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Leveling Maintenance Mechanism by Using the Fabry-Perot Interferometer with Machine Learning Technology

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Abstract: This study proposes a method for maintaining parallelism of the optical cavity of a laser interferometer using machine learning. The Fabry-Perot interferometer is utilized as an experimental optical structure in this research due to its advantage of having a brief optical structure. The supervised machine learning method is used to train algorithms to accurately classify and predict the tilt angle of the plane mirror using labeled interference images. Based on the predicted results, stepper motors are fixed on a plane mirror that can automatically adjust the pitch and yaw angles. According to the experimental results, the average correction error and standard deviation in 17-grid classification experiment are 32.38 and 11.21 arcseconds, respectively. In 25-grid classification experiment, the average correction error and standard deviation are 19.44 and 7.86 arcseconds, respectively. The results show that this parallelism maintenance technology has essential for the semiconductor industry and precision positioning technology.

Keywords: Fabry-Perot interferometer; interference image; leveling maintenance; machine learning; optical measurement

1 INTRODUCTION

The precision machinery and semiconductor industries are critical to high-precision positioning technology, such as semiconductor production, μLED mass transfer, and wafer positioning processing, which demand extremely high positioning accuracy [1, 2]. As technology advances and human needs require smaller and more efficient products, positioning accuracy has increased from sub-micron to nanometer scale. Therefore, positioning technology is currently one of the most important and critical technologies in these industries [3, 4].

However, traditional requirements for straightness and parallelism are insufficient to meet the demand for higher-precision mechanical components. A better active leveling maintenance system is required to meet industry demands for parallel positioning correction.

This research focuses on the development of a leveling maintenance mechanism (LMM) system that uses machine learning in conjunction with Fabry-Perot interferometer. The system is designed with considerations for optical structure, machine learning control, and feedback to enhance current industry technologies for precision parallelism correction. Based on the interference image, this study utilizes machine learning for training, effectively avoiding the accuracy and sensitivity issues caused by traditional methods.

2 THEORY AND PRINCIPLE

To construct an active parallelism maintenance system using non-contact optical interference methods, we introduce the theory of the optical structure and the machine learning methods of LMM as follows.

2.1 Fabry-Perot Interferometer

The Fabry-Perot interferometer (FPI) is an optical instrument consisting of two parallel reflecting mirrors that form a resonant cavity, as shown in Fig. 1. When light reflects inside the cavity, a series of interference fringes is formed, which are related to the parallelism of the resonant cavity [5]. When the parallelism of the two mirrors is better, the contrast and clarity of the interference fringes will be higher. Therefore, by observing the variation of interference fringes, we can determine the parallelism of the resonant cavity [6].

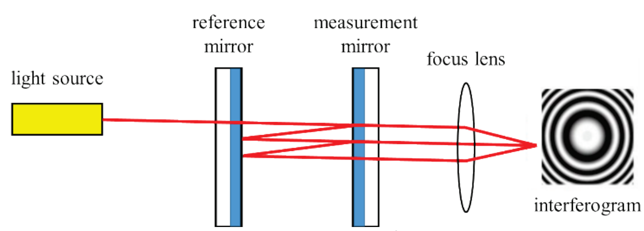

Figure 1 Fabry-Perot interferometer

The parallelism of the resonant cavity can be determined by calculating the angle of reflection mirror displacement from the number of interference fringes, as shown in Fig. 2. The relationship between fringes and angles is direct: the angle of displacement of the reflection mirror is proportional to the number of interference fringes. As the angle of displacement increases, so does the number of fringes, and vice versa. Eq. (1) illustrates the relationship between interference fringes and angles, based on optical principles.

$$2d \cdot \sin\theta = N \cdot \lambda \tag{1}$$

The letter d represents the distance between the resonant cavities, N is an integer representing the N^{th} dark fringe, and λ is the wavelength of the laser light, which is 632.8 nm. The distance between the resonant cavities is calculated as 6mm multiplied by the sine of the angle θ between the two mirrors. This formula can calculate that a displacement of 1 dark fringe corresponds to an angle θ of 0.003°, which is approximately 10.8 arcseconds. As the number of interference fringes is used as the basis for deviation, an error of approximately 10.8 arcseconds is associated with a deviation of ±1 interference fringe.

