A STUDY OF EXTRAPOLATION OF FREEFORM SURFACES TO IMPROVE THE EDGE EFFECT IN SURFACE FILTERING

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ABSTRACT
Surface filtering is a hot research topic especially in the field of freeform surface metrology, since filtering is an important data processing technique before further characterization of the measured surfaces. There is a large number of surface filtering algorithms developed by researchers to improve the robustness and accuracy of the filtering results. However, the filtering result is still far from complete which is particularly true in the edge area where is always found to have large distortion. This is so-called the edge effect which is mainly caused by a lack of data when performing convolution in the edge area in the filtering algorithms. In this paper, a Gaussian process machine learning-based surface extrapolation method of the measurement data is presented to extend the measured surface before conducting surface filtering. A Gaussian process data modelling method is utilized for the surface extrapolation and hence a Gaussian filtering method is used for the surface filtering. A series of simulation and practical measurement experiments have been conducted to evaluate the performance of the proposed method. The accuracy and efficiency of the new filtering method are demonstrated and analyzed in the experiments. The results show that the edge effect can be significantly improved and the efficiency can also be improved by introducing the extrapolation method. The proposed method provides a new way for surface filtering and thus surface characterization for the complex freeform surfaces.

KEYWORDS: freeform surface, surface filtering, edge effect, extrapolation, precision metrology

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INSTRUCTIONS

Filtering is an important data processing technology in many domains such as time domain, frequency domain and spatial domain. Since almost every process and measurement introduce noise, and the noise mixes up in the final result, filtering is the most common method to separate the useful signal and the unwanted signal.

Characterization of precision surfaces usually requires separation of the surface form, waviness and roughness from the single dataset obtained from the measurement instruments and it requires a 3D surface filtering. This has been resulted in the development of international standards such as ASME B46.1 [1] and ISO 25178-2 [2]. One of the most commonly used filtering algorithm is Gaussian filter. Based on the Gaussian filter, many studies have been carried out to further enhance the performance of the original algorithm, such as Gaussian regression filtering [3] and robust Gaussian filtering [4], or improve the computational speed by using GPU technique [5]. However, it is well known that the filtering process introduces distortion in the result especially in the edge area since there is insufficient data in the edge area for the convolution process, which is the core function in the filtering process. This drawback greatly affects the performance of characterization of the precision surfaces.

To address this issue, this paper proposes a method to extrapolate additional data at the edge area, using the Gaussian process machine learning method. With the extrapolated data, the area of the new dataset is enlarged. Using the new data to perform the Gaussian filtering and hence removing the data in the enlarged area for the new filtering result, it can on one hand reduce the influence for the edge effect, and on the other hand utilize the implementation of the original Gaussian filtering algorithm to reduce the computational complexity. A simulation and an actual measurement experiment have been conducted to verify the effectiveness of the proposed method and the results show that it has significantly improved the filtering performance regarding the edge effect.

GAUSSIAN PROCESS MACHINE LEARNING - BASED EXTRAPOLATION AND FILTERING METHOD

The schematic diagram of the proposed Gaussian process machine learning – based extrapolation and filtering method is shown in FIG. 1. The original surface is first extrapolated using the Gaussian process machine learning method [6] and then enlarged with creditable data. Hence, the enlarged surface is filtered with the Gaussian filtering algorithm. The filtered surface has the same size with the enlarged surface. Lastly, the filtered surface is trimmed with the edge area removed and resize to the same size with the original surface. With the edge area removed, the influence of the edge effect is eliminated. In this study, the final result is compared with the one obtained by the Gaussian regression filter to demonstrate the improvement regarding the edge effect.

