Quality Inspection of Nanoscale Patterns Produced by Laser Interference Lithography Using Image Analysis Techniques

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Abstract – This paper introduces the quality inspection of nanoscale patterns produced by the Laser Interference Lithography (LIL) technology using image analysis techniques. In this paper, patterns of two-beam and four-beam interferences are considered. Image analysis techniques based on the Hough transform (HT) and Maximum Likelihood Estimation (MLE) have been applied to detect and estimate various quality parameters for the two types of textures. The HT and a modified grey-scaled HT are introduced as a global approach for the analysis of the two-beam interference patterns. Surface parameters, such as the period, depth, and their uniformities, can be obtained directly without a priori knowledge of the textures. Due to different pattern structures and strong noise effects, the four-beam patterns are dealt with a different approach, using a statistical method based on the likelihood function to estimate each circle’s center and shape. Taking into consideration of noises and defects, another further rejection step is introduced to filter out noises and defects. Results from experimental samples are presented.

Index Terms – Quality inspection, laser interference lithography, Hough transform, maximum likelihood estimation

I. INTRODUCTION

The LIL technology has been widely researched and used for micro and nano manufacturing of periodic and quasi-periodic surface patterns in recent years. Different techniques have been developed for the surface pattern fabrication process, such as the MIT’s ‘Nanoruler’ [1] and the more recent maskless approach with higher-power laser pulses [2]. The quality of the fabricated patterns using different technologies varies. Especially the maskless approach is sensitive to various environmental factors, such as the laser intensity’s homogeneity, temperature and dusts. During the work, it has been found that it is essential to have an automated method to define and evaluate the quality of the patterns. This will be essential for the quality control process in industrial mass production, and also of great importance for laboratory experiments. This paper introduces a probabilistic method based on image analysis techniques for automated quality inspection of such technology.

Although many quality inspection techniques have been well developed and used in industry over the last few decades, it is found that most of them are not directly applicable here to the LIL patterns due to some special features presented in this application. Some specific aspects of the quality inspection need to be taken into account and will be addressed in this paper.

Most research work on quality inspection has been focusing on the roughness estimation or defect detection of uniform plane surfaces. However, surfaces of this application present periodic textures, either parallel gratings or evenly distributed circles, depending on the system setup. Moreover, in this application, rather than only detecting possible defects, it is also particularly of interest to characterise the parameters of the desired texture features, such as the uniformity of the radius of the circles, depth, and period.

In section II of this paper, the LIL technology and related work on quality inspection are reviewed. Due to the different patterns produced by different system setups, it is followed by two separate sections presenting the proposed methods for the quality inspection of different cases. One of them describes the patterns generated using the two-beam setup, while the next one introduces the quality inspection for the four-beam setup. The results are shown with samples from experiments.

II. BACKGROUND

A. Laser Interference Lithography

The interference patterns, generated from multiple coherent beams of laser radiation, can be arrays or matrices of laser beam lines or dots. When using such radiation to interact with materials, feature sizes down to a fraction of the laser
wavelength can be created. This technology provides a way for micro and nano manufacturing of periodic and quasi-periodic patterns that are spatially coherent over large areas.

Fig. 1(a) shows the principle of two-beam laser interference, and laser beam lines are formed. The pattern period is basically governed by \( \lambda / 2 \sin \theta \) as shown in Fig. 1(a), where \( \lambda \) is the wavelength and \( \theta \) is the incidence angle of the beams. Fig. 1(b) shows a configuration of four-beam laser interference and laser beam dots are formed.

![Two-beam laser interference (a) and four-beam laser interference (b).](image)

Fig. 1 Two-beam laser interference (a) and four-beam laser interference (b).

A general form of \( N \)-beam interference can be described as the superposition of the electric field vectors of \( N \) laser beams \((\vec{E}_1, \vec{E}_2, \vec{E}_3, \ldots \text{ and } \vec{E}_N)\), as formulated below

\[
\vec{E} = \sum_{m=1}^{N} \vec{E}_m = \sum_{m=1}^{N} A_m \vec{p}_m \cos(k\vec{n}_m \cdot \vec{r}_m \pm 2\pi vt + \phi_m) \quad (1)
\]

where \( A_m (m=1, 2, \ldots, N) \) is the amplitude, \( \vec{p}_m (m=1, 2, \ldots, N) \) is the unit polarization vector, \( k = 2\pi/\lambda \) is the wave number, \( \vec{n}_m (m=1, 2, \ldots, N) \) is the unit vector in the propagation direction, \( \vec{r}_m \) is the position vector, \( \nu \) is the frequency, and \( \phi_m (m=1, 2, \ldots, N) \) is the phase constant.