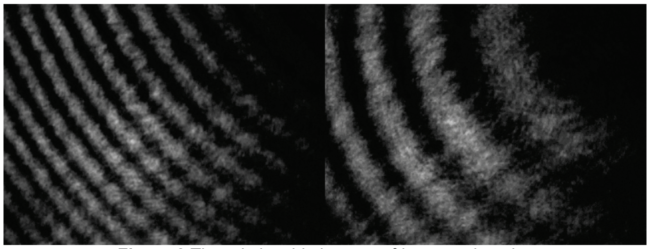

Figure 2 The relationship between fringes and angles

2.2 Machine Learning

Machine Learning is a process that uses algorithms to train data for prediction. Once a prediction model is obtained through Machine Learning, it can be used to predict new data based on the model [7, 8], as shown in Fig. 3. Machine Learning can be roughly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning, as shown in Fig. 4. Supervised learning involves training a model on labeled data, where the correct output is provided for each input. Unsupervised learning involves training a model on unlabeled data, where the goal is to discover hidden patterns or structures in the data [9]. Reinforcement learning involves training a model to make decisions in an environment by receiving feedback in the form of rewards or punishments [10].

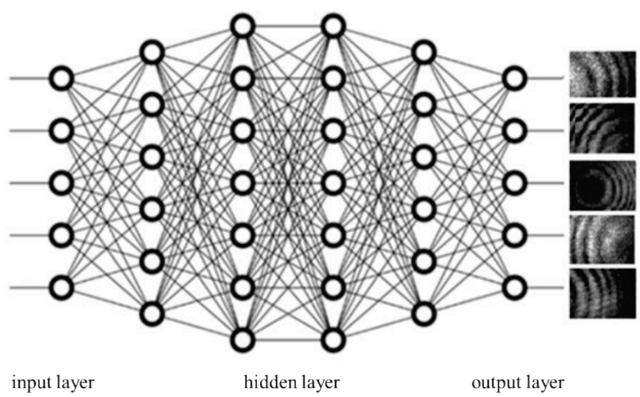

Figure 3 Machine learning algorithms

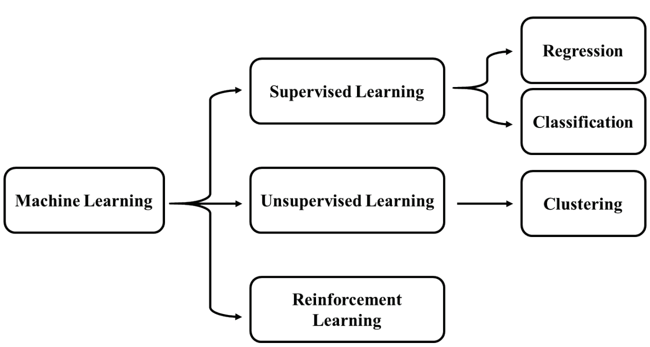

Figure 4 Machine learning categories

The experiment in this research used supervised learning, specifically classification. Supervised learning uses a training dataset to generate a model that can detect patterns and relationships between input data and output data. When new data is obtained, the model can produce accurate predictions results. In supervised learning, classification is a type of algorithm that accurately assigns test data to specific categories. It identifies specific data in a database and attempts to label or define that data to draw conclusions [11] [12]. Therefore, in this study, this method is applied to classify and train a predictive model for collected interference fringes. An interference fringe image database is established by categorizing the images into 17-grid and 25-grid categories, and machine learning is used to identify the current inclination position of the interference image, as depicted in Fig. 5 and Fig. 6.

