” or “etch back,” respectively. This is important because the multiple steps involved here can result in errors, resulting in the need for metrological measurements by those technicians.

An automated fabrication and on-site inspection system could alleviate this problem. Unlike human-based inspection systems, automated inspection systems offer several advantages\textsuperscript{3}. For example, technicians are freed from the dull labor of inspecting sample after sample, which can be psychologically demanding. Secondly, throughput improves, thereby reducing labor costs. Although many automatic techniques have been used to inspect lithographic patterns and features for defects, to the authors knowledge there has been no report of a single instrument that can both pattern desired features and then directly scan the pattern to inspect for defects\textsuperscript{2}. This paper discusses the development of an automated defect detection capability on a laser scanning maskless lithography tool.

The Laser Scanning Microscopy Defect Detection (LSMDD) system described here is based on the idea that reflected light from a focused laser beam scanning a PR-laden substrate containing contains intensity changes due to both the desired pattern and defects in that pattern. Development of this system in terms of data collection and processing is discussed in detail.

This paper is organized as follows. First, appropriate background of optical detection techniques is discussed, along with a description of the tools used for experiments in this work. Materials and methods are then described, including development of the opto-
electronic detection system, defect classification, and image processing routines. Results for simulations and experiments are then shown, with subsequent conclusions.

2 Background
Techniques that have been used to accomplish defect detection and semiconductor pattern inspection include of the use of optical techniques, atomic force microscopes, scanning electron microscopes, transmission electron microscopes, X-ray microscopes, and critical dimension scanning electron microscopes\(^4\)\(^-\)\(^9\).

Atomic force microscopes are limited by their relatively low scanning speed, making a high throughput scan difficult. Moreover, their resolution is limited by the size of the cantilever tips, potentially inducing additional artifacts\(^5\). Scanning electron microscopes require sample vacuum chambers, which are typically not designed to handle 1 m class samples or dielectric surfaces. Transmission electron microscopes additionally require destructive sample preparation, and have very small the field-of-view (FOV) of the sample\(^6\)\(^-\)\(^7\). X-ray microscopes very often display diffraction patterns, reducing resolution and increasing the number of image artifacts\(^8\). Critical dimension scanning electron microscopes share many of the same issues, including calibration with an atomic force microscope\(^9\).

Because of these issues, a system with the following characteristics is needed. It should write and inspect patterns without requiring an intermediate mask fabrication. It should require minimal sample preparation and not require a vacuum. The system should
also be non-destructive, easy to use, and fast. These requirements lend themselves to using a laser scanning microscope (LSM) approach\textsuperscript{10-11}.

The work described here involves the use of the University of Arizona’s Maskless Lithography Tool (MLT)\textsuperscript{12}. The MLT is composed of eight system blocks, which are shown in Fig. 2. An Argon Ion laser beam (1) is sent through a series of reflection mirrors into a closed-loop laser beam stabilization servo system (2), which compensates for beam drift. A modulation sub-system is used to control the laser beam for binary patterning (i.e. on and off) (3). This modulation system can also serve to vary the power for grayscale (i.e. 0 to 255) patterning, if desired. The scanning system (4) uses an air-bearing rotating multi-faceted polygon to sweep the beam across the flat sample in one direction (fast scan direction), while the sample is transported in an orthogonal direction (slow scan direction) (5). The laser power servo system (8) uses a power detector to sample laser power and compares the generated signal from the detector with the acousto-optic modulator (AOM) setting to obtain constant laser power at the start of each scan line. The input pattern (in bitmap format) is sent from a graphical user interface (GUI) to software (7) that controls input to the AOM. Position control electronics (6) accurately indicate pattern location to allow overwriting and stitching.
The LSMDD instrumental setup for detection of pattern defects is shown in Fig. 3. Light emitted from the laser is set to a consistent power level by the AOM. Reflected light is directed to a detector that produces an electrical signal. Signals are recorded synchronously with the scan line and are recorded in an image buffer. Because the fast scan direction covers more area horizontally than the slow scan direction vertically, more pixels are collected in the horizontal direction in order to maintain the aspect ratio of the collected images.
Fig. 3 Laser scanning microscope defect detection (LSMDD) implementation in the MLT. The argon laser sends light through MLT and scans over the sample through a beamsplitter. The differences in intensity are relayed back to a silicon detector. A focusing lens of 50 mm is added to focus the beam onto the center of the detector. An additional operational amplifier is added in order to increase the gain of the signal [29]. This signal proceeds into an oscilloscope for analysis. This reflection-based method allows the use of differences in light intensity to determine reflectance information and surface topography.