When processing materials, rather than only the conventional resist writing method, direct processing of materials has also been performed [2], enabling an easier maskless approach for pattern processing. However, the quality could be severely affected by various environmental factors. Figs. 2 and 3 are two samples of the maskless method using the 2-beam and 4-beam systems respectively, obtained via an Atomic Force Microscope (AFM). As can be seen in Fig. 2, the pattern from the 2-beam system presents parallel lines at a specific angle. Quality parameters that are of interest in this case include the angle of the parallel lines, period, possible defects, and depth. While for the 4-beam setup, periodic textures, which are circles here, are produced. In this case, it is particularly targeted at measuring the pattern period, each circle’s center and radius, and their uniformities.

![2-beam LIL pattern example.](image)

Fig. 2 2-beam LIL pattern example.

B. Quality inspection

In general, textures can be categorized into two types: structural (patterned) and statistical (unpatterned) textures. Most of the defect detection approaches are based on the latter type of textures, where defects can be identified using a threshold method or similar ones. The LIL patterns in this work obviously belong to the former type.

Regarding the quality inspection techniques, various approaches have been made. The most popular one is the template matching method, which has been widely used in industry, such as the quality inspection for the Printed Circuit Board (PCB) manufacturing [3]. However, a generic template must be obtained beforehand to perform the work, which is normally not available, due to the variations of textures caused by laser fabrication effects on different materials and experimental circumstances.

Some work has been performed for the orientation measurement of laser interference fringes [4], which has used two randomly selected patches from the texture. By a fringe matching method along one direction, the phase shift between fringe patterns can be then used to obtain the fringes’ angle. A priori knowledge of an approximate wavelength is still needed to decide the patch size. Lavrik utilized the Hough transform (HT) and the Wavelet transform to analyze nano-meter scaled parallel linear textures [5]. Another approach using the HT was applied to analyze interference fringes based on an empirical sinusoidal model [6]. In [3], the Fourier transform was proposed to filter out the dominant frequency component to obtain relative uniform surfaces, which makes defects more detectable.

Concerning the patterns produced by the four-beam setup, related work can be found from a few areas on analysis of
periodic or structural textures [7, 8]. Spatial-frequency analysis techniques, such as the Wavelet or Gabor transform, have been popularly used as an effective means for defect detection in both structural and statistical textures [8, 9]. The use of such techniques are applied as a preprocessing stage in obtaining individual frequency components, where normally the dominant frequency components must present stronger amplitudes and defects or abnormal features can be observed in other frequency components. Also, it is summarized that applications of using spatial-frequency methods are also often found to be in texture classification and segmentation [3].

As mentioned above, depending on the setup of the system, the patterns produced by the LIL are presented with either parallel gratings or periodically distributed dots. The parameters that are of interest also vary for each different case. In the next two sections, the two-beam and four-beam patterns are discussed separately.

III. TWO-BEAM PATTERN ANALYSIS

To evaluate the quality of 2-beam interference patterns, several parameters and their statistical distributions need to be measured, such as the period, depth, fringe orientation, and defects. It is proposed to use a global approach based on the HT, which will allow a straightforward way to obtain the required information.

A. Standard Hough transform

In order to measure the period of a pattern, it is essential to define a unified concept of a period in the context of this application. In general, it can be defined as the frequency of occurrence of a similar grey-scaled pattern or texture spatially. It will become ambiguous when the uniformity of period is also of interest. The period in the former definition can be directly obtained by the template matching approach [4], which, however, cannot provide the uniformity information. Therefore, in terms of the period uniformity, the period needs to be estimated by the occurrence frequency of edge pairs of the same direction. As an example, Fig. 4 illustrates a profile of the grey-scaled image along the angle perpendicular to the gratings, and each individual cycle can be measured when the grey value exceeds a threshold as shown in the figure. In other words, the period uniformity needs to be presented associated with a given threshold value. As illustrated in Fig. 4, the variance of period can be given as $\text{var}(p_1, ..., p_n)$.