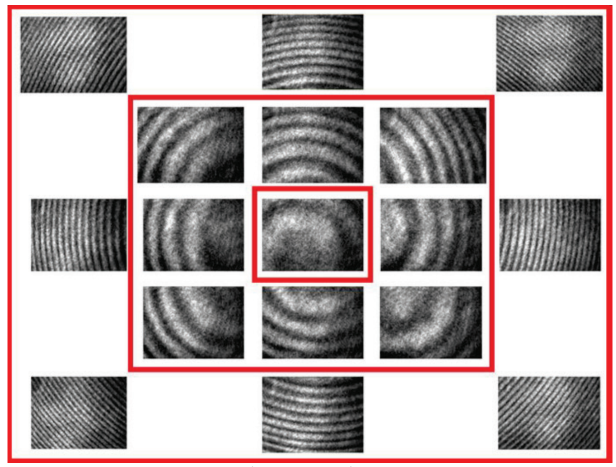

Figure 5 17-cell classification chart

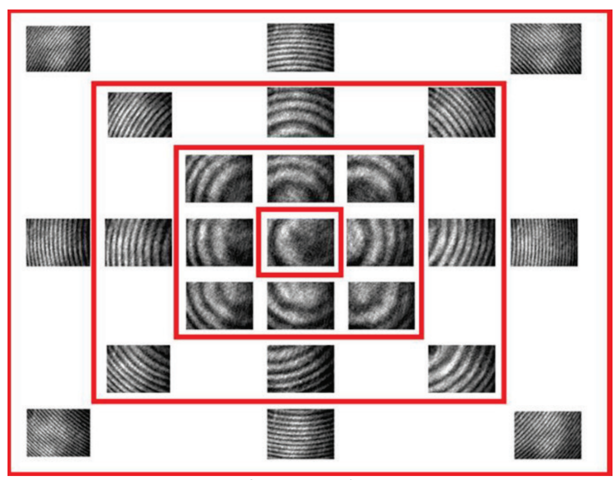

Figure 6 25-cell classification chart

The Inception v3 neural network architecture has been widely used in image recognition and computer vision tasks due to its exceptional performance in capturing complex patterns and features [13, 14]. In this study, we proposed a novel approach that utilizes Inception v3 for the automated detection of interference fringes in images captured by Fabry-Perot interferometers. Interference fringes are critical in various fields, including precision measurement and sensing, where the accurate detection of these patterns is essential for obtaining reliable data.

3 DESIGN OF PROPOSED LMM SYSTEM

The proposed LMM system is based on a Fabry-Perot interferometer, the optical structure of which is shown in Fig. 7. A laser light source that passes through a collimator, enters the beamsplitter, and then reaches the two main interferometer mirrors. The interference result is reflected back to the beamsplitter, and the interference result is obtained by the CCD.

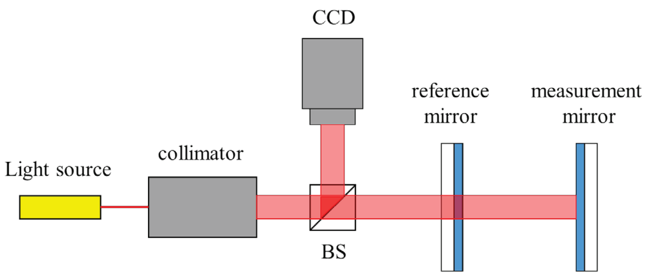

Figure 7 the structure of the LMM system

To automatically correct the parallelism of the resonant cavity, a stepper motor with adjustable angles was installed behind the measurement mirror in this study (as depicted in Fig. 8). Once the offset angle is determined, the motor can be controlled to adjust the pitch and yaw angles.

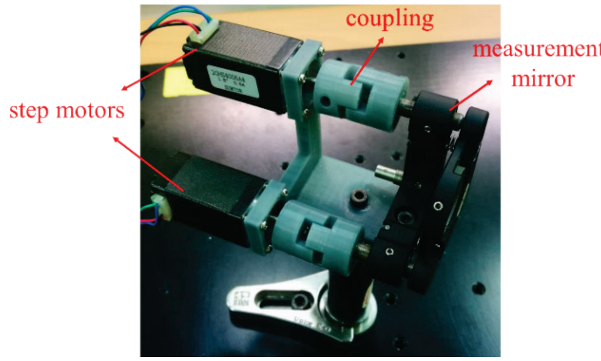

Figure 8 Parallelism adjustment mechanism

The experimental procedure of this study involves obtaining the current interference image and using a machine learning-based detection mechanism to identify whether the parallelism of the resonant cavity has shifted. After converting the recognition result into an angle, the angle can be adjusted by controlling the stepper motor. The interference image is then obtained again for confirmation. The experimental procedure is illustrated in Fig. 9.

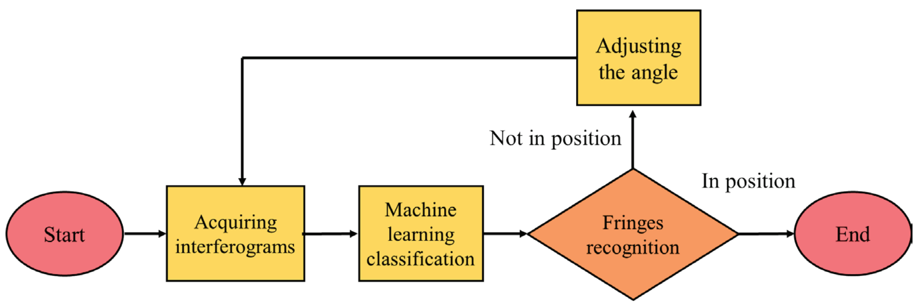

Figure 9 Flowchart of the experimental procedure

4 EXPERIMENT RESULT AND ANALYSIS

The experiments using 17-grid and 25-grid classifications were implemented in this research, as shown in Fig. 5 and Fig. 6. During the experiments, the resonance cavity angle was randomly adjusted, and the machine learning algorithm was used to predict the direction of the angle deviation. After the stepper motor was controlled to correct the angle deviation, the correction process was repeated until the predicted result was the center of the interference image.

The experiment results for the 17-grid classification are as follow. According to the experimental results, an average of three corrections could restore the parallelism of the resonator cavity, as shown in Fig. 10. The average parallelism error was ±32.38 arcseconds, as shown in Fig. 11, and the standard deviation of the error after correction was approximately ±11.21 arcseconds.

