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Combining In-Line Atomic Force Microscopy and Scatterometry for Metrology of 3D Holographic Patterns In Roll-to-Roll Nanoscale Manufacturing

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INTRODUCTION

Roll-to-roll manufacturing at the nanoscale faces many challenges in precision control and overlay before it will be able to fulfill its potential as a continuous, high-throughput, low-cost fabrication technique [1]. These challenges include web instabilities like flutter, warping, twisting, slipping, wrinkling, and stretching [2], [3] which create a substrate that is difficult to control and monitor to the extent that is necessary for micro/nano production. Current technology reliably patterns single-layer features onto the flexible webs, but overlay between multilayer products remains out of reach [4]. By leveraging the ability to make precise structures that only require a single exposure using near-field interference lithography, such challenges can be averted [5].

However, evaluating 3D nanoscale structures on a flexible, moving substrate creates metrology challenges that require robust and flexible multiscale techniques. By pairing precise in-line atomic force microscope (AFM) metrology at the individual feature level with larger scale optical and scatterometry based measurements, we can execute holistic evaluation of the manufactured pattern. To this end, we aim to leverage machine learning techniques to integrate multiscale real-time metrology data which would enable real-time process control through feedback and fault detection.

HOLOGRAPHIC PATTERN MANUFACTURING

The samples currently used for conceptual testing of the proposed manufacturing methods are made in a batch-to-batch process based on the final manufacturing design. A diagram of the proposed manufacturing system can be seen in Figure 1 (left) and features a conformal nanostructured optical mask loop interacting with the photoresist-covered substrate web. The polydimethylsiloxane (PDMS) mask is aligned with the substrate and exposed to an ultraviolet (UV) light source to create the near-field holographic structures within the thick layer of photoresist. An example of the resulting pattern can be found in Figure 1 (right), although refinement to the process and manufacturing environment is necessary to improve pattern quality. Also, further inverse modeling of the structures can be used to create a mask that produces 3D structures with desired properties or geometry

MULTISCALE METROLOGY

The 3D holographic structures created by the system require metrology at multiple scales to ensure high quality features across the span of the entire web. Metrology goals include topographical imaging of the pattern at the individual feature level, assessment of the quality of the periodic internal structure of the pattern, and measurement of the material properties of the exposed resist.

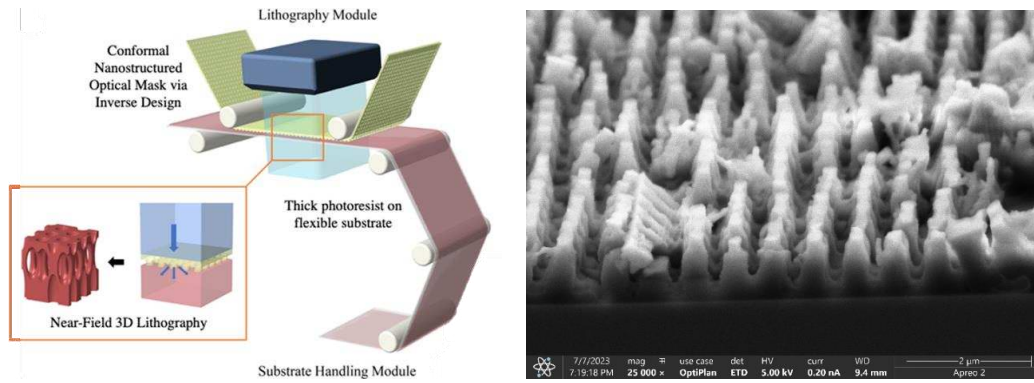


FIGURE 1. (Left) Diagram of proposed 3D holographic pattern manufacturing system. (Right) SEM image of 3D holographic lithography pattern.