However, due to the imperfect quality, the amplitudes of the beams are not evenly and continuously distributed. When performing the threshold method, some lines are broken into pieces, as shown in Fig. 5. This will make it difficult to estimate the period using the above method. Instead, it is therefore proposed to use the HT for this purpose, which can detect the edges directly, and the noisy distribution of the edges can be also observable.

The HT is a useful method for the detection of straight lines in an image. It can be described as a transformation of a point in the $(x, y)$-plane to the parameter space. A binary form, containing only edges in the image, needs to be created at first. The parameter space is represented by an accumulator array, which can be described as the sum of the edge map along the straight lines defined by the polar parameter $(\rho, \theta)$. In brief, in the HT parameter space, a straight line can be represented by a local maximum, defining the line’s angle and distance from the origin. This can be formulated as

$$H(\rho, \theta) = \int f(x, y) \delta(\rho - x \cos \theta - y \sin \theta) dx dy$$

where $f(x, y)$ is a binary image here, $H$ represents the HT transform in the parameter space, $x$ and $y$ are the coordinates of the pixel in the image, $\rho$ is the perpendicular distance from the line to the origin, and $\theta$ is the angle between the image’s $x$-axis and the normal to the line.

![Fig. 4 Threshold-crossing period measurement.](image)

![Fig. 5 Threshold method of two-beam interference pattern.](image)

With the edges extracted from the binary form (Fig. 5), another step is needed to filter out one side of each beam with the gradient information at the edges. Fig. 6 shows the HT domain of this example. Clearly, at angle 95°, a strong periodic trend can be observed, where the amplitudes are also the highest. This indicates that angle 95° is the orientation of the parallel beams. Fig. 7 shows the data at this angle (95°) in the parameter space. With this information, the period can be easily obtained via either a 1D Fourier transform or similar. In addition, it can be seen that each local lobe represents a line in the edge map. In other words, one local peak indicates the accumulated points of one edge and its surrounding noisy points are also accumulated around the local peak, representing the straightness and variations of the corresponding edge. With the knowledge of period, each local lobe can be segmented out separately. The statistical parameters, such as the variance and the mean, can be therefore obtained from each separate segment.
B. Grey-scaled Hough transform

However, as the HT transform utilises only the binary edge map, the period presented there is only based on the calculation of the detected edges, which are apparently not sufficient for very accurate measurement. In addition, the grey scales are not considered, that makes it impossible to obtain the depth information or detect any defect in the image. It is therefore proposed to apply the grey scales in the original image to the transform, instead of the discrete points. \( f(x, y) \) in Equation (3) can be then replaced by the grey scales here. This actually becomes identical to the Radon transform. Fig. 8 is the result of the grey Hough transform. Similarly, at angle 95°, strong periodic trend can be observed, as shown in Fig. 9.

In order to obtain the distribution of the grey scales, it needs some modifications to the original Radon transform in the implementation. Along the direction of the gratings, the grey scales of a line with a perpendicular distance to the central point need to be recorded at the grating angle in the Radon transform domain. By folding all cycles and averaging the data, a unified model of the pattern can be obtained, which will help analyse the roughness of the surface, estimate parameters of the depths, and identify the potential defects. In this case, the depth is defined as the value of the difference between the maximum value and the minimum value in one single cycle. Fig. 10 illustrates the amplitudes of one spine line and one valley line respectively (A and B in Fig. 9). The average of the two amplitude series represents the depth at the corresponding cycle. Also, the amplitude series in Fig. 9 needs a further step of normalisation according to the number of pixels at each location. This is because that some gratings are actually truncated in the rectangle image.

To describe the roughness of a surface, the most commonly used parameter is the standard deviation of these grey scales. As the Matlab implementation of the Radon transform will first divide each grid into four equal parts, the grey scale of each grid is then divided by 4 [10]. Therefore, an approximate standard deviation would be four times of the standard deviation of the amplitude values in the Radon transform domain, thanks to the linear property of the standard deviation function.