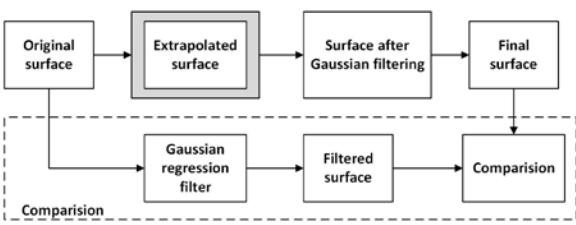

FIGURE 1. The schematic diagram of the proposed Gaussian process machine learning – based extrapolation and filtering method

The original measured surface can be determined by

$$z = f(x) + \varepsilon, \tag{1}$$

where z is the measurement result, $f(x)$ is the true value, with x representing the measured location, and ε is the measurement noise which can be determined by

$$\varepsilon \sim N(0, \sigma^2), \tag{2}$$

which means it Gaussian distributed with zero mean and variance σ^2

The true value of the surface $f(x)$ is unknown and the Gaussian process machine learning method is used for its estimation:

$$f(x) \sim GP(m(x), k(x, x')), \tag{3}$$

where $m(x)$ and $k(x, x')$ are the mean function at location x and covariance function at x and x'. Prediction of new data f_* at new location X_* can be determined by

$$\begin{bmatrix} z \\ \mathrm{f}_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X,X)+\sigma^2 I & K(X,X_*) \\ K(X_*,X) & K(X_*,X_*) \end{bmatrix}\right), \tag{4}$$

Yields

$$\mathrm{f}_* \mid X, z, X_* \sim N(\overline{\mathrm{f}}_*, \mathrm{cov}(\mathrm{f}_*)) \tag{5}$$

The new location can be outside the area of the original dataset, this is the implementation of the Gaussian process machine learning – based extrapolation.

Gaussian filtering for a 3D surface is the convolution of the surface using a weighting function which is the product of two Gaussian function:

$$S(x,y) = \frac{1}{\alpha^2 \lambda_{xc} \lambda_{yc}} \exp\left[-\left[\pi\left(\frac{x}{\alpha\lambda_{xc}}\right)^2 + \pi\left(\frac{y}{\alpha\lambda_{yc}}\right)^2\right]\right], \tag{6}$$

While the regression filter which is designed to improve the effect has the following weighting function:

$$S_{MOD}(kx, px, ky, py) = \frac{S(kx, px, ky, py)}{\sum_{ly=1}^{ny}\sum_{lx=1}^{nx} S(kx, px, ky, py)}, \tag{7}$$

where $S(kx, px, ky, py)$ is given by

$$S(kx, px, ky, py) = \frac{1}{\alpha^2 \lambda_{xc} \lambda_{yc}} \exp\left[-\left[\pi\left(\frac{px-kx}{\alpha\lambda_{xc}}\right)^2 + \pi\left(\frac{py-ky}{\alpha\lambda_{yc}}\right)^2\right]\right] \tag{8}$$

It is noted that the computational complexity of the Gaussian regression filter is much higher than that of the ordinary Gaussian filter. As a result, the proposed method incorporated with the ordinary Gaussian filter can improve the efficiency as well.

EXPERIMENTAL VERIFICATION OF THE PROPOSED METHOD

The proposed Gaussian process machine learning – based extrapolation and filtering method is verified via a simulation experiment and an actual measurement experiment.

Simulation

A sinusoidal surface is simulated as shown in FIG. 2 and it is determined by

$$\mathrm{z} = \sin\left(\frac{\pi}{10}x\right) + \cos\left(\frac{\pi}{10}y\right) + N_m \tag{9}$$

where N_m is the normal distributed measurement noise with zero mean and 0.1 mm standard deviation.

The extrapolated surface and the filtered surface with edge removed are shown in FIG. 3 and FIG. 4 while the error map compared with the design surface is shown in FIG. 5. The result shows that the error is evenly distributed without large distortion in the edge area. The RMS (root-mean-squared) of the error is 0.028 mm.