Feature Scale Metrology: Atomic Force Microscopy System

The existing AFM metrology tool is capable of in-line metrology of R2R samples [6]. It consists of a single-chip, micro-electro-mechanical system (MEMS)-based AFM mounted to a flexure-based gantry system as seen in Figure 2 (left) [1], [6], [7]. The single-chip AFM (sc-AFM) contains full actuation for taking a scan within a $20\text{ }\mu\text{m}$ by $20\text{ }\mu\text{m}$ area and the gantry allows the AFM chip to be suspended above the web and maintains the position of the AFM relative to the moving web. This, in combination with a flexure system stabilizing and actuating the gantry, allows the web to move continuously and the AFM to move with it for the length of the scan. The flexure-mounted AFM system can then lift and reset position to take another moving scan. This system is known as the nanopositioning subsystem for the remainder of this paper. This subsystem is actuated in the XZ plane by voice coil linear motors driving a pair of biaxial double parallelogram flexures with a gantry suspending the AFM in between. The x-axis allows for the AFM to move in tandem with the moving web for the duration of the scan while the z-axis motion regulates the approaching and disengaging actions of the probe. The flexure-gantry system is pictured in Fig. 2 (left).

Testing of AFM imaging with moving scans is still underway, but static scans of samples made using the holographic interference lithography process can be seen in Fig. 2 (right). This figure shows an sc-AFM scan of a 60 mJ/cm^2 exposed sample with an un-sharpened tip (radius $> 100\text{ nm}$) and demonstrates the device's ability to detect defects including missing features and pattern collapse. Physical limitations of the flexure nanopositioning system and AFM scan throughput results in limited sampling ability at this scale. Additionally, the scan location cannot be repositioned relative to the width of the web. Therefore, this metrology technique can only provide topographic and material property data at a relatively low sampling rate, generally under $100\text{ }\mu\text{m}^2$ every 10-20 seconds. To assess the entire web, larger-scale metrology is needed.

Web-Scale Metrology: Scatterometry

Where AFM will provide periodic sampling of individual feature-scale characterization, scatterometry will provide continuous feedback across the entire web. Additionally, the use of optical modeling of the ideal physical system and comparison to the real-time measurements will create the opportunity to characterize the internal periodic structure. The periodic nature of the pattern will result in predictable reflectance. These characteristics are dependent on both the wavelength of light used for detection and the sample structure. Experimental scatterometry results can be seen in Figure 3 (left), where samples produced more damped reflectance amplitudes and longer periods at higher dosages. By monitoring the modulation phase and amplitude, it is possible to determine over or under exposure, which is further indicative of internal pattern defects that affect the reflectance spectra.

The experimental data can then be compared to an optical model performed using finite-difference time-domain (FDTD) methods [8]. The 3D holographic interference pattern created by the optical model is then used to create a binary model of the shape created in the photoresist. A transfer-matrix method (TMM) simulation is then performed on the binary resist model to generate a reflectance spectra model [9].

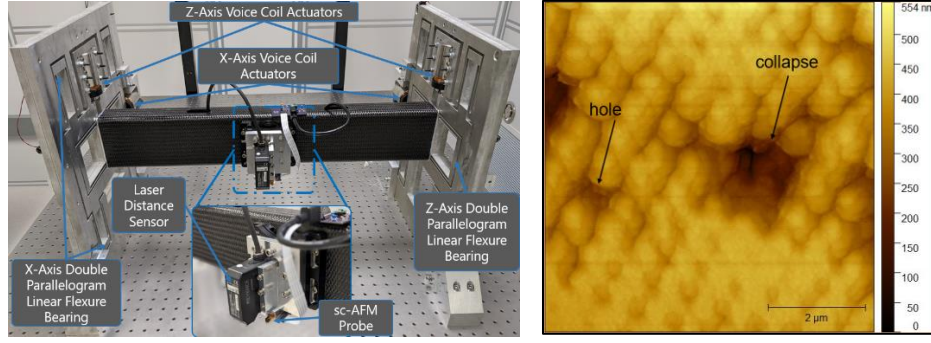


FIGURE 2. (Left) The double-parallelogram and gantry of the nanopositioning system with view of sc-AFM mounting subsystem. (Right) Static sc-AFM scan of 60 mJ/cm² exposed sample with local defects highlighted.