The experiment results for the 25-grid classification are shown as follow. On average, four corrections were sufficient to fix the parallelism of the resonator cavity based on the experimental results (Fig. 12). The average angle deviation was ±19.44 arcseconds (Fig. 13) and the standard deviation of the error after correction was around ±7.86 arcseconds.

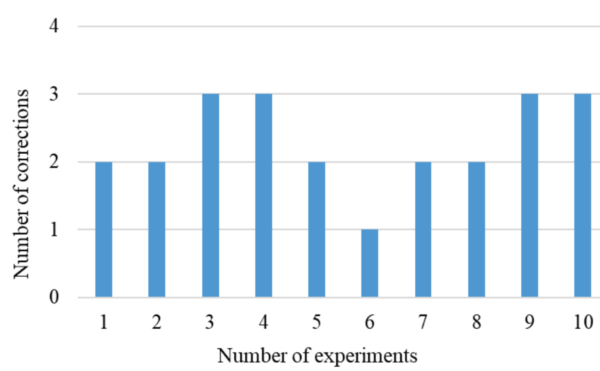

Figure 10 Number of corrections in 17-grid classification

Our proposed approach using Inception v3 and parallelism provides a powerful tool for accurate and efficient interference fringe detection in Fabry-Perot interferometers, with potential applications in precision measurement, sensing, and imaging. The combination of

Inception v3 and parallelism opens up new possibilities for enhancing the performance of interference fringe detection in various fields.

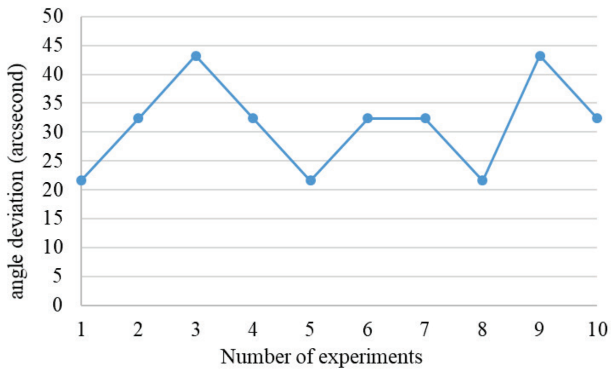

Figure 11 Angle deviation of 17-grid classification

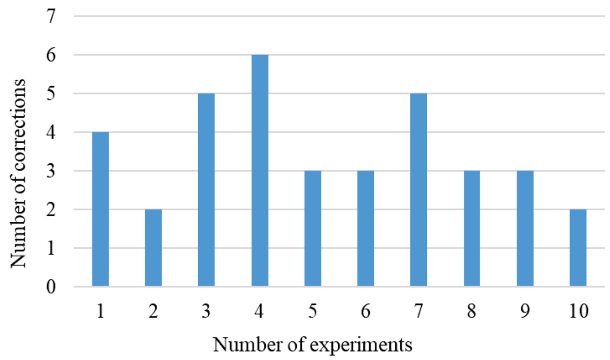

Figure 12 Number of corrections in 25-grid classification

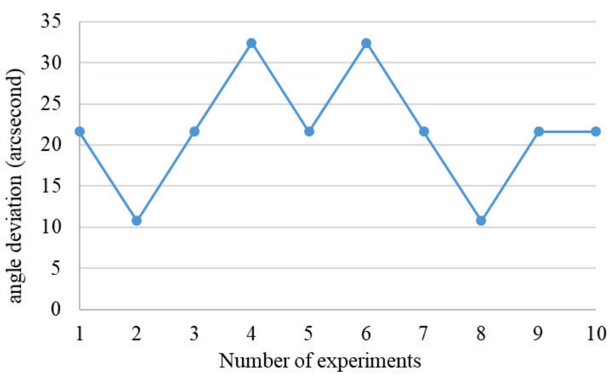

Figure 13 Angle deviation of 25-grid classification

5 CONCLUSION

This study applies machine learning to an interferometer system. According to the experimental results, the system has a resolution of 10.8 arcseconds. In the 17-grid classification experiment, the parallelism can be restored on average after three corrections, with an average correction error of 32.38 arcseconds and a standard deviation of approximately 11.21 arcseconds. In the 25-grid classification experiment, the parallelism can be restored on average after four corrections, with an average correction error of 19.44 arcseconds and a standard deviation of approximately 7.86 arcseconds.

Based on the latest research findings, it is evident that the proposed LMM system holds significant potential in enhancing precision machinery and semiconductor industries, effectively meeting their application requirements. Moving forward, further improvements will be made by integrating advanced imaging software and control systems, as well as expanding the data classifications to create a more comprehensive calibration system.

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