The flexibility of the MLT to incorporate additional optical components presents a unique opportunity to combine a high speed laser writer with an inspection tool. A single instrument is used to write the pattern in PR, and then detect the pattern for defects, where inspection speed and reliability are quantified. Acceptable reliability is defined as the threshold at which an inspection system detects a minimum percentage of the total defects present.

For the defect detection task, it is necessary to compare the measured image to a reference image. The first step in this comparison is image registration. Various
techniques in order to register and calculate the associated errors between the reference bitmap images and their experimental counterparts fall into the categories of Fourier transforms\textsuperscript{13-14}, edge detection\textsuperscript{15-17}, visual alignment\textsuperscript{18}, and stochastic optimization\textsuperscript{19}. Fourier transform techniques generally involve finding the associated spatial frequencies of each image and looking for the peak intensity in the Fourier domain\textsuperscript{14}. Inverse Fourier transforms are applied to align the images. While this approach works well for small datasets, the computation time necessary to run the algorithms is too expensive for the computations required here (i.e. 40,000 x 12,000 pixels), and is therefore not as useful. Edge detection and stochastic optimization cause similar problems. These techniques all involve much smaller images and \textit{a priori} knowledge of information between pixels\textsuperscript{15-18}. As a result, any interpolation and multiple-order partial derivatives necessary to run the algorithms on a 40,000 x 12,000 pixel image is very time consuming, and therefore is not pursued. Instead, an automatic cross-correlation-based technique is used which is in the next section.

3. Materials and Methods
Fused silica substrates are first cleaned in an ultrasonic methanol bath. Next, they are vacuum-spun, washed with a sequence of acetone, methanol, and isopropyl alcohol. After a bake at 250 C, the substrates are spun-coat with a thin layer of 1822 PR. This step is followed by soft-baking and writing the pattern with the MLT. After sample exposure and development, the substrate is placed into a 0.25 mol concentration sodium hydroxide
solution where the exposed aluminum is etched away. Residual PR is removed with acetone and alcohol.

Design and construction of the opto-electronic detection system involves various ideas from the literature\textsuperscript{20-23}. An illustration of the system used here is shown in Fig. 3. Because of large data volume and time requirements, a special-purpose image buffer is developed with assistance\textsuperscript{24}. Part oscilloscope, part processing computer, the image buffer takes raw data from the silicon detector and amplifier and converts it into workable images, from which further image processing and analysis can take place. The computer has a Quad-core 2.6 GHz, 32 nm processor running Windows\textsuperscript{™} 7 Ultimate 64-bit. The system also has 12 GB of memory, with 3, 1 TB hard drives for storage and data acquisition. A LabVIEW\textsuperscript{™} interface is used for control of data acquisition. The image buffer system has the ability to set its trigger delay, sample rate and number of samples per scan line from the MLT, as well as the number of lines scanned. Data are saved in a .bin file, allowing it to be sent to MATLAB\textsuperscript{™} for further analysis. System software can show both waveforms and images, with various scaling, colormap, and viewing options.