Figure 3 (right) shows an example comparison between the simulated reflectance spectra and the experimental data. In this figure, the internal structure of the pattern most significantly affects the period of the spectral modulation. The models were able to achieve period matching within 2% error. The phase shift notable within the figure is due to differences in photoresist thickness, which is not yet accounted for in the model. Using the model comparison, changes in the period of reflectance modulation can be used to indicate imperfections in the internal structure of the pattern as well as provide exposure dosage information. Reviewing areas of concern indicated by the scatterometry measurements with the AFM metrology system can provide more detailed characterization of manufacturing imperfections to allow for robust quality control.

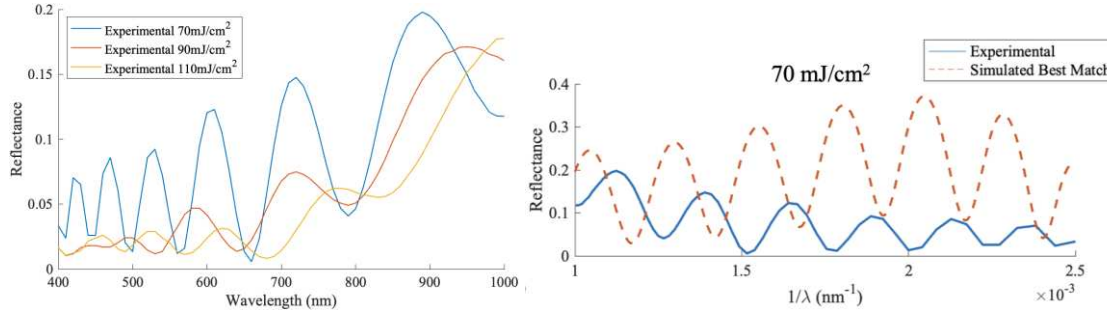


FIGURE 3. (Left) Reflectance measurements of fabricated samples with 70, 90, and 110 mJ/cm² exposure dose versus wavelength. (Right) Best-match reflectance spectra between experimental results and simulation.

MACHINE LEARNING-BASED DATA FUSION

The pair of aforementioned metrology techniques create a multiscale, multifrequency, multimodal (i.e., using disparate sensing modes) set of measurements to combine into useful process control information. These challenges arise from the significant difference in scale and scan speed of the AFM system in relation to scatterometry. A 10 by 10-micron AFM image is many thousands of times smaller than the spot size of the scatterometry module across the width of the web, and can only capture images at a rate well below 1 Hertz. This type of multidimensional analysis creates a collection of scaling challenges that would require expert evaluation to extrapolate useful relationships, which may be automated by machine learning-based data fusion techniques. [10].

Fortunately, the fairly successful implementation of Machine Learning algorithms (specifically Deep Learning-based) for modelling biological systems [10], for in-situ 3D printing process evaluations [11], etc., create the foundations for our analysis of such multimodal data. High resolution, low speed AFM scans, if independently used, enable characterization of local defects and can be evaluated with image processing schemes. The higher speed, lower resolution scatterometry data would provide insights into web-wide uniformity, product porosity, the presence of periodic defects such as those due to faulty masks, etc. We shall explore the use of generative models such as Generative Adversarial Networks (GANs) to compensate for the dearth of high-resolution AFM image data due to their ability to generate realistic high-resolution images by learning the underlying probability distribution corresponding to the training data, which in this case shall be the AFM scans [12]. Scatterometry signals can be

converted to images which would then enable the use of a Convolutional Neural Network (CNN) to fuse the AFM and scatterometry data, at appropriate frequencies [11].

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KEYWORDS

Atomic Force Microscopy, roll-to-roll, in-line metrology, multimodal machine learning, scatterometry