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A Gaussian process and image registration based stitching method for high dynamic range measurement of precision surfaces

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ABSTRACT

Optical instruments are widely used for precision surface measurement. However, the dynamic range of optical instruments, in terms of measurement area and resolution, is limited by the characteristics of the imaging and the detection systems. If a large area with a high resolution is required, multiple measurements need to be conducted and the resulting datasets needs to be stitched together. Traditional stitching methods use six degrees of freedom for the registration of the overlapped regions, which can result in high computational complexity. Moreover, measurement error increases with increasing measurement data. In this paper, a stitching method, based on a Gaussian process, image registration and edge intensity data fusion, is presented. Firstly, the stitched datasets are modelled by using a Gaussian process so as to determine the mean of each stitched tile. Secondly, the datasets are projected to a base plane. In this way, the three-dimensional datasets are transformed to two-dimensional (2D) images. The images are registered by using an (x, y) translation to simplify the complexity. By using a high precision linear stage that is integral to the measurement instrument, the rotational error becomes insignificant and the cumulative rotational error can be eliminated. The translational error can be compensated by the image registration process. The z direction registration is performed by a least-squares error algorithm and the (x, y, z) translational information is determined. Finally, the overlapped regions of the measurement datasets are fused together by the edge intensity data fusion method. As a result, a large measurement area with a high resolution is obtained. A simulated and an actual measurement with a coherence scanning interferometer have been conducted to verify the proposed method. The stitching result shows that the proposed method is technically feasible for large area surface measurement.

1. Introduction

In precision metrology, one challenge is the high dynamic range measurement of precision surfaces, which require both large measurement area and high resolution data [1]. This is especially true for the measurement of surfaces with multi-scale characteristic which have large scale topographic and small scale structure. Due to the limited field of view (FOV) and resolution of the camera, it is difficult to obtain a result with a satisfactory range in a single measurement which measures multi-scale information. One of the possible solutions is to perform multiple measurements and stitch the results together to form a dataset with a larger area to reveal the large topographic information without losing the high resolution information to characterize the micro-structure pattern [2].

Stitching has been reported for a sub-aperture stitching interferometer for both spherical and flat surface measurements [3–6]. Preibisch et al. [7] used a phase-correlation method to find the translation matrix between image pairs and performed global optimal stitching. Chen et al. [8] proposed a sub-aperture stitching and localization algorithm for spherical and planar surfaces. Moreover, they developed a coarse-to-fine stitching strategy. Zhang et al. [9] developed a simultaneous reverse optimizing reconstruction method which is based on system modelling technique for aspheric sub-aperture stitching interferometer. Ye et al. [10] used an optimal stitching planning method to measure large aspheric optical surface with ±4 mm range of probe and 20% of overlapped region. Wiegmann et al. [11] evaluated the accuracy of the sub-aperture stitching method using virtual experiments and found that the overall accuracy of stitching result outperformed the direct mea-

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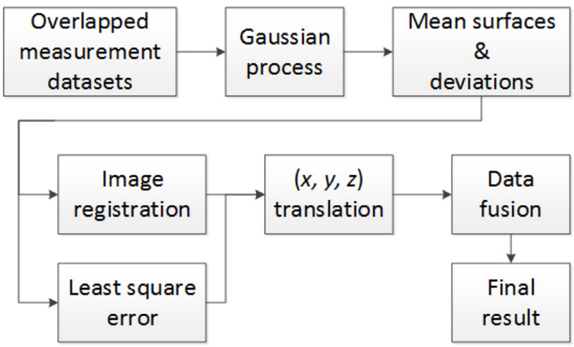

Fig. 1. Diagram of the Gaussian process based stitching method.

surement method by a factor of about 3. For surface measurement instruments such as coherence scanning interferometers, which are widely used today for precision surface measurement, some commercial products can provide a stitching function for relatively flat surfaces [12].

However, most of the stitching methods make use of six degrees of freedom for registration in the overlapped regions and the computational complexity is relatively large. For instance, the Iterative Closest Point (ICP) algorithm [13] has $O(N_pN_x)$ complexity for a single iteration. For a registration with N_t and N_q initial translations and rotations, the total complexity is $O(N_pN_xN_tN_q)$ which is considerably high. Moreover, the error caused by the stitching algorithm is accumulated when the number of sub-surface measurements is increasing, especially for the rotational error, which is difficult to compensate. Marinello et. al [14] pointed out that the translational error is biggest source of errors, while the Roll, Pitch and Yaw error can be as small as several arc-sec. With the help of high precision linear stages in which the rotational error can be considered to be minimal or negligible, registration can be simplified to a three degrees of freedom translation problem with the complexity reduced to $O(N_pN_xN_t)$.