The technique used for alignment between the reference image and the test image is automatic cross correlation\textsuperscript{25}. This technique finds the scale factor, translation, as well as rotation angle of an unregistered image, and applies necessary changes for registration. MATLAB’s Image Processing Toolbox allows for the definition of “control points,” or points of similarity, to be matched between two images. These control points are part of the patterns themselves, defined as 30x30 pixel white “X’s” in the four corners of a square image, surrounded by a black background. The overhead required in the input
bitmap for the control points is approximately 900 pixels out of 1 million, or less than 0.1% of the area. Once the control points are chosen, the program uses a nearest-neighbor algorithm to check the correlation matrices in nearby pixels, with the highest value used to form a transformation matrix. This matrix is then multiplied onto the unregistered image, and results in a registered image. The technique allows the user to define control points within a specific region of interest in the entire array, avoiding unnecessary computation. The common area between the registered image and the original bitmap is selected and used for further analysis, including the generation of a difference image to highlight defects, and a median filter to heighten the visibility of faint defects. The subsequent processed image is then compared to the ideal bitmap.

The two types of defects evaluated are programmable defects, in which a feature is intentionally placed to distinguish it from the ideal case (e.g. lines, dots), and random defects, in which a feature is not intentionally placed, but is present and distinguishable from the ideal case (e.g. smudge, scratch). Reference bitmap image patterns in this paper consist of regularly spaced white lines on a black background 10 pixels apart of varying thicknesses (1 to 3 pixels) in horizontal, vertical, and diagonal directions, where a pixel is defined as the MLT sampling with a 2.1 μm period (though the image buffer system actually oversamples at a 1.05 μm period). Programmed defects for these patterns include removal of a varying number of white pixels (1 to 10) and placement of additional white pixels along diagonal directions. Note that contrast flipped versions (where the background and features have their intensities reversed) are also used in this work. The
contrast flipped patterns also had their interior lines biased so as to prevent the lines from disappearing during development.

There are four classifications for defects: (1) true positive, (2) false positive, (3) false negative, or (4) true negative. From this information, one graphs (1) vs. (2), and generates a receiver operating characteristic (ROC) curve. This curve varies with a given threshold that the user applies to determine whether or not a feature is classified as a defect. The area under an ROC curve is the discriminability with a maximum value of 1.0. In practical terms, discriminability defines the probability that a random pixel is a true positive (correct detection) as opposed to a false positive (incorrect detection), which is important when discussing figures of merit.

Figure 4 describes the image processing routine. After an acquisition, the AOM input bitmap, which is what was used to generate the PR pattern, is loaded (4a). The raw measured image is then loaded (4b). A small subsection, which is defined as the smallest repeatable feature in the pattern that matches the features of the input bitmap is then analyzed (4c). Though the smaller image could be evaluated with other registration techniques, using the current method allows one to vary the size of the pattern. This image is then resized to match the dimensions of the input bitmap to streamline the image processing (4d). Using a series of control points (typically either x’s in the image corners or the corners of the inner square), 4a and 4d are registered to one another (4e). After each step, the processed image is normalized on an 8-bit scale. A background removal tool is then used to remove digital noise by revaluing pixels +/- 3 standard deviations about the overall image mean to the mean value itself (4f). Next, a 2D median filter of
2x2 pixels is applied (4g), followed by a 1D median filter on the columns with width 4 pixels (4h). These filters make the measured image more closely match the reference image. For the input bitmap, a Gaussian blur filter (4i) of 3x3 pixels and image shift correction (4j) are applied to the input bitmap. These steps make the input bitmap more closely match the measured image. As a final matching tool, a contrast reversal on the processed measured image is performed (4k). This image is then subtracted from (4j), giving a difference image (4l). A threshold, between the values of 0 and 255 is applied, which produces the positive image (4m) that contains both the true positives and false positives. Next, a defect map, containing only the programmed defects, is loaded (4n). The defect map is multiplied by the positive image in order to determine the number of true positives (4o). Similarly, the complement of the defect map is multiplied by the thresholded image to determine the number of false positives (4p). It is important to note that much of the image processing routine helps to model the printing and scanning behavior of the imaging system by removing elements that impede proper defect identification.
It should be noted why two measured images, one with and one without defects, are not used in the image processing routine. The image processing routine works best when an ideal image is compared to a measured image. This fact is due to several reasons. First, power variations in the laser (i.e. banding effects, possible curvature of the scan line, etc.) are compounded when viewing the difference of two measured images, and are not easily removed with other processing tools. Secondly, it is harder to register the two measured images together due to the decline in quality of the alignment marks. Thirdly, random defects will appear more frequently, thus skewing the numbers of false positives. And finally, the actual number of true positives can be reduced by random defects that might be present (and not easily visible) in one image cancelling the programmed defects in the other. Use of an ideal image as a reference minimizes laser
power variations, increases the accuracy of the registration tools, and preserves the true number of both the true and false positives.