In summary, it has been shown that the grey HT is a convenient method for quality inspection of 2-beam interference patterns. Compared to the template matching method, one advantage of using the above approach for the quality estimation is that it does not require any priori knowledge about the features. In addition, template matching is more vulnerable to the variation of textures. On the other hand, the transformation of parameter space allows convenient
measurement of the amplitudes and depths of any individual grating. Although it is slightly more computational, the experiment performance on a PC has shown a reasonable speed for real time applications.

IV. FOUR-BEAM PATTERN ANALYSIS USING MLE

The four-beam setup produces patterns with periodic circular features. The standard HT is not suitable to be applied directly here for the detection of circles. The main reason is that the standard HT will not be effective enough to detect the desired circles from the noisy boundaries. In addition, different from the two-beam patterns, the circular HT will not provide a direct view of the period information. Another challenge of this is that the desired textures are more easily mistaken to the noises, due to their comparable shapes and sizes. To overcome the above mentioned problems, a two-stage strategy is proposed here, including a probabilistic approach for the circle feature estimation and a defect or noise rejection stage.

A. Estimation of circle features

The probabilistic approach for the circle feature detection is a modified Hough transform based on the Maximum likelihood Estimation (MLE). Similar to the standard HT, a binary form of the image should be created based on a simple threshold method, where boundaries of the detected potential features should be extracted. With a set of boundary points of an enclosed region, the centre position and its optimal radius can be then estimated.

The boundaries of a noisy circle can be modelled as [11]

\[ \mathbf{p}_i = \mathbf{c} + r\mathbf{u}(\theta)_i + n_i \]  

(3)

where \( \mathbf{p}_i = (x_i, y_i)^T \), \( i = 1, \ldots, N \) represents the \( N \) measured positions of the circle boundary, \( \mathbf{c} = (x_c, y_c)^T \) is the circle centre, \( r \) is the radius, and \( n_i \) denotes the errors of the measurement. \( \mathbf{u}(\theta) = (\cos \theta, \sin \theta)^T \) transforms the angle \( \theta \) to the Cartesian coordinates. Instead of accumulating only the points laid on circle’s circumference, the likelihood function of the above model can be formulated based on a Gaussian noise distribution assumption, as below [11]:

\[ L(c, r, \theta | p_i, i = 1, \ldots, N) = \frac{1}{(2\pi\sigma^2)^N} \prod_{i=1}^{N} e^{-\frac{1}{2\sigma^2} \left( \frac{\| \mathbf{p}_i - (\mathbf{c} + r\mathbf{u}(\theta)) \|^2}{\sigma^2} \right)} \]

(4)

Taking the logarithm of the above function, the likelihood function can be yielded as:

\[ \log L(c, r, \theta) = \sum_{i=1}^{N} \| \mathbf{p}_i - (\mathbf{c} + r\mathbf{u}(\theta)) \|^2 \]

(5)

Optimally, the value \( \mathbf{u}(\theta) \) can be approximated as \( (\mathbf{p}_i - \mathbf{c})/\| \mathbf{p}_i - \mathbf{c} \| \), and the radius can be estimated as the mean of the distances from all boundary points to the center

\[ \hat{r} = \frac{1}{N} \sum_{i=1}^{N} \| \mathbf{p}_i - \mathbf{c} \| \]

Substituting these to Equation (5), the likelihood function can be derived as

\[ \log L(\mathbf{c}, r) = \sum_{i=1}^{N} \| \mathbf{p}_i - \mathbf{c} \|^2 - \frac{1}{N} \left( \sum_{i=1}^{N} \| \mathbf{p}_i - \mathbf{c} \|^2 \right) \]

\[ = N \text{var} \left( \| \mathbf{p}_i - \mathbf{c} \| \right) \]

(6)

where \( \text{var} \left( \| \mathbf{p}_i - \mathbf{c} \| \right) \) denotes the variance of \( \| \mathbf{p}_i - \mathbf{c} \| \). The centre position and the radius can be thus determined for each possible region.