In this paper, a stitching method based on Gaussian process and image registration together with an edge intensity data fusion is developed. The working principle of the method is discussed. A simulation and an actual measurement were conducted to verify the method. Some technical aspects are also discussed and the edge effect is improved as compared with the traditional method. The results of the experiments show that the proposed method is suitable for stitching of measurement results of areal measurement instruments, which provides a technically feasible solution for high dynamic range optical measurement for precision surfaces.

2. The principle of the Gaussian process and image registration based stitching method

The framework of the proposed Gaussian process and image registration based stitching method is shown in Fig. 1. First, the sub-aperture measurement datasets are modelled using a Gaussian process [15] so as to obtain the mean surfaces, which can reduce the registration error caused by measurement noise and outliers. The datasets are converted to two-dimensional images and the images are registered using an intensity based algorithm, which can determine the (x, y) translation parameters. The MATLAB Image Registration Toolbox [16] has been used to implement this algorithm. In this study, 20 % overlapped area for the measurement datasets is chosen for the best balance between efficiency and accuracy [17]. After the (x, y) translation is determined, the z axis translation is calculated by using a least-squares error method so as to minimize the z distance between the two mean surfaces. The next step is to calculate the data in the overlapped region with an edge intensity data fusion method. Finally, the datasets are stitched together to form a dataset combining all the (x, y, z) translation information and fused overlapped data.

2.1. Gaussian process modelling of original surfaces

Noise in the measurement processes and outliers in the result may affect the registration accuracy. Huang et al. [18] pointed out that both the standard deviation of the noise and the mean error of the noise have influence of the registration error. Traditional methods utilise filtering techniques to remove noise and outliers in the original measurement results. However, filtering is limited by distortion and edge effects [19]. The Gaussian process modelling involved in the proposed stitching method aims to improve the registration accuracy [20]. The original measurement results can be described as a discrete function of $z(x_i, y_i)$, which means the z-coordinate of the i-th point is a function of the lateral position (x_i, y_i). Let $\mathbf{v}_i = (x_i, y_i)$, so the measured datasets can be represented as $z(\mathbf{v}_i)$, $i = 1, 2, \ldots, N$, where N is the number of points. The measurement process can be considered as a Gaussian process which is a stochastic process, with underlying surface and measurement noise, which can be expressed as

$$z(\mathbf{v}_i) = f(\mathbf{v}_i) + \varepsilon \tag{1}$$

where $f(\mathbf{v}_i)$ is the underlying surface and ε is the measurement noise, which is assumed to have a Gaussian distribution $\varepsilon \sim N(0, \sigma_\varepsilon^2)$, with zero mean and σ_ε^2 variance.

In order to model the underlying surface, Gaussian process modelling is used in this study. A Gaussian process is a random process where the probability distribution function to the associated observation is normal and the joint probability distributions associated with any finite subset of the observations are also normal. A Gaussian process can be modelled as a mean function and a covariance function, which can be expressed as:

$$f(\mathbf{v}_i) = GP(m_z(\mathbf{v}_i), k_z(\mathbf{v}_i, \mathbf{v}_j)) \tag{2}$$

where $m_z(\mathbf{v}_i)$ is the mean function, $k_z(\mathbf{v}_i, \mathbf{v}_j)$ is the covariance function with $m_z(\mathbf{v}_i) = E[z(\mathbf{v}_i)]$ and $k_z(\mathbf{v}_i, \mathbf{v}_j) = E[(z(\mathbf{v}_i) - m_z(\mathbf{v}_i))(z(\mathbf{v}_j) - m_z(\mathbf{v}_j))]$. The mean function represents the expected z value at $\mathbf{v}_i$ while the covariance function represents the variance of the z value when $\mathbf{v}_i = \mathbf{v}_j$ and the covariance between the z values when $\mathbf{v}_i \neq \mathbf{v}_j$.

In this study, the mean function is designed to be zero function since the measured surface is unknown. Moreover, a squared exponential function is used to represent the covariance of the Gaussian process model:

$$k_z(\mathbf{v}_i, \mathbf{v}_j) = \sigma_z^2 \exp\left(-\frac{\|\mathbf{v}_i - \mathbf{v}_j\|^2}{2l^2}\right) \tag{3}$$

where $\|\mathbf{v}_i - \mathbf{v}_j\|$ is the distance between $\mathbf{v}_i$ and $\mathbf{v}_j$, σ_z^2 is the constant variance of the Gaussian process model and l is the characteristic length-scale.

The parameters of the covariance function corresponding to unit characteristic length-scale and unit signal standard deviation are first initiated to be zeros and the likelihood parameter was initiated to be log(0.1), which denotes the standard deviation of the noise to be 0.1 mm. The parameters of the Gaussian process was then optimized by minimizing the negative log marginal likelihood. After the parameters are optimized, the mean surface and the covariance surface of the measured data are fully determined. In this study, the implementation of the Gaussian process modelling is based on the Gaussian processes for machine learning (GPML) toolbox [21].

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