![Fig. 5 Illustration of true and false positives. (a) true positives detected after signal processing (b) false positives detected after signal processing.](image)

4. Results
An example of an image is shown in Fig. 6, where an AOM input bitmap is compared against an ideal bitmap, and programmed defects are highlighted in white. The ROC curves for different DC offsets using the bitmap in Fig. 6 is shown in Fig. 7. A comparison was also performed between patterns made with aluminum on glass versus PR on glass. The ROC curve for this study is shown in Fig. 8, with a higher discriminability for the aluminum sample. Moreover, a reversing the contrast of the images was also explored, with results shown in Fig. 9.
Fig. 6 Experimental test pattern. (a) The reference bitmap image. (b) The measured image. (c) The difference between C and A. (d) The difference between C and A quantized. The purpose of this figure is to illustrate, using real samples, a more complex level of detection with the image buffer system. Each image has a size of 250 x 250 pixels. Lessons learned from this test are used in later images.
Fig. 7 ROC curves for different DC offsets. In order to generate these curves, the image with defects is subtracted from the difference image. This leaves only the true positive pixels, which are counted. Knowing the total number of non-zero pixels gave the number of false positive pixels. Discriminability values here range from .497 to .726.

Fig. 8 ROC curves for different DC offsets using Al on glass (reverse contrast). Here, the color scheme of the experimental image is contrast-reversed, so that black backgrounds appear as white, and white features appear as black. As shown, the quality of the curves is reduced.
Table 1 Discriminability Values for ROC Curves.

<table>
<thead>
<tr>
<th>Mode</th>
<th>+4 DC</th>
<th>+2 DC</th>
<th>+0 DC</th>
<th>-2 DC</th>
<th>-4 DC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>0.613</td>
<td>0.726</td>
<td>0.497</td>
<td>0.646</td>
<td>0.670</td>
</tr>
<tr>
<td>White</td>
<td>0.729</td>
<td>0.624</td>
<td>0.690</td>
<td>0.709</td>
<td>0.648</td>
</tr>
</tbody>
</table>

Averaging the discriminability values for each offset gives values of 0.63 for a black background and 0.67 for a white background. This is a considerable improvement from the starting images, which generally had poor image quality. Furthermore, one could extrapolate the results here to the time required to test a 1 m class sample. Given the LSMDD can cover a 1 in² area in about 12 seconds, one could cover a 1 m class sample in about 18,600 seconds, or approximately 5.5 hours.

5. Conclusions
Patterning and inspection of micro-scale photoresist (PR) features over large areas (i.e. > 10⁵ mm²) presents challenging problems for minimization of defects and defect detection. To remedy this problem, we have designed a Laser Scanning Microscopy Defect Detection (LSMDD) system. Based upon the idea that light can reflect off a photoresist-laden fused silica sample containing defects, allowing height and depth information to be obtained through intensity changes, we have shown that defects with sizes approaching 2 μm can be resolved in various shapes, sizes, and orientations. The subsequent image processing routine involves matching the images as closely as possible before performing a threshold analysis, allowing the user to determine the location and size of defects. Finally, extrapolation to larger array samples shows this system could be used for industrial size patterning evaluation.
6. Acknowledgments

We would like to thank the II-VI Foundation for the generous support that has allowed us to engage in such an interesting and challenging project. Additionally, we would like to acknowledge Delbert Hansen, Warren Bletscher, Phat Lu, and the rest of our research group for their expertise and assistance during various points of our work. Special thanks go out to Matt Lang at AML Consulting™ for his design and debugging of the image buffering system.