B. Criteria of detecting defects

In addition to the circular feature estimation, another challenge in this application is to detect possible defects. With the threshold method used above for boundary detection, noises in the patterns would be also included. In order to filter out the possible noises, another two criteria are proposed for a subsequent rejection stage. These two conditions are:

1. The desired features must present a strong periodic trend;
2. The circle sizes must not vary very much.

As noises are normally found to be randomly located and also their sizes tend to vary from each other, the above two conditions would be able to filter them out from the periodic patterns. The rejection function for the likelihood can be then given as

\[ L_w(\mathbf{c}, r, k) = L_p \cdot L_s \]

(7)

where \( L_p \) denotes the periodic likelihood, and \( L_s \) is the likelihood estimated by its size.

Depending on the individual texture, the periodic likelihood can be modelled accordingly. As an example shown in Fig. 3, it is assumed that, for one circle, the 6 closest neighbour nodes are located around it with the same distance. It can be then simply formulated as

\[ L_{ph} = \frac{1}{\sqrt{2\pi\sigma_p}} \exp \left\{ \frac{-(d_{ik} + \ldots + d_{Mk} - M\bar{d})^2}{2\sigma_p^2} \right\} \]

(8)

where \( d_{ik} \) denotes the distance between the \( i \)th neighbour node and the target feature, \( M \) is the number of neighbour nodes, and \( \bar{d} \) is the averaged distance of \( d_{ik} \). In practice, exceptions must be taken into consideration if there are not enough \( M \) desired features around, especially when the feature is at an edge of the pattern or any real feature has not been detected with the threshold filtration. In this case, the number \( M \) should be adjusted appropriately to the valid number.

The size likelihood of the \( k \)th circle can be given as

\[ L_s = \frac{1}{\sqrt{2\pi\sigma_s}} \exp \left\{ -\frac{(r_i - \bar{r})^2}{2\sigma_s^2} \right\} \]

(9)

where \( r_i \) is the radius of the \( k \)th circle, and \( \bar{r} \) is the averaged radius.
Similarly, taking the logarithm of $L_w$, a simpler form of the rejection likelihood function will be yielded as:

$$
\log L_w(c,r) = -\frac{(d_{ik} + \ldots + d_{MK} - M\bar{T})^2}{2\sigma_p^2} - \frac{(r_i - \bar{r})^2}{2\sigma_r^2}
$$

(10)

This likelihood estimation can be used for defect rejection by defining a threshold. Features that are below the threshold will be marked as possible defects. In fact, this function can be combined with Equation (4) together to create a unified form. However, due to the different texture sizes, a unified function is not possible to be constructed directly, and empirical data have shown that the two-stage approach is effective enough to detect possible defects or irregular features.

Fig. 11 is the result of the pattern in Fig. 3. It can be seen that features at the edges are marked as defects due to their truncated shape and the biased estimated centres. Other parameters, such as the uniformity of feature sizes and periods, can be thus obtained. In this example, the diameter of the circular features is 163nm, and presented with a standard deviation of 14.3nm. Fig. 12 shows a single circle and its noisy boundary, and the graph below is the difference between the real boundary and the desired circumference.

![Image](image1.png)

**Fig. 11 Circle detection example (unit: pixel).**

![Image](image2.png)

**Fig. 12 Desired circle vs real boundary (a) and their difference (b).**

As a summary, to estimate the quality and detect defects in the four-beam setup patterns, the preliminary tests with the proposed strategy have shown an effective result. This method allows measuring any individual feature, and irregular textures can be effectively identified. In practice, depending on the real type of patterns, the criteria for constructing the likelihood functions need to be customized.

**V. CONCLUSION**

This paper has introduced the methods of quality inspection for the nanoscale patterns produced using the LIL technique. Two types of system setups, including the two-beam interference and four-beam interference, have been discussed separately. For the two-beam setup, the Hough transform and its derivation based on the grey scales are applied for the quality estimation, which can provide parameters, such as the period, depth, and the uniformity. Due to the periodic circular textures presented in surfaces of the four-beam setup, a two-stage strategy has been introduced for estimating the circle properties, such as the centre positions and their radius, and rejecting possible noises or defects. The results from the experimental samples have shown that the methods are effective/useful for quality inspection of the nanoscale patterns produced using LIL.

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