Interferometric profiling of wafer surface using deep learning and two-frame interferometry

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In this paper, we propose a new interferometric profiling method with only two interferograms based on deep learning. Unlike the conventional multi-frame interferometric technique, the surface of a silicon wafer can be measured by two-frame interferometry with the proposed method. Instead of using the real interferograms as training datasets, we generate simulation datasets by linear combinations of the Zernike polynomials. Once a network is trained by a large number of simulation datasets, the trained network can predict a phase map from two input interferograms in real-time. Experimental results demonstrate its outstanding performance through various metrics, in terms of high accuracy and error compensation over the conventional multi-frame techniques. It is confirmed that the proposed method based on deep learning can measure the surface shape of the silicon wafer precisely with only two interferograms.

1. Introduction

Silicon wafer is a primary element to produce semiconductor chips essential for many kinds of electronic devices. To raise the performance of these devices, a lot of new technologies have been developed such as wafer stacking [1], wafer-level packaging [2, 3], and through silicon via [4]. In these technologies, the importance of the precise inspection and management of the wafer surface is increasing.

Many studies have been reported, and among them, a wavelength-tuning Fizeau interferometry can provide the fast and accurate measurements with the non-contact wafer surface profiling. The light from a laser source is reflected on sample and reference surfaces and interferes with each other. And then, the phase difference between two reflected beams can be observed as an interferogram. During the wavelength scanning, the observed interferogram changes its brightness. A phase map corresponding to the surface information can be profiled by using these interferograms. In the wavelength-tuning interferometer, it is not necessary to consider the vibration and tilt from mechanical movements of piezoelectric transducer and damages from sample contact. However, many frames of interferograms are required and this leads to the error accumulation on the final result and time-consuming measurements. Therefore, we contrive several ways of reducing the number of interferograms while taking advantage of wavelength-tuning interferometry.

Inspired by the development of deep learning techniques, we consider our problem as a kind of image translation from interferograms to a phase map [5, 6]. Therefore, we design two-frame interferometry based on the image translation field in deep learning which can predict the surface phase map from only two interferograms. Instead of collecting a large number of real data, the simulation data generated from linear combinations of Zernike polynomials are employed as the training datasets. A few structures of neural networks are adopted as the prediction tools of the desired phase maps. Once two-frame interferograms are input to the train the complete model, the phase map can be predicted. The result phase maps are compared with those from the conventional methods which use many interferograms and show almost same or better results. The experimental results indicated that the proposed two-frame interferometry based on deep learning is more accurate and efficient compared with conventional techniques.

2. Method

2.1 Generation of simulation dataset

In the wavelength-tuning Fizeau interferometer, the interferograms are captured at a uniform shift interval during the scanning. This means that all interferograms have uniform shift values and by using the interferograms with appropriate shift values, the phase map can be determined. However, since it is impossible to modulate the shift values exactly uniformly, linear and nonlinear shift errors are inevitable. Here, for the insensitivity to these errors, two interferograms with zero and random shift values are generated.

For optimal training and outstanding result, high-quality and appropriate number of training datasets are necessary. The simulation phases are generated by the linear combinations of the Zernike polynomials describing the aberration of optical systems. The simulation interferograms are generated according to the below signal intensity equation considering the second harmonic component.

$$I = A + B_1 \cos\left(\delta - \varphi\right) + B_2 \cos\left[2\left(\delta - \varphi\right)\right] \quad \text{Eq. (1)}$$

where A is background intensity, B_1 and B_2 are the intensities of the fundamental signal and 2nd harmonic component, respectively, δ is the shift value, and φ is the phase.

A single training dataset is composed of two-frame interferograms and one surface phase map which are the input and output of the network.

2.2 Design of neural network

Prediction of the phase map indicating the surface shape of the silicon wafer from two-frame interferograms can be regarded as the image translation in deep learning. Unet [7] and Pix2pix [5] architectures are utilized as the phase-extraction tools. The Unet is known as an image segmentation tool that has an encoder, a decoder, and skip connections. The Pix2pix is a kind of GAN [9] with a generator and discriminator which generates fake data and discriminates the fake and real data. The weights of each network are updated in an adversarial relationship. We use the Unet and a PatchGAN as the generator and discriminator, respectively.

After the optimal training is finished, the two real interferograms of a silicon wafer are input into the trained model for the verification. The outcomes are unwrapped, and the continuous phase maps can be obtained. The result phase maps are compared with those from the multi-frame conventional techniques and numerical analysis are performed. The phase maps from the proposed method show the better results in comparison and analysis than those by the conventional techniques.

3. Conclusions

In this research, the new method of measuring the surface shape of the silicon wafer based on deep learning is proposed. Only two-frame interferograms are necessary for the interferometric profiling of the wafer surface, unlike the multi-frame conventional techniques. The phase maps from the proposed method show the almost same or better results than those by the conventional techniques.

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