7. References


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24. AML Consulting, 5960 Mill St., Excelsior, MN 55331.


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Biographies and photographs of the other authors are not available.

**Caption List**

**Fig. 1** Photoresist etching process.

**Fig. 2** Flow chart for MLT operation.
Fig. 3 Laser scanning microscope defect Detection (LSMDD) implementation in the MLT.

Fig. 4 Image processing routine.

Fig. 5 Illustration of true and false positives.

Fig. 6 Experimental test pattern.

Fig. 7 ROC curves for different DC offsets.

Fig. 8 ROC curves for different DC offsets using Al on Glass (reverse contrast).

Table 1 Discriminability values for ROC curves.
APPENDIX-B: SUPPLEMENTAL TOPICS

B.1 MLT Description

As has been discussed earlier, this work cannot be accomplished without the use of the Maskless Lithography Tool, or MLT. In this section, we provide a brief description of the tool [1, 6].

To begin, an Argon Ion laser beam (1) is sent through a series of reflection mirrors into a closed-loop laser beam stabilization servo system (2). This system compensates any beam drift present. To control the laser beam for binary patterning (i.e. on and off), there is a modulation sub-system (3). This modulation system can also serve to vary the power for grayscale (i.e. 0 to 255) patterning, if desired. The scanning system (4) uses an air-bearing rotating multi-faceted (12-sided) polygon to sweep the beam across the flat sample in one direction (fast scan direction) in such a manner that for every complete rotation of the polygon, the sample is transported in an orthogonal direction (slow scan direction) (5).

The laser power servo system (8) uses a power detector to sample laser power at the writing plane. It also compares the generated signal from the detector with the set signal in the acousto-optic modulator (AOM) to obtain constant laser power at the start of each scan line. The input pattern (in bitmap format) is delivered from a graphical user interface (GUI) to software (7) that controls the input of the AOM. Position control electronics (6) accurately indicate pattern location to allow overwriting and stitching.
B.2 OEDS Development

While discussed previously, for purposes of completeness, a description of the development of the Opto-Electronic Detection System, or OEDS, is provided.

As shown in Fig. B.1.2, light reflected off a sample placed on the MLT repeats its travels through the scanning system. Before the light reaches the AOM, it is siphoned off using a beamsplitter. The light is then collected into a silicon detector. A lens of f=50 mm was added to focus the beam onto the center of the detector. An additional operational amplifier was added in order to increase the gain of the signal, and hence match the dynamic range of the signal processing tools [44-45]. This signal is then sent into an oscilloscope for analysis. This reflection-based method allows the use of differences in light intensity to determine height information and surface topography [1].
As a corollary, a digital signal capture system is also constructed to display the data. Due to initial budgetary constraints, an Infiniium™ DSO8104A oscilloscope is used [60]. Three different inputs are connected to the oscilloscope: the output from the silicon detector, a position origin signal giving the scan location, and a pulse signal to synchronize the scans. In particular, the oscilloscope is programmed to collect a certain number of points for each scanline (in most cases 512), which allowed us to produce image ‘slices.’ After so many slices are collected (in most cases 2400), we take the output .csv file generated by the oscilloscope, and load it into a custom-built MATLAB™ program for reconstruction analysis. This analysis allows for the construction of an 8-bit positive image (i.e. bright spots are deeper than dark spots).

Figure B.2.1 Diagram of OEDS (Part 1) [1].
B.3 Additional LSMDD Information

B.3.1 LSMDD System Requirements

In this section, it would be prudent to further discuss the Laser Scanning Microscopy Defect Detection (LSMDD) system that has been used to improve data speed and reliability, specifically in terms of its specifications. This discussion will begin with a re-description of what the system is supposed to do. After that, we will discuss the system components.
As we know from Section B.1, feedback from the write laser in the UA Maskless Lithography Tool can be used to generate height information of the sample by use of a Silicon detector. As the laser scans over a sample, the detector voltage is collected and stored to be later reconstructed into a surface profile map. At the start of each line, a trigger signal is generated, called a “start of line” (SOL). The LSMDD makes it possible to acquire and reconstruct height information obtained from the MLT itself.