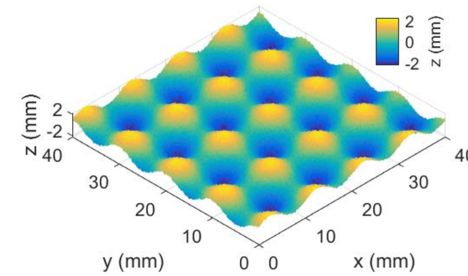

FIGURE 2. Simulated sinusoidal surface

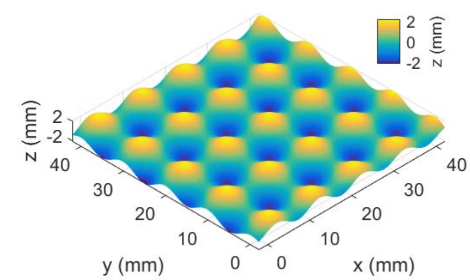

FIGURE 3. Extrapolated surface

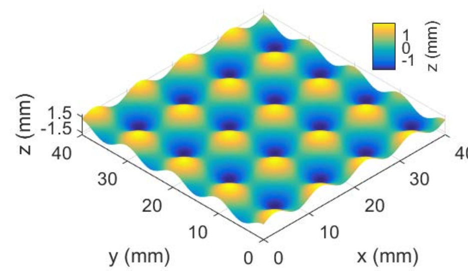

FIGURE 4. Filtered surface with edge removed

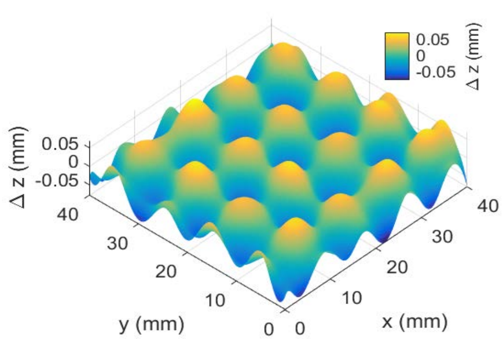

FIGURE 5. Error map compared with the design surface

The result is also compared with the one filtered with Gaussian regression filter. The result filtered with Gaussian regression filter and the error map are shown in FIG. 6 and FIG. 7. The edge effect is obvious and the RMS of the error map is 0.035 mm. It proves that the proposed method has better performance than the regression filter.

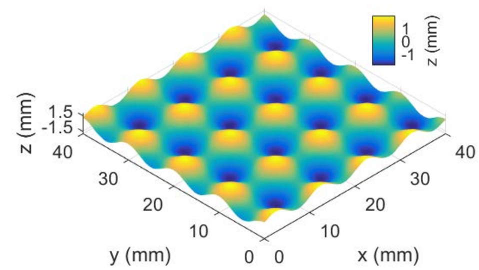

FIGURE 6. Surface filtered with Gaussian regression filter

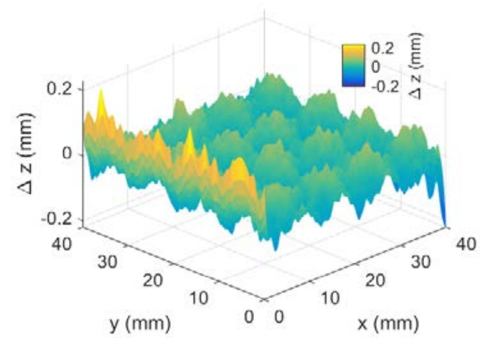

FIGURE 7. Error map compared with design surface

Actual measurement

In the actual measurement, since the underlying surface is unknown, the reference surface is obtained using below method: the original measured surface is first filtered using the ordinary Gaussian filter and the filtered surface is trimmed to a smaller surface as the reference surface. The removed data is the one within the edge effect area. Next, the original surface is also trimmed to be the same size with the reference surface and the trimmed surface is to replace the original surface. The new data is used in the data processing steps afterwards.

A diamond turned surface is used in this experiment and the surface is measured with a Zygo CSI (coherence scanning interferometer), the measurement result is shown in FIG. 8. The reference surface determined by the above method is shown in FIG. 9.

The result filtered with the Gaussian regression filter is shown in FIG. 10 and the deviation from the filtered result to the reference surface is shown in FIG. 11. The result shows a large deviation from the reference surface which is caused by the edge effect. The RMS value of the deviation map is 0.025 µm while the PV (Peak-To-Valley) value is 0.5 µm.

The result processed with the proposed method is shown in FIG. 12 and the deviation from the reference surface is shown in FIG. 13. The result shows that the deviation is much smaller. The RMS value of the deviation map is 0.003 µm while the PV (Peak-To-Valley) value is 0.06 µm, which demonstrates a large improvement comparing with the Gaussian regression filter.