With regard to component and performance metrics, the system needed to contain data acquisition hardware, as well as a controlling PC, in order to read voltages from the detector and SOL signal, saving that data to a portable hard drive. The computer then needed to process this data into an image, with the goal of collecting a dataset of 1-2 GB in under 4 minutes.

Shown in Tables B.3.1 through B.3.3 are specific requirements of the LSMDD.

<table>
<thead>
<tr>
<th>Table B.3.1 Data Acquisition Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Memory Bit Depth</td>
</tr>
<tr>
<td>Analog Input Channels</td>
</tr>
<tr>
<td>Sample Rate</td>
</tr>
<tr>
<td>Buffer Memory</td>
</tr>
<tr>
<td>Input Range</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
Table B.3.2 PC Requirements

<table>
<thead>
<tr>
<th>Requirement</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU</td>
<td>Quad-core 2.6 GHz 32 bit processor</td>
</tr>
<tr>
<td>Memory</td>
<td>12 GB RAM</td>
</tr>
<tr>
<td>Hard disks</td>
<td>3x 1 TB (one for OS &amp; long term storage) (two for RAID0 data acquisition and near-term storage drive capable of streaming data from DAQ hardware at 100 MB/s or faster)</td>
</tr>
<tr>
<td>OS</td>
<td>Windows 7 Ultimate 64-bit</td>
</tr>
<tr>
<td>Misc.</td>
<td>DVD burner; graphics capable of supplying a D-SUB video port</td>
</tr>
</tbody>
</table>

Table B.3.3 Software Requirements

<table>
<thead>
<tr>
<th>Requirement</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>LabVIEW style interface</td>
<td>that allows control of data acquisition, including sample rate, trigger delay, number of acquisition points per trigger, and implements auto-saving of both detector voltage and SOL data. It also will allow file name indexing when pattern reading is complete.</td>
</tr>
</tbody>
</table>

As one can see, the LSMDD system is very sophisticated, and is designed to upload, process, and store large amounts of data easily and quickly.

B.3.2 Fault-Indicator Algorithms

This section provides additional information on the fault-indicator algorithms.
In this first part of the code, again previous variables are cleared. Next, the original bitmap file is loaded as a .mat file. The mosaic image file is also loaded. After this step, the images are registered to one another. Several features that are common in all the images are selected as control points. In the unregistered image, these points are used for a correlation transform in MATLAB to align them to the same points in the original image, removing scale, translation, and rotation differences. Through initial testing, the RMS error between these images is approximately 1%, or 2.74 DN for an 8-bit image.

The user inputs the pixel sensitivity that they want to see, which determines the acceptable difference between the reconstructed mosaic image and bitmap file. Subsequently, pixel-by-pixel, error pixels are flagged. This step is performed by changing any pixel in the mosaic image outside of the acceptable pixel sensitivity to white, and leaving the remaining pixels black. Specifically, the mean level of a floor value (over a small portion of the sample) is calculated and then removed, along with surrounding
pixels determine by that region’s standard deviation. These terms are defined in the next figure.

Figure B.3.2 Illustration of background processing terms. (a) pixel window (b) mean level and standard deviation range.
In this final part of the procedure, the fault mosaic array is then saved as a file. In order to improve the image quality, median filters, background removal tools, and image shift corrections are then applied to highlight edge differences using an imaging threshold. Finally, the difference image is displayed, and the program operations cease.

B.4 Other Topics

B.4.1 OptiScan Simulations

Moreover, this work would not have been possible without the use of the in-house MATLAB-based program OptiScan. Here, how “OptiScan” simulates scanning a photoresist-laden sample with a low dose of light, and collects it into a working image, is described.

To begin, a diagram of the entire system is shown, and explained sequentially. This diagram can be found in Fig. B.4.1.
Proceeding left to right, there is first and foremost a reddish, star-like figure. This object is the source of the system. If one opens the dialog box, the parameters needed to make it work are shown.
Going to the right-hand side, and selecting “Replace a Piece” under the Menu Items gives a series of options of what types of sources can be created. The option selected here is a “circular” source (of size 4 microns square). Next, proceed to the “Properties” and set the dimensions of the source, as well as the offsets (here 0) and sampling (200 points). Clicking on the “Source Type” tab, one can choose a coherent source and set the wavelength and power levels for the source.

Next, one should look at the blue oval, which is the “Lens” icon. Clicking on “edit” causes the following dialog box to come up.
If one clicks on “Menu Items,” the types of propagation one wants (shown is a direct input to the entrance pupil to a focused spot, with 1-to-1 mapping) can be set, as well as any aberrations and sampling (again 200 points) needed. Returning to the dialog box in Fig. B.4.3, one can also scroll down under Menu Items and select the “Lens Editor,” allowing a prescription for as many surfaces as needed. For the current setup, the lens has a diameter of 4 mm.

The next icon is the “Target” icon, denoted by a bull’s-eye. Selecting that icon gives the following dialog box.
Figure B.4.4 Target Dialog Box.

Here is a target from a prior simulation. Not that under the “Target Mask,” “Bulk Reflection” is selected. If one goes under Menu Items, and selects “Replace a Piece,” another image is imported. If one selects “Properties,” the following dialog box opens.
Here, the dimensions (62.5 microns x 62.5 microns), offsets (0) of the target, as well as the sampling (again 200 points), can be changed. One can also change the “window,” or area that is actively involved in the simulation, by clicking on the “Window Dimensions” tab. An example of the window is shown next.
Here one can choose the dimensions of the window size (1 μm²), as well as where it is centered. It is very important to note that where the four corners of the window are located, as this information will be needed for scanning.

Next, one can see another lens, acting as a collector (whereas the prior lens was a illuminator). Finally, there is the detector, which has the following dialog box.
Here one can choose the dimensions of the detector size (here 4 mm$^2$), and so forth. Always leave this the size at least 100x the feature being viewed.

In order to initiate the simulation, a “Gooey Delta” icon, or pink triangle, that will automate the shifting of the window, is needed. Here is an example of the Gooey Delta dialog box.
Here two parameters for automation, the x and y window centers, can be selected. The initial value, step value (here 1 μm steps), and how many samples (or modulo count) in each direction, can be changed. When using the “Y Win Center,” please designate a flag operation that will return the x value to its starting position for every change in y. An example of this procedure would be something akin to the following: [1:10:1000], where every 10th value starts a new row.
Finally, to run the simulation, click on the “Calc” tab in the original simulation window. There will be an input field to select the chain count (or individual samples to be calculated, which here is set at 400) as well as a wavelength (here 365 nm) to use.

**B.4.2 Additional Information: Machine Vision**

In this section, some additional information is presented on machine vision that is useful and adds to the reader’s understanding the work done here.

Machine vision, as it sounds, is a process of using a variety of methods and technologies for inspection systems that are image-based [62]. In general, this process has the following steps. First, there is an acquisition of the image from an object under test, either through using a camera, CCD array, or even a lens system. This imaging can be from various parts of the electromagnetic spectrum (i.e. infrared, visible, x-rays), depending upon the application. Next, the image is processed using a software package in order to retrieve the information necessary to characterize the object under test. This step can be completed through segmentation, in which a specific intensity level of the image is used, pattern recognition, in which shapes contained in the image are compared against a reference, or even using a barcode. From this step, there is usually a “decision matrix,” in which, based upon a variety of factors, an object either passes or fails inspection. A diagram of a machine vision system is shown Fig. B.4.9.
Figure B.4.9 Machine Vision Diagram.
REFERENCES


ADDITIONAL RESOURCES