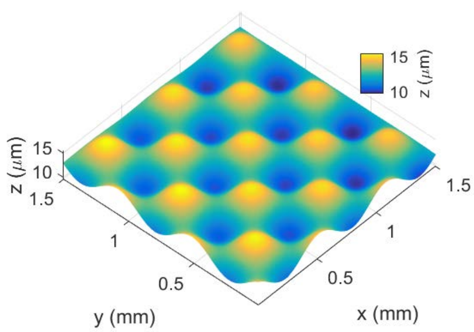

FIGURE 8. Original measured surface

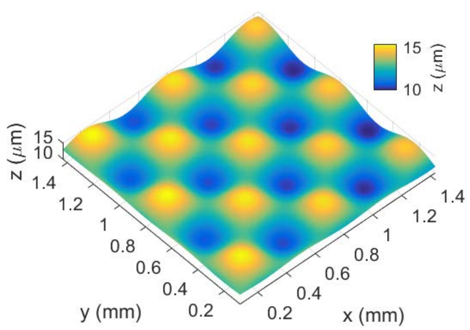

FIGURE 9. Reference surface

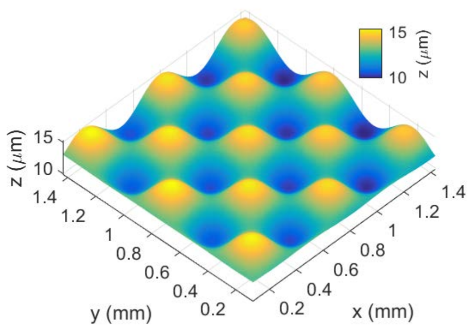

FIGURE 10. Result of Gaussian regression filter

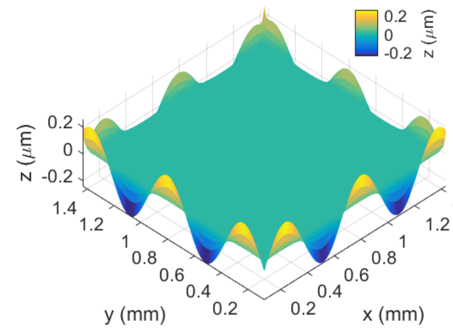

FIGURE 11. Deviation from the result of Gaussian regression filter to the reference surface

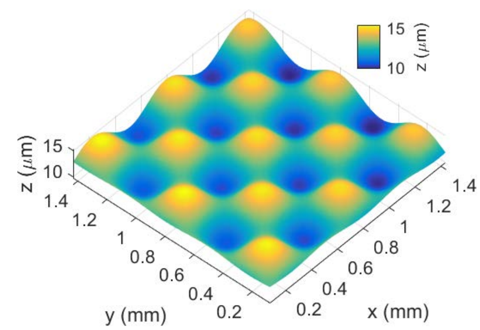

FIGURE 12. Result of the proposed method

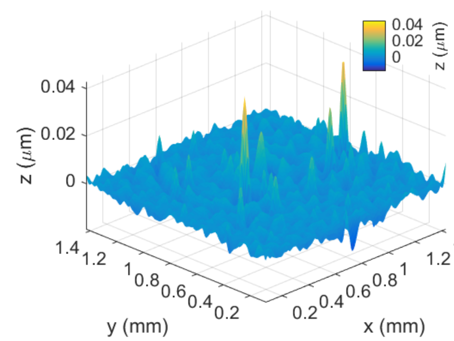

FIGURE 13. Deviation from the result of proposed method to the reference surface

CONCLUSION

This paper proposed a filtering method aimed to improve the edge effect which is commonly found in the field of surface filtering. It imposes the Gaussian process machine learning method to extrapolate the original measured surface and then implements the ordinary Gaussian filter to process the enlarged surface. The final surface is then cut to the same size of the original surface. With the help of the additional data, the edge effect is greatly improved. Simulation and actual measurement experiments show the effectiveness of the proposed method. Successfully implementation of this method helps to improve the accuracy of surface characterization.

ACKNOWLEDGMENT

The work was supported by a PhD studentship (project account code: RTHC) from The Hong Kong Polytechnic University.

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